DISSERTATION

ENVIRONMENTAL HEALTH RISKS, INEQUALITY AND WELFARE BEYOND GDP

Submitted by

Angela Cindy Emefa Mensah

Department of Economics

In partial fulfillment of the requirements

For the Degree of Doctor of Philosophy

Colorado State University

Fort Collins, Colorado

Fall 2023

Doctoral Committee:

Advisor: Edward B. Barbier

Stephan Weiler
Ray Miller
David W. McIvor

ABSTRACT

ENVIRONMENTAL HEALTH RISKS, INEQUALITY AND WELFARE BEYOND GDP

A seemingly overlooked impact on economic well-being and inequality is the mortality and morbidity attributed to the environment, such as air, soil and water pollution, ecosystem degradation, unsafe water and sanitation, temperature balance and other environmental quality changes. These environmental health risks are impacting welfare worldwide. The World Health Organization estimates that 24% of all global deaths are linked to environmental factors, or around 13.7 million mortalities per year (Prüss-Üstün et al. 2016). Air pollution accounts for 7 million of these deaths, and around 3 billion people face health risks from using polluting fuels such as solid fuels or kerosene for lighting, cooking and heating (WHO 2020). Particulate matter alone kills more than 4 million people each year, mainly in emerging market and developing economies (Nansai et al. 2021). Over half the world's population is exposed to unsafely managed water, inadequate sanitation and poor hygiene, resulting in more than 800,000 deaths annually (WHO 2020). These exposures reduce the average life expectancy and constrain human capital accumulation, thereby reducing the quantity of human capital per person and adversely impacting income distribution, especially among poor countries who already have low human capital. This dissertation examines two channels by which these environmentally health risks impact the economy.

The first chapter of this dissertation examines inequality convergence over the past three decades and asks if environmental health risks (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 of the environment.

The second chapter of this dissertation examines the impact of environmental health risk on welfare through its impact on average life expectancy. Employing the Global Burden of Disease (GBD) dataset of environmentally related mortality and morbidity across 163 countries over 1990-2019, we modify the consumption-equivalent macroeconomic welfare measure developed by Jones and Klenow (2016) to include these risks. We use the GBD estimates of environmentally related morbidity as a lower bound estimate of these risks to adapt the expected lifetime component of the Jones-Klenow welfare measure for each country relative to the United States. Similarly, we use the GBD's estimates of environmentally related disability adjusted life years (DALYs) as an upper-bound estimate of adjusting life expectancy for environmental health risks. Our results suggest that, across all 163 countries over 1990-2019, including environmental health risks in welfare is significant when compared to income (GDP) per capita or to welfare that excludes these risks. While welfare in advanced economies is considerably high and closer to the United States, emerging market and developing economies who suffer the most from environmentally related mortality and morbidity diverge substantially from the United States. This divergence in welfare is especially prominent among low and lower middle-income countries, who are disproportionately affected by environmental health risks.

The findings of the first two chapters reaffirm the need to aggressively target and successfully implement the Paris Agreement, Agenda 2030 and its linked Sustainable Development goals. For example, achieving the target on green energy transition, not only promote energy efficiency but will also significantly cut down the number of mortality and health risks associated with polluting solid fuel and kerosene usage in developing countries. Similarly, the target on improving access to clean water and sanitation, when achieved, will improve welfare and reduce, if not eliminate, the about 827,000 deaths associated with unclean water and poor sanitation each year (see WHO

2020). Thus, the strategies for improving welfare, which is the focus of my research, are very much tied to the successful implementation of the Sustainable Development Goals.

The third chapter analyzes the impact of crowding and ecosystem externalities flowing from the industrial fishery sector to the artisanal fishery sector. Both externalities are the results of illegal trawling of small pelagic stock (which is the legal target stock of artisanal fishery) as by-catch by the industrial fishery sector. To explore this issue, we develop a two-sector bioeconomic model with empirical application for the case of fishery in Ghana. We demonstrate that both externalities impact the productivity and profitability of the artisanal fishery. Our empirical results show that, between 1986 and 2013, by-catch ranges from 18% - 95% of total artisanal catch except for some extreme outliers. We also found that industrial fishing effort has being increasing since 2007 but with less than a proportionate increase in legal annual catch, when compared to previous years. This seems to have coincided with significant increases in by-catch. The conjectured is that the extra increases in industrial fishing effort may have been moved toward illegal trawling of by-catch. This may explain why effort is increasing with less than a proportionate increase in industrial fishery's annual landings. We estimated the optimal tax rate to be approximately 11%. However, given the data challenges, we believe that the true optimal tax rate lies between 100% and 10%. Consequently, when the optimal tax rate is applied, the amount of by-catch chosen by the industry fishery in the decentralized equilibrium is identical to the amount chosen by the government. We conclude that if the government's priority is to increase the productivity of the artisanal fishery, then the current level of by-catch should be reduced through monitoring and effective tax structures.

ACKNOWLEDGEMENTS

I would first like to express my deepest gratitude to my advisor and mentor, Prof. Edward Barbier, for his guidance and support since I got into the first year of the PhD program and throughout the writing of my dissertation. His encouragement, has been and continues to be an invaluable part of my research and academic successes. He changed my life.

Many thanks to Dr. Stephan Weiler for his enthusiasm and invaluable feedback during the early stages of my research. I would like to acknowledge the great contributions of Dr. Ray Miller to my research. His inputs and feedback on the empirical strategy of my models greatly helped shape the focus of my research. Thanks to Dr. David W. Mclvor for his input and feedback throughout the writing of this dissertation. I would also like to acknowledge Dr. Sammy Zahran and Dr. Guy Numa for their advice and encouragement.

I also want to acknowledge that the first chapter of this dissertation is funded by the United Nations University World Institute for Development Economics Research as part of the UNU-WIDER project on Income Inequality. It is published as a UNU-WIDER working paper and it is available at (https://doi.org/10.35188/UNU-WIDER/2022/244-7).

And finally to God almighty and my Lord and Savior Jesus Christ, for walking beside me through thick and thin. I never could have made it without you, I would have lost it all.

DEDICATION

This dissertation is dedicated to my loving mother, Peace Adamah and my Godparents Betty and Vince Scheetz.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Chapter 1

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

1.1 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 causing living standards to converge standards (Bénabou 1996). Countries that evolve towards 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 than countries starting with low inequality.[1]

Current evidence supports a tendency towards inequality convergence, while at the same time demonstrating that inequality within countries has worsened considerably (Pande and Enevoldsen 2021; Ravallion 2003, 2018). 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: 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.

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

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 factor is 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, 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 would 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 underestimate the speed of convergence. Our aim here is further explore 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 of 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 such deaths each year, mainly in emerging market and developing economies (Nansai et al. 2021).[2]

In all, the WHO estimates that 13.7 million deaths, representing 24% 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

[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. 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 (World Bank n.d.).

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 they therefore tend to grow faster. Under this assumption, a poor country tends to grow faster than a richer country through accumulating more human capital than 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. The effect of EIH may not be homogeneous within a country, but because it lowers the income of those who are disproportionately impacted, it influences the distribution of income and lowers the average income of the entire population (ie. per capita income). Clark (2011) finds evidence in support of this argument that negative health outcomes (infant mortality) depress 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 influences 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 over time. In other words, environmental impacts on health 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 over time, leading to faster inequality convergence. These possibilities have important implications for growth and inequality reduction in developing countries, which 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 a high initial level of inequality (see Banerjee and Duflo 2003; Bénabou 1996; Chen and Ravallion 2001; Milanovic et al. 2011; Ravallion 1997, 2001, 2012). However, Ravallion (2003) found very little effect of initial inequality on the rate of inequality reduction. This raises the question of whether the slow speed of inequality convergence is due directly to the effect of EIH. Alternatively, do environmental impacts on health 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 that of 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) (UNU-WIDER 2021) and employing the autoregressive technique, we find evidence of cross-country inequality convergence over the period 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 (GBD) dataset available on the Global Health Data Exchange (GHDx) (GHDx 2019). 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, environmentally related impacts of health offset the impact of growth in per capita income on inequality reduction, regardless of the measure of inequality adopted. Thus, the hypothesis that environmentally related impacts of health 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 over time—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 EIH. Section 3 provides the theoretical framework that links the incidence of EIH to inequality through the Lorenz curve. Section 4 provides the data and descriptive statistics, while Section 5 details the empirical strategy and results. Section 6 concludes.

1.2 Patterns of inequality and EIH

We begin by examining the key trends and patterns of inequality and 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 environmental impacts on health in emerging market and developing countries remain substantially higher than those found in advanced economies.

1.2.1 Inequality convergence

Figure 1.1 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 1.1 indicate the fitted regressions lines for each income group of countries: low, lower middle, upper 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]

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 high-income group of 47 countries, which has 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.

[3]To smooth the graph in Figure 1.1, we drop seven outliers: Azerbaijan, Bulgaria, Romania, Latvia, São Tomé and Príncipe, Luxembourg, and Uzbekistan.

[4]The estimates of the slope and t-score of the regression lines in Figure 1.1 are obtained by regressing the log Gini index in 1990 on the annualized growth in inequality. Standard errors are robust to heteroscedasticity (White test). The range of annualized reduction in inequality in each of the income groups is obtained from the summary statistic at the group level.

In sum, while income inequality has been falling globally, the proportionate rate of decline is slower among lower-middle-income countries compared with 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 stagnant 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.

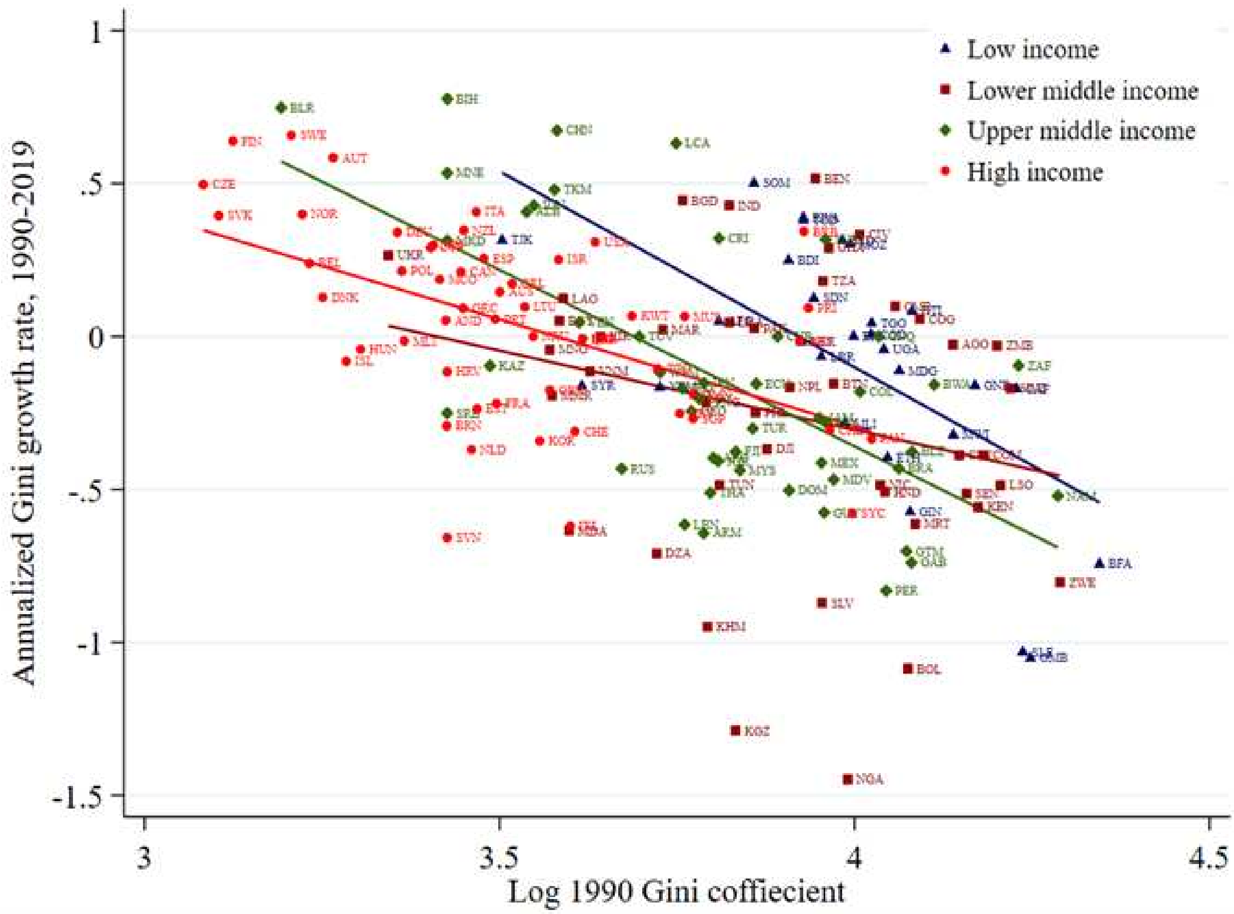


Figure 1.1: Inequality convergence—growth in inequality plotted against initial inequality.

1.2.2 Global Gini index and EIH

Figure 1.2 compares the trends from 1990 to 2019 in the global Gini index and EIH as measured by environmentally related 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% reduction (see Figure 1.2). Over this period, world environmentally related deaths fell by just 8%: from about 12 million to 11 million (see Appendix Figure A.1).[5] At the same time, we observe a significant shrinking of the tail of the kernel distribution of environmentally related DALYs in 2019, compared with the elongated and flatter distribution in 1990 (see Appendix Figure A.2).

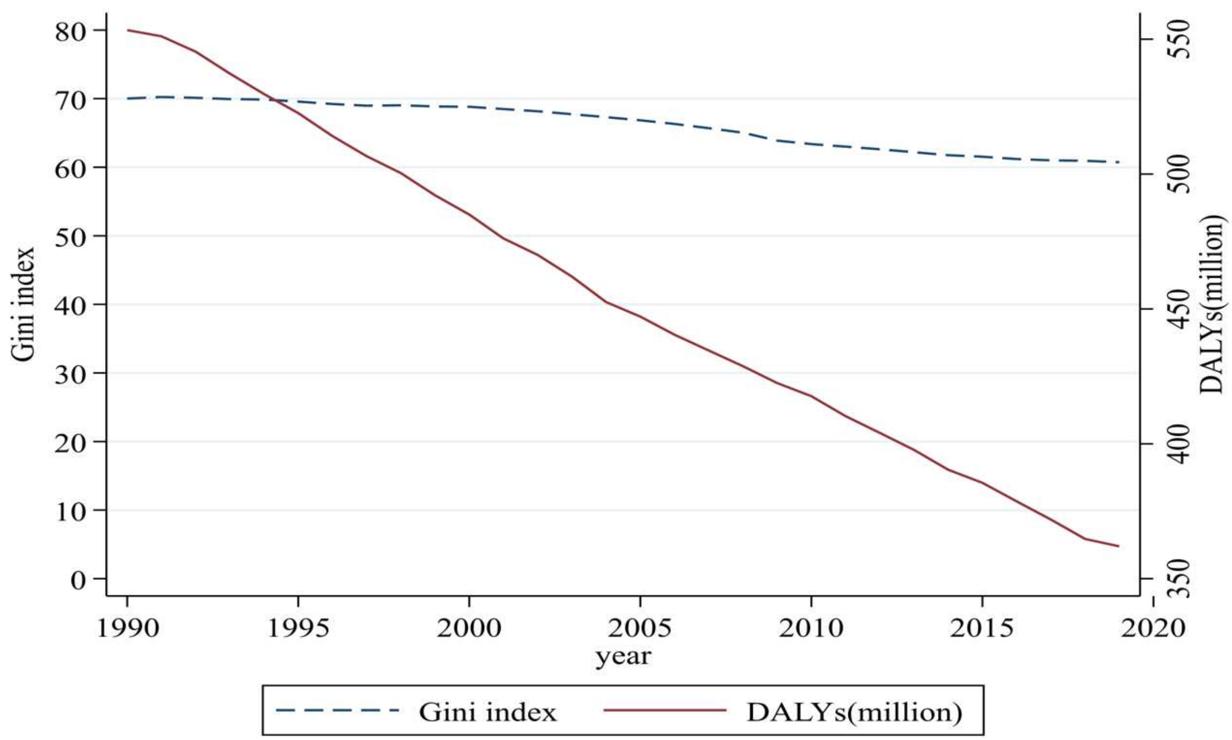


Figure 1.2: World Gini coefficient and environmentally related DALYs.

[5]The actual numbers of total environmentally related DALYs and total environmentally related deaths could be larger than those shown in Figure 1.2 and Figure 1.3 and Appendix Figure A.2, 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) and other environmental risks associated with residential radon and lead exposure.

1.2.3 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 1.3 shows, environmentally related DALYs are substantially higher in low- and middle-income countries than in advanced economies. However, the slopes of the curves suggest that lower-middle-income countries are reducing environmentally related DALYs much faster than high-income countries.

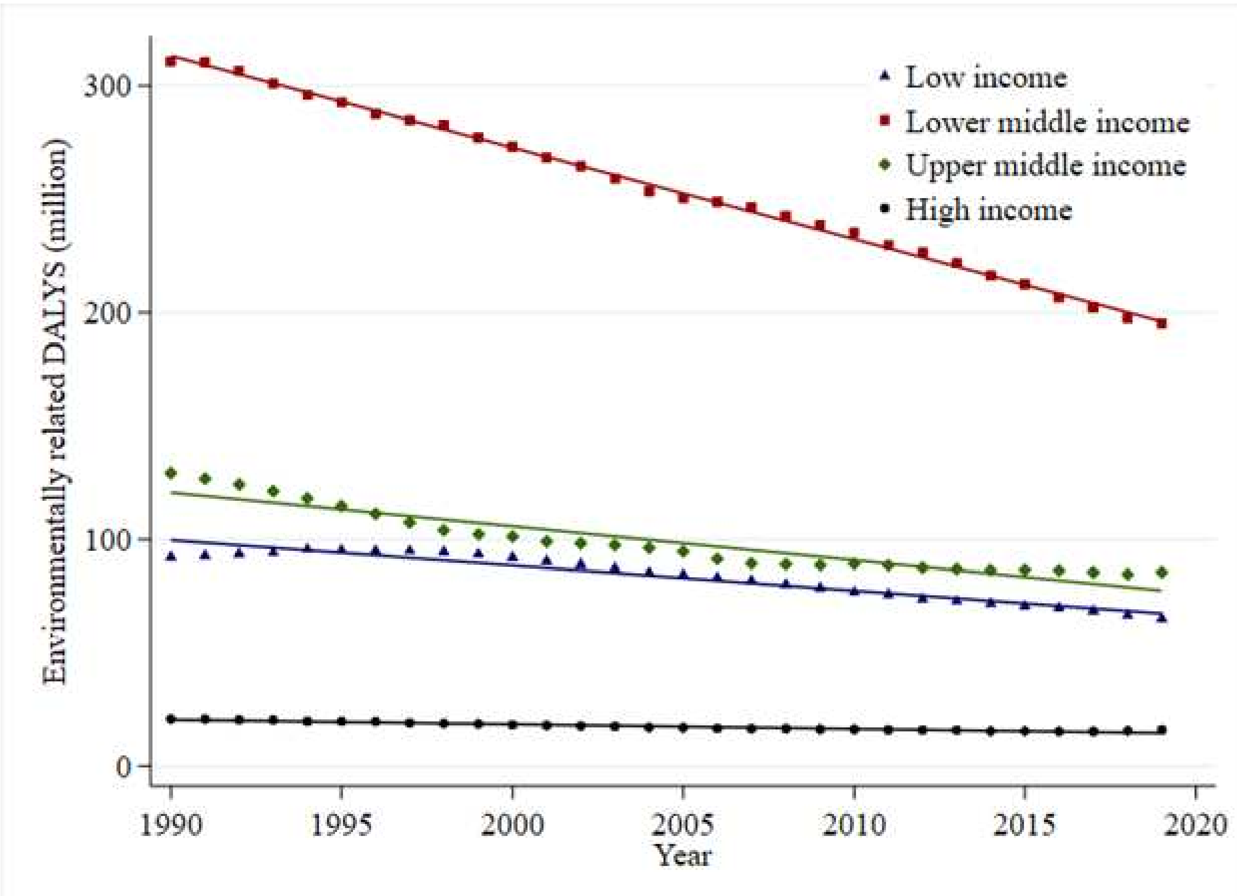


Figure 1.3: Environmentally related DALYs by income groups.

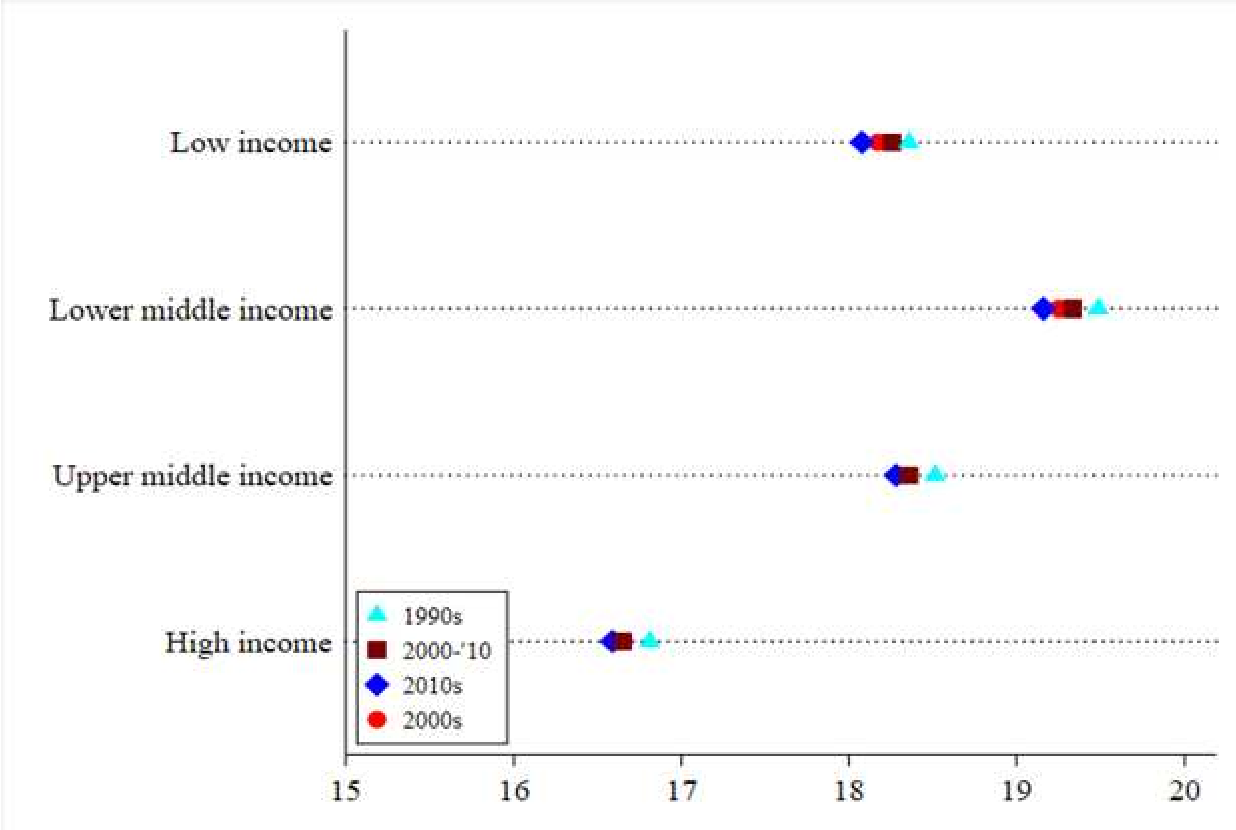


Figure 1.4: Decadal average of log of environmentally related DALYs by income groups.

Figure 1.4 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 with 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 GHDx 2019).[6]

[6]Values plotted in Figure 1.3 and Figure 1.4 are the total estimated sum of all environmentally related mortality and morbidity for each of the income groups as of 2019 (see GHDx 2019).

1.2.4 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 1.5 shows that these developing countries are reducing the level of EIH faster than advanced countries. Thus, the evidence in Figure 1.5 could be loosely described as 'convergence in EIH'.

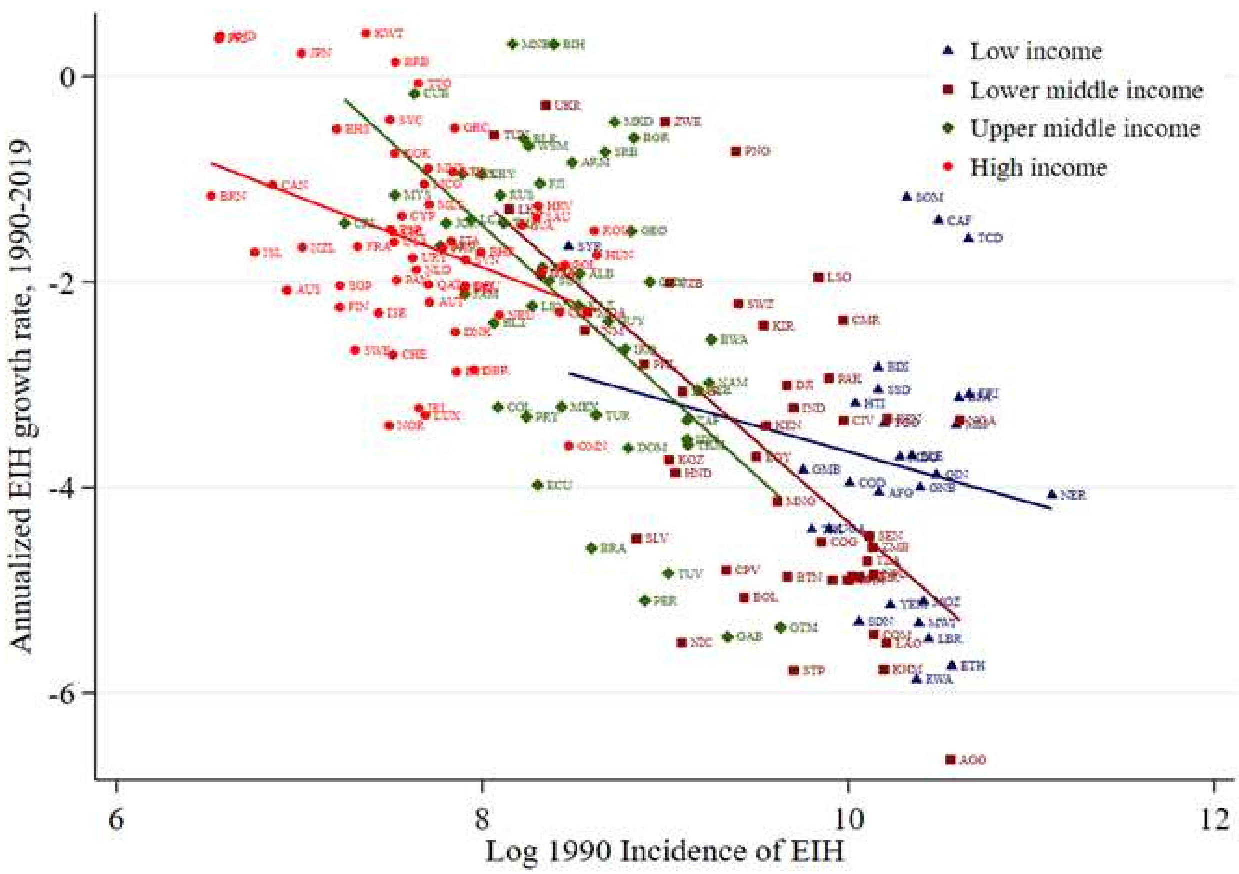


Figure 1.5: Growth in incidence of EIH plotted against initial levels of EIH

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, the

[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.

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% 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 GHDX 2019). Such a reduction in EIH 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.

1.3 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 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 homogeneous 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 $\mu = \int_0^\infty y dF(y) = \int_0^\infty y f(y) dy$ is defined as:

$$L(p) = \frac{1}{\mu}\int_0^p F^{-1}(t)dt, \quad L_p = \frac{\partial L}{\partial p} = \frac{y(p,\sigma)}{\mu} > 0, \quad L_{pp} > 0, \quad 0 \leq p \leq 0 \tag{1.1}$$

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:

$$g = L_p^{-1}\frac{z(\sigma)}{\mu}, \quad \frac{\partial g}{\partial \sigma} > 0 \tag{1.2}$$

Equation 1.2 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 leads 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 empirically test these hypotheses include measures of inequality, mean income, and incidence of EIH.

1.4 Data and descriptive statistics

We construct a measure of EIH for 179 countries spanning 1990 to 2019 from the GBD dataset, (GHDx 2019). The incidence of EIH (σ) is the proportion of the population exposed to environmentally related 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 account 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 the 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]

While the Gini index is less sensitive to the two extremes of the income distribution, MLD is particularly sensitive to the bottom 40% of the distribution, GE(-1) shows 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 coun-

[8] GE represents generalized entropy. The generalized entropy indices are used to measure inequality within groups of the population. For example, the GE(1) index assess how much any given income distribution is far from the perfect uniform distribution while weighting each observation by its share of the total income. However, in the case of GE(-1), the inequality factor for weighting within the groups is their respective share of the population. Ordinarily, GE(0) is equivalent to mean-log deviation (MLD), which is a relative inequality measure like the Gini index in that both depend on the ratio of incomes to the mean (Gradín 2021).

tries compared with the sample average (see Table 1.1). The statistics of the GE(-1) show that inequality is much higher in low-and lower-middle-income countries than the levels revealed by the Gini index. Thus, depending on the distributive sensitivities under focus, the conclusions about the weight of inequality decline shown in Figure 1.2 may be 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.

Table 1.1: 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 A.3 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 %.

The mean income (μ) is captured by per capita GDP constant in 2017 US dollars. The data on inequality variables and per capita GDP are obtained from the most recent version of the UNU-WIDER WIID dataset (UNU-WIDER 2021). This could be described 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 1950–2019. This allows us to test our hypothesis over a broader range of inequality indices.

1.5 Empirical strategy and results

As summarized in Durlauf et al. (2005), there are many different econometric specifications for measuring convergence empirically. 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 cross-sectional ordinary least square (OLS) estimations over intervals of ten 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 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. There is a significant conceptual difference between our hypothesis and that of Ravallion (2012). Ravallion (2012) specifies a regression indicating that the change in poverty over time could be influenced 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.

1.5.1 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 literature is that changes in inequality over time will be influenced by the level of initial inequality, which is commonly expressed as:

$$\gamma(g_{it}) = \lambda_0 + \lambda_1 \ln(g_{it-\tau}) + \epsilon_{it} \tag{1.3}$$

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 Equation 1.3 is:

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

which is the annualized change in the log of inequality index and thus represents the growth in inequality, and depending on the sign could also be called the rate of inequality reduction. A negative $\gamma(g_{it})$ implies that the inequality index for the current year is lower than that of the previous year, and the reverse is true for positive values. As such, increases in $\gamma(g_{it})$ are 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 Equation 1.3 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 want to examine the effect of initial incidence of EIH on the convergence parameter, λ_1, which is formally expressed in Equation 1.2 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 Equation 3 to include initial incidence of EIH as follows:

$$\gamma(g_{it}) = \lambda_0 + \lambda_1 \ln(g_{it-\tau}) + \lambda_2 \ln(\sigma_{it-\tau}) + \epsilon_{it} \tag{1.4}$$

Equation 1.4 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 $\lambda_2 > 0$, 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 Equations 1.3 and 1.4 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 of Equations 1.3 and 1.4 using the OLS estimator are summarized in Table 1.2. 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, 2000–19, and 2000–10.

In all five 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 are revised upwards 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 with the earlier studies. While Ravallion (2003) and Bénabou (1996) use the Deininger and Squire (1996) 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 with the earlier studies. In addition, our analysis covers a much later period, from 1990 to 2019.

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 1.2). The associated elasticity is positive and ranges from 0.1 to 0.16, suggesting that a 10% reduction in the initial incidence of EIH would improve the change in Gini index by 1.0 to 1.6%. 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 1.2, when initial EIH incidence is included with initial inequality, in all regressions, λ_1 is more negative and significant at the 1% level.[9]

Table 1.2: Estimates of the effects of initial inequality and incidence of EIH on inequality reduction

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; heteroscedasticity-consistent robust standard errors (White) in parentheses; † significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

[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, it did not significantly improve the coefficient on our variable of interest, $\ln(\sigma_{it-\tau})$. For example, when we estimate Equation 1.4 and include the income share of the bottom 40% as a control, λ_1 increases from the -1.06 reported in column 2 of Table 1.2 to -2.71 with a t-score of -20.84 but λ_2 falls from 0.1 to 0.009 and is statistically insignificant even at the 10% level. λ_2 does 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, statistically significant at the 5% level. This should be expected, since the annualized Gini growth rate that 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 cancels 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.

Finally, we 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 Table A.1). 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 the weak instrument problem. Thus, the OLS estimates are preferred because the convergence parameter estimates are unbiased, consistent, and low enough to generate convergence towards medium inequality.

In conclusion, our estimations of Equations 1.3 and 1.4 suggest that, over 1990 to 2019, there is 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. The incidence of EIH and Gini index complement each other, in that a high initial incidence of EIH implies that the component of income inequality attributable to EIH is 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. 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.

1.5.2 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 than 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 Equation 1.4 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:

$$\gamma(g_{it}) = \lambda_0 + \lambda_1 \ln(g_{it-\tau}) + \lambda_2 \ln(\sigma_{it-\tau}) + (\beta_0 + \beta_1 \sigma_{it-\tau})\gamma(\mu_{it}) + \lambda_3 Z_{it} + \epsilon_{it} \tag{1.5}$$

where $\gamma(\mu_{it}) = \ln\left(\frac{\mu_{it}}{\mu_{it-\tau}}\right)/\tau$ is the annualized change in the log of mean income and thus represent the growth in per capita income, Z_{it} is vector of control variables.In addition to testing for the null hypothesis $\beta_0 + \beta_1 = 0$, 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 has an indirect influence through 'adjusting' the growth elasticity of inequality reduction. As such the inequality-reducing impact of income growth in Equation 1.5 can be specified as $(1 - \sigma_{it-\tau})\gamma(\mu_{it})$.[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 0 (1) at a sufficiently high (low) incidence of EIH.

Table 1.3 depicts the various regressions of Equation 5 for 179 countries over various periods from 1990 to 2019. As before, we can reject the null hypothesis that $\lambda_1 = \lambda_2 = 0$ at the 1% or 5% significance 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 2000–19. These results indicate that income growth does not influence changes in inequality at the 5% significance 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.

The regressions also indicate that we can accept the homogeneity restriction $\beta_0 + \beta_1 = 0$ in all of the samples except for 2000–19. The corresponding β coefficients from the restricted model reported in columns 2,4,6, and 10 in Table 1.3, are not statistically significant at the 5% level even

[10] In the case that $\lambda_1 = \lambda_2 = \lambda_3 = 0$ and $\beta_0 = 0$ both hold, the regression in Equation 1.5 further resolves to $\gamma(g_{it}) = \lambda_0 + (\beta_0 + \beta_1 \sigma_{it-\tau})\gamma(\mu_{it}) + \epsilon_{it}$, $\beta_0 = 0$. The inclusion of control variables to estimate λ_3 does not significantly improve our variable of interest, $\ln(\sigma_{it-\tau})$. As in Table Table 1.2 , the inclusion of the income share of the bottom 40% as a control significantly improves 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 falls from 0.1 to 0.02 and is statistically insignificant even at the 10% level. λ_2 does not improve when we include GDP per capita and GE(-1). Meanwhile, the coefficients on the income share of the bottom 40% (i.e. -1.82) and annualized income growth rate (0.03) are both statistically significant at the 5% level.

when we include control variables. However, at the 10% significant level we find a positive growth elasticity of inequality reduction conditional on initial incidence of EIH.

Table 1.3: 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† [0.384]	-0.13† [0.047]	4.18† [0.475]	-0.08 [0.058]	6.77† [0.884]	0.18** [0.082]	2.29† [0.540]	-0.13** [0.057]	3.62† [0.763]	-0.10 [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 does not improve with the inclusion of control variables such as GDP per capita, income share of the bottom 40%, and other inequality indices such as GE(-1) and GE(0); heteroscedasticity-consistent robust standard errors (White) in parentheses; † significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Unlike the positive poverty-reducing impact of growth found in Ravallion (2012), we find 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. The impact of growth on the rate of inequality reduction is insignificant in most periods, and in the case of the one exception (2000-2019), the estimated impact is close to zero. This latter result is consistent with Ravallion (2014), who posits that there may be a trade-off between reducing inequality and reducing poverty. Thus, the observed higher growth has not reduced inequality within countries but rather that decreasing global inequality is due to falling inequality between countries (Ravallion 2014).

We also estimate Equations 1.4 and 1.5 over 1990–2019 for the four major income groups: low-income, lower middle-income, upper middle-income, and high-income countries. Table 1.4 depicts the results. Like the cross-country estimates for the full sample reported in Tables 1.2 and 1.3, 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 percent in high-income countries.

However, the estimates of the effects of the initial incidence of EIH on changes in inequality over time for the subsamples of income groups differ significantly from those for the full sample in Tables 1.2 and 1.3. 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 on changes in inequality over 1990–2019, but also it interacts with per capita growth to have a negative and significant impact 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.

Table 1.4: 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†	3.39**	4.97†	-0.10	2.50**	1.31	-0.73	-0.3**	4.62†	4.73†	5.45†	-0.30†	3.46†	3.14†	3.47†	0.21**
	[1.652]	[1.265]	[1.388]	[0.073]	[0.942]	[1.268]	[1.406]	[0.116]	[1.341]	[1.246]	[1.427]	[0.104]	[0.721]	[0.884]	[1.210]	[0.085]
Log of Gini index, initial year 1990, $\ln(g_{it-\tau})$	-1.28†	-1.55†	-1.66†		-0.69†	-0.91†	-1.25†		-1.26†	-1.25†	-1.22†		-0.96†	-0.94†	-0.82†	
	[0.414]	[0.404]	[0.432]		[0.240]	[0.251]	[0.279]		[0.343]	[0.381]	[0.411]		[0.202]	[0.187]	[0.207]	
Log incidence of EIH, initial year 1990, $\ln(\sigma_{it-\tau})$		0.27*	0.15			0.21	0.57†			-0.02	-0.12			0.03	-0.06	
		[0.132]	[0.124]			[0.133]	[0.143]			[0.147]	[0.187]			[0.097]	[0.162]	
Growth rate, annualized change in log mean income of the two periods, $\gamma(\mu_{it})$			0.16†				0.21**				0.03				-0.11	
			[0.048]				[0.082]				[0.044]				[0.113]	
Growth rate interacted with incidence of EIH in 1990, $\gamma(\mu_{it})\sigma_{it-\tau}$			-0.0**				-0.00†				0.00				0.00	
			[0.000]				[0.000]				[0.000]				[0.000]	
EIH-adjusted growth rate $\gamma(\mu_{it})(1-\sigma_{it-\tau})$				0.02				0.06				0.08*				-0.06
				[0.035]				[0.039]				[0.040]				[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	55	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; dependent variable is the annualized change in the log Gini index; 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 Figure ?? for list of countries for which EIH is available; heteroscedasticity-consistent robust standard errors (White) in parentheses; † significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Regarding income growth, we find no evidence of a relationship between inequality reduction and income growth in high and upper middle-income countries, but we find two opposing forces in low and lower middle-income countries: income growth as a standalone variable worsens the rate of inequality reduction, but when interacted with initial incidence of EIH, the rate of inequality reduction improves. For example, a 10% increase in income growth worsens the rate of inequality reduction by 1.6% among low income countries and 2.1% among lower middle-income countries And when interacted with initial incidence of EIH, a very small reduction in inequality is observed. Though negligible, this indirect effect of income growth suggests a feedback loop between incidence of EIH and income growth in a manner that improves the rate of inequality reduction. In the case of low-income countries, the initial incidence of EIH interacts with growth to impact changes in inequality only over 1990–2019. Also, 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 columns 4 and 8 respectively in Table 1.4 are not statistically significant at the 5% level even when we include control variables. As a result, 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.

As a robustness check, we regroup the low- and lower-middle-income countries as one sample and high- and upper-middle-income countries as a second sample; this does not change the results significantly (see Appendix Table A.2). 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 a few points' standard deviation from the average of the coefficient estimate from Table 1.4. For example, the convergence parameter in Table 1.4 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 A.2), approximately 0.23 deviations from the combined mean of -0.99.

1.6 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 Table 1.2 - 1.4, we next ask: at the current 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 35.3 over the period 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 our estimations of equations 1.3 and 1.4 and assumes that for a selected group of developing countries, their respective initial inequalities are represented by the average over 1990–2019. Table **??** shows the estimated number of years required by each country to converge to 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 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 our estimations of equations 1.3 and 1.4, the 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 to the benchmark inequality.

We see a trend between the percentage reduction in EIH and the number of years required to converge. On average, countries with the lowest reduction in EIH require a higher-than-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%, has the highest number of years to converge to the benchmark inequality. Lower-middle-income countries may require more than a century to reach the benchmark inequality index of 35.3, despite their strong economic performance in recent years (see Johnson and Papageorgiou 2020).

Table 1.5: Number of years required by selected lower-middle-income countries to converge to benchmark average Gini index of high-income countries (35.3)

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) is based on the average Gini index of individual countries (g_t) and the average Gini index of 56 high-income countries (g_T) over the entire period of 1990–2019 and the annualized rate of inequality reduction (r); using the compound growth expression $g_T = g_t(1+r)^n$ and solving for n as $n = \frac{(\ln g_T - \ln g_t)}{\ln(1+|r|)}$; r is the predicted values of $\gamma(g_{it})$ from Equations 3 and 4 respectively; countries with positive annualized rate of inequality reduction were dropped.

1.7 Robustness check

To check the robustness of our estimations that use 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 the bottom 40% of the population, GE(-1) shows 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 important light on the findings of this paper.

We find that inequality indices (i.e. MLD or GE(0) and GE(-1)) that place more emphasis on the bottom of the income distribution are more sensitive to the effects of EIH. The direct effect of incidence of EIH on change in inequality is more profound in GE(-1) models than in the Gini index models (compare Table 1.2 or 1.3 and 1.6). The associated elasticity is positive, ranging from 0.4 to 0.9 compared with corresponding estimates from the Gini mode that range from 0.1 to 0.16. This implies that while a 100% increase in the incidence of EIH would worsen the change in Gini index by 10 to 16%, the change in GE(-1) index worsens by 40 to 90%. This result exposes the dangers of EIH in widening the inequality gap between the bottom and the top of the income distribution as well as corroborating the narrative that the income of the bottom of the global distribution has remain fairly stagnant in recent decades (see Gradín 2021). Likewise, the estimated convergence parameters from the GE1 (-1) models, ranging from 1.1 to 3.2%, are much higher than corresponding estimates obtained in the Gini model (i.e. 0.5 to 2%). The GE(1) models have the lowest convergence parameters.

In summary, the regressions in Table 1.6, 1.7, and 1.8 consistently corroborate the estimates in Table 1.2 and 1.3 and point to evidence of cross-country inequality convergence. As before, the convergence parameter is generally higher when we include incidence of EIH and we find 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 1.6: 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† [0.698]	1.2 [1.288]	0.4 [1.540]	7.2† [0.993]	4.4† [1.472]	3.3* [1.887]	11.7† [1.836]	8.9† [2.624]	9.3† [3.007]	4.0† [1.162]	-1.6 [1.691]	-1.2 [2.058]	6.0† [1.934]	0.3 [2.326]	0.9 [2.714]
Log of GE (-1) index, initial year 1990, $\ln(g_{it-\tau})$	-1.3† [0.185]	-1.6† [0.215]	-1.6† [0.210]	-1.8† [0.256]	-2.1† [0.296]	-2.0† [0.290]	-2.9† [0.486]	-3.1† [0.543]	-3.2† [0.562]						
Log of GE (-1) index, initial year 2000, $\ln(g_{it-\tau})$										-1.1† [0.307]	-1.6† [0.340]	-1.7† [0.338]	-1.6† [0.482]	-2.1† [0.563]	-2.1† [0.558]
Log incidence of EIH, initial year 1990, $\ln(\sigma_{it-\tau})$		0.6† [0.182]	0.6† [0.209]		0.4** [0.199]	0.5** [0.236]		0.4 [0.325]	0.4 [0.391]						
Log incidence of EIH, initial year 2000, $\ln(\sigma_{it-\tau})$											0.9† [0.251]	0.9† [0.307]		0.9† [0.347]	0.9** [0.435]
Growth rate, annualized change in log mean income of the two periods, $\gamma(\mu_{it})$			0.2 [0.140]			0.2 [0.166]			-0.0 [0.142]			-0.2 [0.165]			-0.1 [0.248]
Growth rate interacted with incidence of EIH in 1990, $\gamma(\mu_{it})\sigma_{it-\tau}$			-0.0 [0.000]			-0.0 [0.000]			0.0 [0.000]						
Growth rate interacted with incidence of EIH in 2000, $\gamma(\mu_{it})\sigma_{it-\tau}$												0.0 [0.000]			0.0 [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)); estimates are for 179 countries for which EIH is available; heteroscedasticity-consistent robust standard errors (White) in parentheses; † significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 1.7: 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† [0.432]	1.9† [0.586]	1.7** [0.683]	4.9† [0.558]	3.5† [0.699]	3.1† [0.858]	7.5† [1.007]	6.2† [1.273]	6.6† [1.421]	2.1† [0.641]	0.4 [0.749]	1.0 [0.871]	3.5† [0.975]	1.4 [1.035]	2.2* [1.235]
Log of GE (0) index, initial year 1990, $\ln(g_{it-\tau})$	-1.0† [0.121]	-1.3† [0.151]	-1.2† [0.148]	-1.4† [0.155]	-1.6† [0.191]	-1.6† [0.190]	-2.1† [0.280]	-2.3† [0.325]	-2.3† [0.334]						
Log of GE (0) index, initial year 2000, $\ln(g_{it-\tau})$										-0.7† [0.182]	-1.0† [0.224]	-1.1† [0.211]	-1.1† [0.272]	-1.5† [0.335]	-1.7† [0.316]
Log incidence of EIH, initial year 1990, $\ln(\sigma_{it-\tau})$		0.3† [0.089]	0.3† [0.101]		0.3** [0.102]	0.3** [0.120]		0.2 [0.161]	0.2 [0.185]						
Log incidence of EIH, initial year 2000, $\ln(\sigma_{it-\tau})$											0.3† [0.114]	0.3† [0.126]		0.4† [0.154]	0.4** [0.180]
Growth rate, annualized change in log mean income of the two periods, $\gamma(\mu_{it})$			0.1 [0.061]			0.1 [0.070]			-0.0 [0.067]			-0.2* [0.091]			-0.2 [0.149]
in Growth rate interacted with incidence of EIH in 1990, $\gamma(\mu_{it})\sigma_{it-\tau}$			-0.0 [0.000]			-0.0 [0.000]			0.0 [0.000]						
Growth rate interacted with incidence of EIH in 2000, $\gamma(\mu_{it})\sigma_{it-\tau}$												0.0 [0.000]			0.0 [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 generalized entropy family index (GE(0)); estimates are for 179 countries for which EIH is available; heteroscedasticity-consistent robust standard errors (White) in parentheses; † significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 1.8: 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)); estimates are for 179 countries for which EIH is available; heteroscedasticity-consistent robust standard errors (White) in parentheses; † significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

1.8 Conclusion

The incidence of environmentally related impacts on health matter to the story of inequality reduction and convergence. We find strong evidence in support of inequality convergence across countries and within income groups. Importantly, we found that although 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.

Lack of evidence in support of the hypothesis that the initial incidence of EIH reduces the inequality-reducing impact of income growth. Higher rates of income growth, per se, do 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) and (2018), who finds that higher growth rate has not improved inequality within countries but rather observes that 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 economies, leading to high inequality within those countries.

Our results hold some important policy implications. Clearly, low and middle-income countries cannot expect to reduce inequality while maintaining high levels of EIH. If they choose inequality reduction as a priority, they must implement policy instruments that will reduce the level of EIH and alleviate the conditions of the vulnerable population who 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).

Chapter 2

Environmental Health Risks, Welfare and GDP

2.1 Introduction

Recent attempts to move "beyond GDP" to a broader economic measure of social welfare have encompassed a variety of approaches that seek either to "correct" GDP or to replace it with an alternative indicator (Fleurbaey 2009; Fleurbaey and Blanchet 2013; Jorgenson 2018; Stiglitz et al. 2010). However, a seemingly overlooked impact on economic well-being is the health risks attributed to the environment, such as air, soil and water pollution, ecosystem degradation, unsafe water and sanitation, and other environmental quality changes. These environmental health risks are significantly affecting welfare worldwide.

For example, the World Health Organization estimates that 24% of all global deaths are linked to environmental factors, or around 13.7 million mortalities per year (Prüss-Üstün et al. 2016). Air pollution accounts for 7 million of these deaths, and around 3 billion people face health risks from using polluting fuels such as solid fuels or kerosene for lighting, cooking and heating (WHO 2020a). Particulate matter alone kills more than 4 million people each year, mainly in emerging market and developing economies (Nansai et al. 2021).[11] Over half the world's population is exposed to unsafely managed water, inadequate sanitation and poor hygiene, resulting in more than 800,000 deaths annually (WHO 2020a).

The aim of this paper is to provide a measure of economic well-being that incorporates the effects of environmental health risks using macroeconomic and health data from 163 countries spanning the period of 1990 to 2019. Our approach modifies the consumption-equivalent welfare measure for use with macroeconomic data developed by Jones and Klenow (2016), who express

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

the expected lifetime utility of a representative individual of a country as a function of average life expectancy, the consumption share of GDP, leisure and income inequality, all relative to the United States. We then use our measure of welfare conditioned on environmental health risks to compare to a measure of welfare without such impacts and to GDP per capita and growth over 1990-2019 for all 163 countries.

Our lower-bound estimate of environmental health risks extends the expected lifetime component of the Jones-Klenow macroeconomic welfare measure to allow for the potential impacts of environmentally related morbidity at current year t for each country relative to the United States. Typically, the average life expectancy derived for a country is the average number of years a newborn is expected to live if the pattern of mortality at birth remains the same throughout its life (Ortiz-Ospina 2017). Although life expectancy at birth aims to project how long an individual born in the current year t is expected to live, this estimation is based on past patterns and trends of mortality in the population from previous years up to year t that are assumed to remain the same throughout the individual's life. Thus, an estimate of life expectancy does not correct for the number of years potentially lost in year t due to any increases in morbidity experienced by the average individual caused by pollution, ecosystem degradation, unsafe water and sanitation, and other environmental quality changes. Adjusting life expectancy for the latter factors is therefore similar to the health-adjusted life expectancy (HALE) approach, which modifies average life expectancy for a variety of health effects that may occur from birth in year t, such as disabilities, disease status and self-perceived health (Jagger et al. 2014; Molla et al. 2003; Stiefel et al. 2010). In a similar way, because environmental quality impacts the quality of life and thus welfare of the representative individual in country i, the factor that adjusts consumption to make welfare equivalent between country i and the United States must also change. Thus, the welfare impact of the change in environmental quality can be measured by the change in the percentage difference in environmental health-adjusted life expectancy weighted by how much a year of life is worth.

However, adjusting life expectancy in current year t just for environmentally related morbidity may underestimate the environmental health risks faced by the average individual of a country.

One problem especially for emerging market and developing countries is lack of access to formal health services resulting in treatment delays or nonreporting of illnesses related to environmentally related diseases and other health impacts, which can lead to underestimation of both environmentally related morbidity and mortality (Peter et al.2008). In addition, if countries or regions are experiencing rising or new sources of pollution, ecosystem degradation, unsafe water and sanitation, climatic impacts and other adverse environmental quality changes, then average life expectancy for at year t will also fail to account for the years lost due to premature death from such increases in environmentally related mortality. Consequently, as an upper-bound estimate of adjusting life expectancy for environmental health risks, we modify the expected lifetime component of the Jones-Klenow macroeconomic welfare measure for the potential impacts of both environmentally related morbidity and mortality in year t for each country relative to the United States.

Our method of incorporating environmental health risks in welfare to allow comparisons across countries and time is consistent with Hall et al. (2020), which as far as we are aware is the only other study that modifies the welfare measure by Jones and Klenow (2016) to allow for such risks. Hall et al. (2020) develop a framework to analyze the maximum amount of consumption, in a welfare context, that would be foregone to avoid the deaths associated with the COVID-19 pandemic. This equivalent-variation calculation of the fraction of consumption that society is willing to give up is the sum of the expected number of deaths from the pandemic, weighted by the value of life as a share of consumption. Similar to our approach, to make this calculation the authors must adjust average remaining life expectancy in years for the risk of mortality from the pandemic, as the fraction of consumption society is willing to forego is the value of an additional year of life multiplied by the expected number of life years that the average individual might lose due to the pandemic.

Our study also contributes to a growing literature in economics that aims and compares aggregate environmental health impacts on welfare across different countries and over time. For example, the approach we develop here is compatible with "macro-environment" approaches in environmental economics, in which a representative agent's willingness to pay (indirect utility) is influenced by changes in the relative prices of market goods and environmental quality (Smith and Zhao 2020). It also accords with recent efforts to adjust the value of statistical life across countries to account for varying risk of mortality from the COVID-19 pandemic (Viscusi 2021) and climate change (Carleton et al. 2021). Our approach is also relevant to other economic measures that seek to estimate the relative consequences of mortality and disease risk, such as comparing the expected number of years of life lost versus the additional years spent in poverty due to the pandemic (Decerf et al. 2021). Similarly, Miller and Bairoliya (2021) develop a welfare framework that builds on Jones and Klenow (2016) to show how expected utility based on quality-adjusted life years reveals that the impacts of poor health combined with the cost of living substantially increases the overall inequality among the elderly in the United States.

To apply our approach, we use the Global Burden of Disease (GBD) dataset of environmentally related mortality and morbidity across 163 countries over 1990-2019, available from the Global Health Data Exchange (http://ghdx.healthdata.org/gbd-results-tool).For our lower-bound measure of environmental health risks, we use the GBD estimates for the number of years of healthy life lost due to disability (YLDs) attributable to the environment to determine the probability that a random individual in year t will lose some life years due to environmentally induced morbidity. Our upper-bound estimate of environmental health risks is based on disability-adjusted life years (DALYs), which combines both YLDs and years of life lost due to premature mortality due to health factors (WHO 2020b). We translate the GBD estimates of disability adjusted life years (DALYs) attributable to the environment into the probability that a random individual in year t will lose some life years due to environmentally induced mortality and morbidity. The probabilities from YLDs and DALYs, respectively, are used to adjust life expectancy to correct for the number of life years lost or actual number of persons lost due to environmental causes by the representative individual in year t. The resulting environmental health-adjusted life expectancy allows us to estimate welfare impacts of countries relative to the United States. For the remaining macroeconomic data required for our welfare estimates, we follow Jones and Klenow (2016) and use publicly available multi-country datasets, such as Penn World Table 10.0, UNU-WIDER World Income Inequality Database and World Bank's World Development Indicators.

Our results suggest that, across all 163 countries over 1990-2019, countries with higher environmental health risks per capita experienced the largest declines in welfare relative to the United States. This outcome is especially significant among emerging market and developing countries, who are disproportionately affected by environmental health risks and have much lower risk-adjusted welfare relative to the US. Although across all 163 countries over 1990-2019, welfare adjusted for environmental health risks and income (GDP) per capita is highly correlated, we also find stark differences between rich and poor countries in whether GDP per capita serves as a good proxy for risk-adjusted welfare. For low-income economies, welfare adjusted for environmental health risks is only 24% to 39% of GDP per capita, for lower middle-income countries the ratio is 44% to 55%, for upper middle-income countries 73% to 79% and for advanced economies 89% to 90% of GDP per capita.

Consequently, our findings indicate that there are considerable welfare differences between rich and poor economies once environmental health risks are taken into account. After adjusting for these risks, advanced economies appear to be converging to the mean welfare per capita of the United States, whereas emerging market and developing economies continue to diverge further away from the US. The 25 economies with the highest welfare after adjusting for environmental health risks are high-income countries, predominantly members of the Organization for Economic Cooperation and Development (OECD), whereas the 30 economies with lowest welfare are low and lower middle-income countries.

The rest of the chapter proceeds as follow. Section 2.2 provides the theoretical underpinning of how we modify the consumption-equivalent welfare measure developed by Jones and Klenow (2016) to allow for environmental health risks. Section 2.3 then explains the macroeconomic and health data sources as well as the methods we use to construct our welfare measure and apply it to our sample of 163 countries from 1990 to 2019. We present the main results in section 2.4 and discuss their implications. Section 2.5 concludes and offers policy and further research insights.

2.2 Theory

A key innovation of Jones and Klenow (2016) is the development of a theoretical framework for relative comparisons of the expected lifetime utility of an individual that includes measures of inequality of consumption and leisure and the incorporation of lifetime income (Jorgenson 2018). Here, we show how their consumption-equivalent welfare measure for use with macroeconomic data (equation (7) in Jones and Klenow (2016)) can be modified to compute welfare in a large sample of countries relative to the United Sates while considering how environmental health risks impact the life expectancy component of this measure of welfare.

Let $\{j, a, i, d\}$ denotes individual j of age $a \in \{1, \ldots, 100\}$ in country i who is at risk of losing some life years due to environmental health risk d. Assume all individuals living in country i have sufficiently similar preferences so that they can be represented by a single individual's expression for expected lifetime utility. If C_{ai} denotes the random individual's annual consumption at age a and l_{ai} denotes leisure plus time spent in home production, then expected lifetime utility for the individual is

$$U_i = \mathbb{E} \sum_{a=1}^{100} \beta^a u(C_{ai}, l_{ai}) S_i(a) \gamma_i(d) \tag{2.1}$$

where $S_i(a)$ is the probability an individual in country i survives to age a, the expectations operator $\mathbb{E}$ applies to the uncertainty that an individual at age a may have with respect to consumption and leisure β^a is the age-specific value parameter that converts utility into a money-metric (i.e., income-equivalent) measure and $\gamma_i(d)$ is the probability that an individual in country i will not lose any life years due to environmental health risks as measured by some variable d.

However, standards of living and life expectancy vary substantially across countries. Thus, for comparison of the welfare of individuals living in different countries, a random individual's expected lifetime utility in country i can be represented as

$$U_i(\lambda_i) = \mathbb{E} \sum_{a=1}^{100} \beta^a u(C_{ai}, l_{ai}) S_i(a) \gamma_i(d) \tag{2.2}$$

where $U_i(\lambda_i)$ denotes expected lifetime utility in country i if consumption is multiplied by a factor λ_i

The benchmark country is the United States, which has one of the highest standards of living and life expectancy in the world. Thus, the factor λ_i that must adjust the consumption of a random individual to make the individual indifferent between living in the United States and some country i is

$$U_{us}(\lambda) = U_i(1) \tag{2.3}$$

Following Jones and Klenow (2016), assume that the flow of utility for a random individual of age a in country i is

$$u(\lambda C_{ai}, l_{ai}) = \bar{u} + \log C_{ai} + v(l_{ai}) \tag{2.4}$$

where $v(l_{ai})$ captures the utility from leisure and home production (domestic labor hours) and $\bar{u}$ is the intercept of the flow of utility (the part of an individual's utility that is independent of income or hours worked, e.g. consumption of social amenities, security etc.).

Suppose that consumption in each country is log-normally distributed across individuals at a point in time, independent of age and mortality, with mean and a variance of log consumption of $\sigma_i^2/2$. Then $[\log C_{ai}] = \log c_i - \sigma_i^2/2$. In the special case adopted by Jones and Klenow (2016), let $\beta^a = 1$ which implies that the income-equivalent value attached to the utility of individuals of different ages is the same. They also make the corollary assumption of a constant growth of consumption, leisure, mortality and morbidity at each age. We additionally assume a common incidence of environmental risk at each age. Based on these assumptions, we can re-specify expected lifetime utility in equation (2.1) as

$$U_i = (1-\rho_i)e_i u(C_i, l_i) = (1-\rho_i)e_i\left(\bar{u} + \log c_i + v(l_i) - \frac{\sigma_i^2}{2}\right) \tag{2.5}$$

where $e_i \equiv \sum_a S_i(a)$ is (average) life expectancy at birth (following Jones and Klenow 2016), $\gamma_i(d) = \sum_a(1-\rho_{ai}) = (1-\rho_i)$ and ρ_i is the probability that a person in country i will lose some life years due to environmental health risks.

Applying $U_{us}(\lambda) = U_i(1)$ from condition (2.3), the consumption-equivalent welfare for a random individual in country i that incorporates environmental health risks is

$$\begin{aligned}\log \lambda_i(\rho_i) = &\frac{(1-\rho_i)e_i - (1-\rho_{us})e_{us}}{(1-\rho_{us})e_{us}}\left(\bar{u} + \log c_i + v(l_i) - \frac{\sigma_i^2}{2}\right)\\ &+ (\log c_i - \log c_{us})\\ &+ (v(l_i) - v(l_{us}))\\ &- \frac{1}{2}(\sigma_i^2 - \sigma_{us}^2)\end{aligned} \tag{2.6}$$

The proof of (2.6) is in Appendix B.3.

Expression (2.6) provides an additive decomposition of the factors that determine welfare (of a random individual) in country i relative to the United States. The first term is the percentage difference in life expectancy adjusted for environmental health risks of country i compared to the United States $\frac{(1-\rho_i)e_i - (1-\rho_{us})e_{us}}{(1-\rho_{us})e_{us}}$ multiplied by the value of how much a year of life is worth in country i $\left(\bar{u} + \log c_i + v(l_i) - \frac{\sigma_i^2}{2}\right)$ i.e. the "utility flow" of an individual living in country i. The remaining terms in (2.6) are the contributions to the welfare of country i relative to the US from differences in consumption $(\log c_i - \log c_{us})$, leisure $(v(l_i) - v(_{us}))$ and consumption inequality $-\frac{1}{2}(\sigma_i^2 - \sigma_{us}^2)$.

Equation (2.6) is our measure of consumption-equivalent welfare in country i relative to the United States with life expectancy adjusted to correct for years health life lost due to environmental risk(see Appendix B.7 for details). A representative individual living in country i with larger susceptibility to these environmental health risks will have lower "adjusted life expectancy" compared to a counterpart in the United States. Thus, (2.6) allows the lifetime utility of individual living in country i to be expressed as a product of adjusted life expectancy and the expected flow of utility each year of that individual relative to the average person in the US.

As explained previously, our approach for incorporating relative environmental health risks of various countries is justified given how life expectancy at birth is estimated (see Appendix B.7). Calculations of the average number of years that a newborn in country i is expected to live assume that patterns of mortality will remain the same throughout the newborn's life (Ortiz-Ospina 2017). There is no correction for the number of years potentially lost due to environmental impacts on the mortality or morbidity of the average individual. Adjusting life expectancy for the probability that these factors may occur over an individual's lifetime is equivalent to the health-adjusted life expectancy (HALE) approach, which modifies average life expectancy for a variety of external health influences that may occur from birth onwards (Stiefel et al. 2010). Similar to our approach, other economic studies that examine mortality and disease risks on consumption-equivalent expected lifetime utility, value of statistical life and expected years of remaining life also take as their starting point adjusting life expectancy at birth for these additional risks (Carleton et al. 2021; Decerf et al. 2021; Hall et al. 2020; Miller and Bairoliya 2021; Viscusi 2021).

2.3 Methodology and Data

To analyze how incorporating environmental health risks impact welfare across countries, we make two additional changes to our consumption-equivalent welfare measure (2.6).

To apply (2.6) to a broad range of countries and over time, it is useful to express welfare relative to income where the latter is approximated by gross domestic product (GDP). This is convenient in comparing welfare across countries for two reasons. First, a country with a low consumption share of GDP will also have lower welfare relative to income.[12] Second, as our benchmark is the United States, the relevant income variable is the GDP per capita of country i relative to that of the US.

In addition, to determine the extent to which environmental health risks impact welfare of countries, we employ two versions of our welfare measure. The first version assumes that there is some probability that a person in country i as well as in the United States will lose some life years due to these risks, i.e. $\rho_i > 0$. The second version assumes that an individual in country i or the

[12] According to Jones and Klenow (2016, p. 2443), "Looking at welfare relative to income simply changes the interpretation of consumption in the decomposition. The consumption term now refers to the share of consumption in GDP. A country with a low consumption share will have lower welfare relative to income, other things equal."

US will not lose any life years due to environmental health risks, i.e. $\rho_i = 0$. These two versions of our welfare measure are, respectively

$$\begin{aligned}\left[\log \frac{\lambda_i(\rho_i)}{\tilde{y}}\right] &= \frac{(1-\rho_i)e_i - (1-\rho_{us})e_{us}}{(1-\rho_{us})e_{us}}\left(\bar{u} + \log c_i + v(l_i) - \frac{\sigma_i^2}{2}\right)\\ &+ (\log c_i - \log c_{us})\\ &+ (v(l_i) - v(l_{us}))\\ &- \frac{1}{2}(\sigma_i^2 - \sigma_{us}^2), \qquad \lambda_i(\rho_i) = exp\left[\log \frac{\lambda_i}{\tilde{y}}\right]\tilde{y}\end{aligned} \tag{2.7a}$$

$$\begin{aligned}\left[\log \frac{\lambda_i}{\tilde{y}}\right] &= \frac{e_i - e_{us}}{e_{us}}\left(\bar{u} + \log c_i + v(l_i) - \frac{\sigma_i^2}{2}\right)\\ &+ (\log c_i - \log c_{us})\\ &+ (v(l_i) - v(l_{us}))\\ &- \frac{1}{2}(\sigma_i^2 - \sigma_{us}^2)\end{aligned} \tag{2.7b}$$

where $\tilde{y}$ is the relative GDP per capita of country i expressed as a percentage of United States' per capita GDP.[13]

Both (2.7a) and (2.7b) are equivalent variation measures of welfare. The ratio, $\log \lambda_i(\rho_i)/\tilde{y}$, in equation (2.7a) shows by what proportion we must adjust consumption of a representative individual who is at risk of environmental health risk in the US(denoted as ρ_{us}) so that her welfare equals that of an individual in another country i who may face a different incidence of environmental risk ρ_i. Similarly, the ratio $\log \lambda_i/\tilde{y}$ in equation (2.7b) represents the equivalent variation when environmental health risks are ignored. From the latter equivalent variant expression, we can derive the same welfare measure as Jones and Klenow (2016), so we adopt their notation and denote this estimate as $\lambda_i = exp\left[\log \frac{\lambda_i}{\tilde{y}}\right]\tilde{y}$.

Choosing an equivalent variation measure yields a conservative estimate of the welfare impacts of environmental health risks. This is especially relevant for low and middle-income countries,

[13] $\bar{y}$ is calculated as $\frac{\text{per capita GDP of country i}}{\text{per capita GDP of the United States}} \times 100$

whose economic well-being appears significantly affected by the health impacts attributed to the environment, such as air, soil and water pollution, ecosystem degradation, unsafe water and sanitation, temperature variations, and other environmental quality changes (Prüss-Üstün et al. 2016; Landrigan et al. 2018; Nansai et al. 2021; WHO 2020a). For example, the welfare measures corresponding to (2.7a) and (2.7b) respectively, are based on the utility flow of an individual living in country i. As the utility of an individual living in a poorer country is relatively small, even though she may face substantial environmental health risks, any resulting adjustment in the number of life years of that individual is likely to be smaller in terms of equivalent variation. That is, even if large declines in life expectancy occur in very poor countries due to higher impact from environmental health risk related, the equivalent variation-based welfare measure is likely to be a conservative estimate of these impacts.[14] Nonetheless, incorporating environmental health risks in welfare is likely to cause it to further deviate from the GDP per capita. Generally, we expect that the welfare estimate associated with (2.7a) to be less than that of equation (2.7b), which in turn will be less than the relative GDP per capita of country i.

Employing (2.7a) and (2.7b) to estimate welfare for a broader set of countries and years requires using publicly available multi-country datasets for estimating environmental health risks ρ_i as well as for the other macroeconomic data required to parameterize and calibrate these equations. Our methods and data used for this calibration are explained in detail in Appendix B. Here, we summarize briefly the approach we employ and key data sources.

The novel parameter distinguishing our welfare measure 2.7a is ρ_i , which represents the probability that an individual living in country i will lose some life years in year t due to environmental health risk. To estimate this parameter, we use the Global Burden of Disease (GBD) dataset of environmentally related mortality and morbidity across163 countries over 1990-2019, available

[14] Jones and Klenow (2016, p. 2433) also choose the more conservative equivalent variation measure for similar reasons: "flow utility in the poorest countries of the world is estimated to be small, so their low life expectancy has a surprisingly small effect on the equivalent variation: flow utility is low, so it makes little difference that people in such a country live for 50 years instead of 80 years. Thus, large shortfalls in life expectancy do not change the equivalent variation measure much in very poor countries."

from the Global Health Data Exchange (GHDx, http://ghdx.healthdata.org/gbd-results-tool). We use these data from the GBD to compute a lower and upper-bound estimate of ρ for each country.

For our lower-bound estimate, from the GBD we aggregate the total number of years of healthy life lost due to disability (YLDs) attributable to the environment for any given country. This comprises the total number of life years lost in a country due to disease burden resulting from unsafe water, sanitation, and handwashing; air pollution including particulate matter pollution, ambient particulate matter pollution, household air pollution from solid fuels, and ambient ozone pollution; other environmental risks including residential radon and lead exposure; and finally, suboptimal temperature including both low and high temperature. Using the size of population in each country, we translate YLDs attributable to the environment into the probability that a random individual will lose some life years in year t due to environmentally induced disability (i.e., morbidity). Denoting this probability as ρ^*, it follows from (2.7a) that the estimate of welfare that incorporates our lower-bound estimate of environmental health risks can be written as $\lambda_i^* = exp\left[\log \frac{\lambda_i(\rho_i^*)}{\tilde{y}}\right] \tilde{y}$.

Our upper-bound estimate of environmental health risks is based on disability-adjusted life years (DALYs), which combines both YLDs and years of life lost due to premature mortality due to health factors (WHO 2020b). From the GBD, we aggregate disability adjusted life years (DALYs) attributable to the environment for any given country, and using the size of population in each country, we translate these DALYs into the probability that a random individual will lose some life years in year t due to environmentally induced mortality and morbidity. Denoting this probability as $\rho**$, it follows from (2.7a) that the estimate of welfare that incorporates our upper-bound estimate of environmental health risks can be written as $\lambda_i^{**} = exp\left[\log \frac{\lambda_i(\rho_i^{**})}{\tilde{y}}\right] \tilde{y}$.

We anticipate that the probability that an individual living in country i will lose some life years in year t due to environmental health risks lies somewhere between $\rho*$ and $\rho**$ and is most likely to be closer to the latter in emerging market and developing countries. Lack of access to formal health services, especially in the rural areas of poor economies, often results to treatment delays or nonreporting of illnesses, including those related to environmentally related diseases (Peter et al.2008). This can lead to the underestimation of environmentally related deaths, but more significantly, of environmentally related morbidity. Thus, for many low and middle-income countries, estimates of $\rho*$ based on the environmentally related YLDs in the GBD may under-represent the environmental health risks faced by the average individual. In addition, if countries or regions are experiencing rising or new sources of pollution, ecosystem degradation, unsafe water and sanitation, climatic impacts and other adverse environmental quality changes, then average life expectancy at year t will also fail to account for the years lost due to premature death from such increases in environmentally related mortality. On the other hand, if environmental quality has not changed significantly over the years, or the sources of environmentally related mortality and morbidity remain largely the same, then the life expectancy for the average individual at year t is likely to take into account any impacts on mortality attributed to the environment. It is for this reason that we consider the probability $\rho{*}{*}$ based on the environmentally related DALYs reported in the GBD to be an upper-bound estimate of environmental health risks.

Finally, calibration of the welfare measures based on (2.7a) and (2.7b) also requires parameterizing the labor supply function and utility function, as well as utility from leisure and home production (see Appendix B.4 for further details). We acknowledge the difficulty in distinguishing leisure and home production, especially in macro-level aggregated data. From a theoretical point, there may be no need to separate them. Both elements react similarly to changes in the socioeconomic environment and satisfy the conditions of a composite inputs; consequently, there is nothing to gain by including them separately (Gronau, 1977). With that in mind, we aggregate leisure and home production into one entity, nonmarket hours, which we loosely called "leisure". Therefore, from the point on leisure is defined as nonmarket hours or both actual leisure plus home production. This is necessary for determining the flow utility in country i as well as the contributions of differences in consumption, leisure, and inequality between each country and the United States. In addition, an estimate of environmental health-adjusted life expectancy is required.

The macroeconomic data required for these calculations for our 163 countries from 1990 to 2019 are also discussed in detail in Appendix B. We use Penn World Table 10.0 (https://www.rug.nl/ggdc/productivity/pwt/?lang=en) for income (GDP), consumption, employment, population and hours worked. We use Gini coefficients from the UNU-WIDER World Income Inequality Database (https://www.wider.unu.edu/project/wiid-%E2%80%93-world-income-inequality-database), which we convert to the standard deviation of log consumption σ under the assumption of log normality as our proxy of consumption inequality. Finally, we obtain average life expectancy at birth from the World Bank's World Development Indicators (https://databank.worldbank.org/source/world-development-indicators).

2.4 Results

Table 2.1 summarizes and compares the welfare measures λ, λ^* and λ^{**} for our sample of 163 countries over 1990 to 2019, including the main groupings of countries by income levels. Each welfare measure is also compared to average GDP per capita of the country groupings relative to the United States $\tilde{y}$. The decomposition of the welfare measures λ, λ^* and λ^{**} depicted in Table 2.1 into their main components can be found in the Supplementary Tables C.1-C.3 in Appendix C.

Across 1990-2019 and for all countries, the average and median value of λ^* is 99% of the welfare measure without environmental health risks λ (see Table 2.1). However, when the upper-bound estimates of environmental health risks are used, the average welfare measure λ^{**} is 84% of the value of λ , and the median value of λ^{**} is 90% of the value of λ . This divergence in welfare measures is especially noticeable for the different income groups of countries. For all the major emerging market and developing country income groups, the ratio of λ^* to λ remains about 99% and rises to nearly 100% for advanced economies. But the ratio of λ^{**} to λ is clearly lower for poorer as opposed to richer countries. For low-income countries λ^{**}/λ is 58%, for lower middle-income countries 76% and for upper middle-income countries 94%, whereas for advanced economies λ^{**}/λ is 97.8%. These results suggest that environmental health risks, especially when measured using the upper-bound estimates of these probabilities, may matter more for poorer as opposed to wealthier economies.

The estimates of ρ^* and ρ^{**} within income groups show that environmental health risks are more significant in poorer countries (see Appendix C.2 and C.3, respectively). For example, across all low-income economies, the probability ρ_i^* that a person in country i will lose some life years due to environmentally related disability (i.e., morbidity) is around 0.5% on average over 1990-2019, whereas for the entire sample of 163 countries this probability is 0.3% and for high-income OECD countries it is 0.2% (see Appendix C.2). The probability ρ^{**} that the average person in country i will lose some life years due to environmentally related morbidity and mortality is 20% in low-income countries but only 7% across all 163 countries and 2% in OECD advanced economies (see Appendix C.3).

Table 2.1: Welfare Summary Statistics, 1990-2019

	λ	λ^*	λ^{**}	$\tilde{y}$	λ^*/λ	λ^{**}/λ	$\lambda/\tilde{y}$	$\lambda^*/\tilde{y}$	$\lambda^{**}/\tilde{y}$	λ^{**}/λ^*
Average	24.5	24.4	23.5	30.8	99.3	84.0	70.9	70.4	63.0	84.6
Median	12.9	12.8	11.4	19.2	99.4	89.6	66.4	65.9	58.2	90.6
Standard Deviation	28.2	28.2	28.5	34.0	0.8	17.1	36.9	36.7	38.6	17.0
Min	0.2	0.2	0.03	0.4	95.1	19.3	4.8	4.7	1.41	19.6
Max	142.6	142.5	146.1	221.3	100.8	105.7	277.1	277.0	283.9	104.9
Income group										
Low income	1.6	1.6	1.1	3.7	99.2	57.7	39.5	39.2	23.8	58.2
Lower middle income	5.2	5.2	4.3	8.9	99.0	75.6	55.9	55.4	44.1	76.3
Upper middle income	16.8	16.6	15.3	22.3	99.1	90.4	79.7	79.0	72.8	91.2
High income	58.3	58.2	57.6	69.4	99.6	97.8	90.41	90.1	88.7	98.2
Non-OECD	45.3	45.0	44.1	72.5	99.3	97.1	84.1	83.5	81.7	97.7
OECD	62.7	62.6	62.2	68.4	99.7	98.1	92.6	92.4	91.1	98.3

Notes: All welfare and income values are denoted relative to the United States (US = 100). λ is welfare that is not adjusted by environmental health risks, λ^* is welfare adjusted for years of healthy life lost due to disability (YLDs) attributable to the environment, λ^{**} is welfare adjusted for years lost due to disability-adjusted life years (DALYs) attributable to the environment, and $\tilde{y}$ is GDP per capita relative to the United States. Regional income groups are based on the World Bank's Country and Lending Groups classification (https://datahelpdesk.worldbank.org/knowledgebase/articles/906519). OECD is Organization for Economic Cooperation and Development.

Table 2.1 also indicates that welfare adjusted for environmental health risks diverges significantly from GDP per capita across all countries over 1990-2019. On average over this period, λ^* is 70% of the average GDP per capita of all countries relative to the United States $\tilde{y}$ and λ^{**} is 63% of $\tilde{y}$. Moreover, this divergence is more substantial for poorer as opposed to richer countries. The ratio of welfare adjusted for environmental risks relative to GDP per capita is 24% to 39%

for low-income countries, 44% to 55% for lower middle-income countries, 73% to 79% for upper middle-income countries and 89% to 90% for high-income countries.

Figure 2.1 further compares how the divergence between welfare with and without environmental health risks in different countries relative to the United State is affected by the magnitude of these risks faced by the average person in these countries. Figure 2.1A plots the percentage change in welfare, expressed as $((\lambda^* - \lambda)/\lambda) \times 100$, averaged over 1990-2019 for each country against environmentally related YLDs per capita averaged over the same period, whereas Figure 2.1 graphs the percentage change in welfare, expressed as $((\lambda^{**} - \lambda)/\lambda) \times 100$, averaged over 1990-2019 for each country against environmentally related DALYs per capita averaged over the same period.

As Figure 2.1 shows, countries with higher environmental health risks per capita experienced the largest declines in welfare relative to the US. There are again stark differences between rich and poor economies. Low and lower-middle income countries generally faced greater environmental health risks per capita and also had the largest declines in welfare. For example, India, Nepal and Pakistan encountered the greatest per capita per capita environmentally related YLDs over 1990-2019, and welfare per person decreased by 2.4% in India, 2.2% in Nepal and 1.9% in Pakistan due to these environmental factors (see Figure 2.1A). Chad and Niger displayed the highest per capita environmentally related DALYs on average over 1990-2019, and the welfare of the average person declined every year by 67% in Chad and 74% in Niger due to environmental causes (see Figure 2.1B). In contrast, some developed countries, including France, Finland, New Zealand, Canada, Australia, and Iceland, experienced very low levels of per capita environmental health risks and saw their welfare relative to the US improve once these risks are incorporated (see Figures 2.1A and 2.1B).

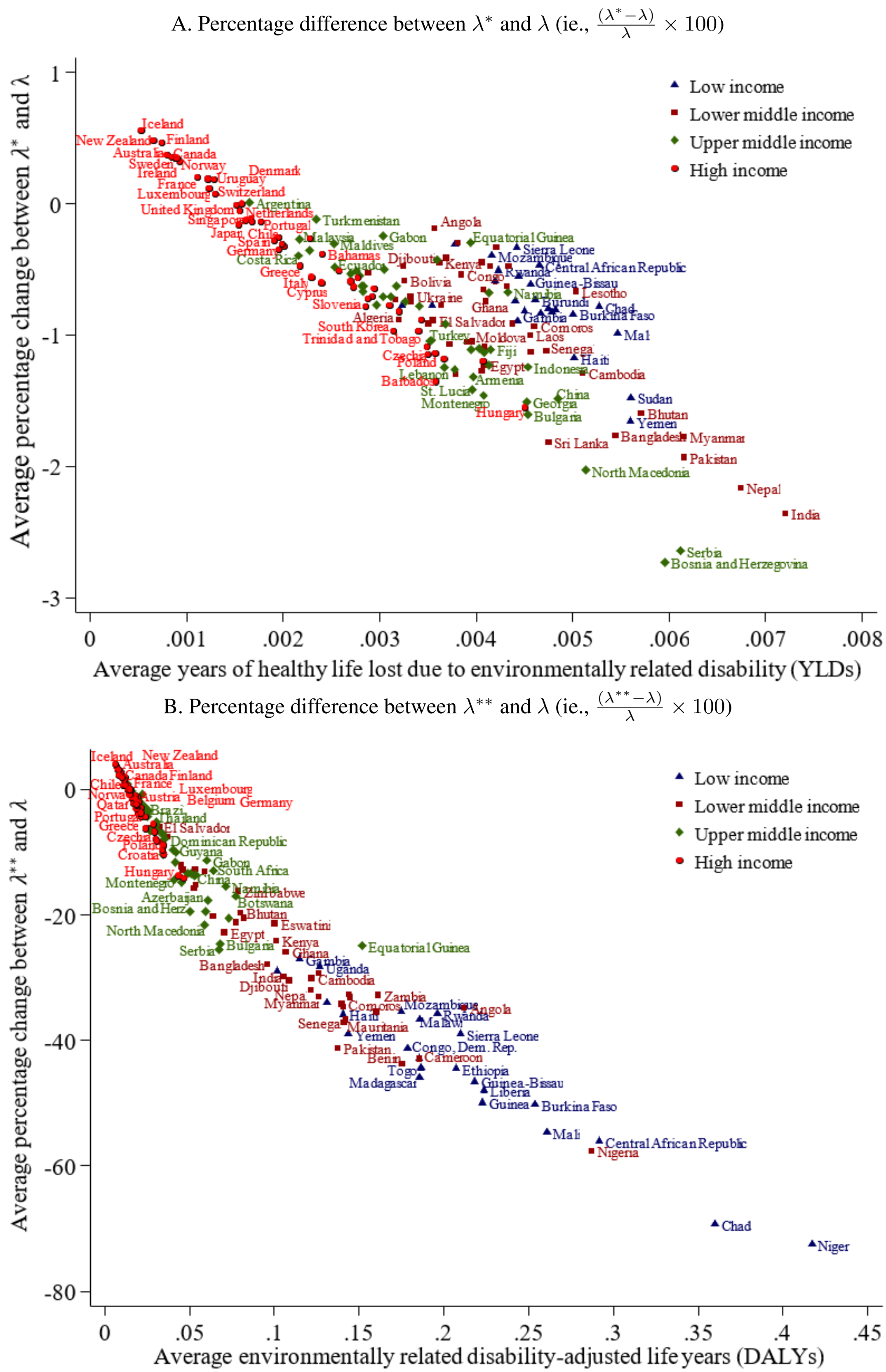


Figure 2.1: Welfare Impacts and Environmentally Related YLDs and DALYs, 1990-2019

The rest of our results explore further the extent to which the impacts of environmental health risks on welfare disproportionately impact poorer as opposed to richer countries.

We first compare our two measures of economic well-being adjusted for environmental health risks, λ^* and λ^{**}, to the standard cross-country indicator of economic welfare, which is GDP per capita. Figure 2.2 provides this comparison for all 163 countries over 1990 to 2019. Figure 2.2A plots the welfare measure λ^* against GDP per person, both relative to the United States, for each country averaged over this time period. Note that since GDP per person is scaled with the United States as the numeraire, we also scale λ^* in the same way (i.e., US = 1). Figure 2B similarly plots λ^{**} against GDP per capita using the same scale.

Both welfare measures appear to be highly correlated (0.88) with income (GDP) per capita across all 163 countries over 1990-2019. However, Figure 2.2 also shows that, for some countries, there are clear deviations from the 45^o line. In particular, on average over 1990-2019, many countries with lower GDP per capita exhibit even lower welfare as measured by either λ^* or λ^{**}. This confirms what we observed with respect to the summary statistics by country income groups depicted in Table 2.1, namely that the divergence between welfare adjusted for environmental health risks and GDP per capita is more substantial for poorer as opposed to richer countries.

To illustrate further this deviation, Figure 2.3 plots the ratio of λ^* and λ^{**} to income against GDP per capita across countries. This figure also allows us to draw inference on how well GDP per capita serves as a proxy of both welfare measures that adjust for environmental health risks. If a country is close to the dotted line, then GDP per capita is a reasonable proxy. However, for countries located above the dotted line GDP per capita tends to understate welfare, whereas for those located below GDP per capita overstates well-being.

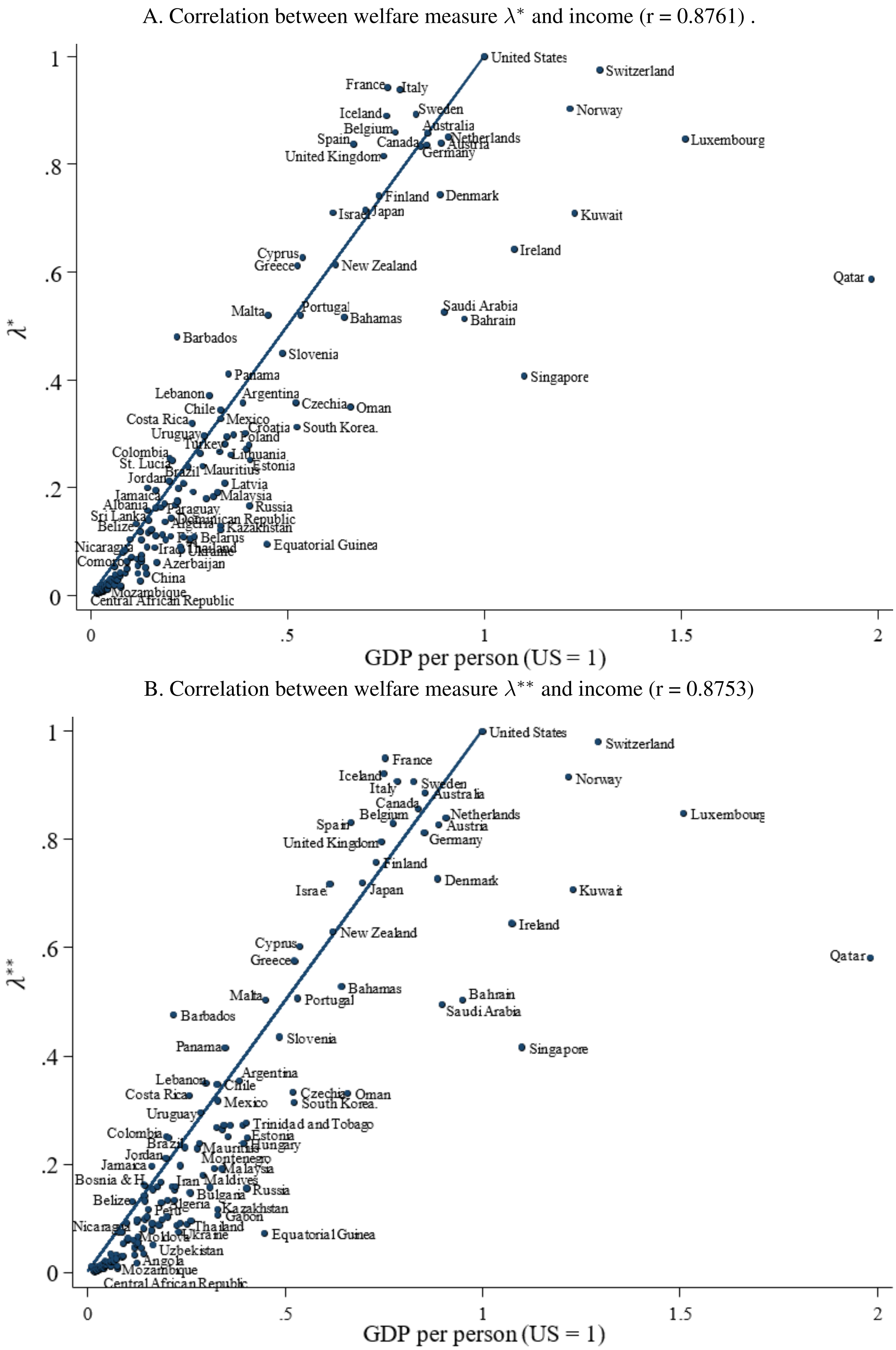


Figure 2.2: Welfare and GDP per capita (1990-2019 average)

In Figure 2.3A, the dotted line at the λ^* to income ratio equal to one represents the benchmark of the United States. As the figure shows, except for a few countries, most high-income countries have an average λ^*-income ratio clustered close to the United States (e.g., near the dotted line or just above it). For most advanced economies, GDP per capita appears to be a reasonably close proxy of λ^* or may even understate it. In comparison, for poorer countries, the ratio falls well below the US benchmark. This drop-off in the welfare-to-income ratio for countries with low levels of GDP per capita is even more noticeable for λ^{**}, which is welfare adjusted for our upper-bound estimate of environmental health risks (see Figure 2.2B). When these environmental health risks are included, GDP per capita is an even less reliable proxy of welfare for poorer countries.

For example, for our entire sample of countries, the absolute deviation from unity is 30% for the ratio of λ^* to GDP per capita and 37% for the ratio of λ^{**} to income per person. However, for high-income countries the deviation from unity is approximately the same (10-11%), regardless of which welfare measure is used. In contrast, for upper middle-income economies, the absolute deviation from unity is 21% for the λ^*-income ratio and 27% for the ratio of λ^{**} to GDP per capita; for lower middle-income countries the corresponding deviations from unity are 45% and 56% respectively, and for low-income economies 61% and 76% respectively. Thus, GDP per capita is a less accurate predictor of welfare for poorer countries, especially when the impacts of environmental health risks are included.

As shown in Appendix C.1, we find that growth in risk-adjusted welfare and income growth are also correlated on average across all 163 countries from 1990 to 2019. The correlation is 0.66 between λ^{**} growth and per capita GDP growth (see Appendix C.1A), and 0.67 between λ^{**} growth and income growth (see Appendix C.1B). Once again, poorer countries tend to deviate from the estimated relationship across the whole sample. It is mainly emerging market and developing countries that display lower growth in welfare adjusted for environmental health risks compared to GDP per capita growth on average over 1990 to 2019.

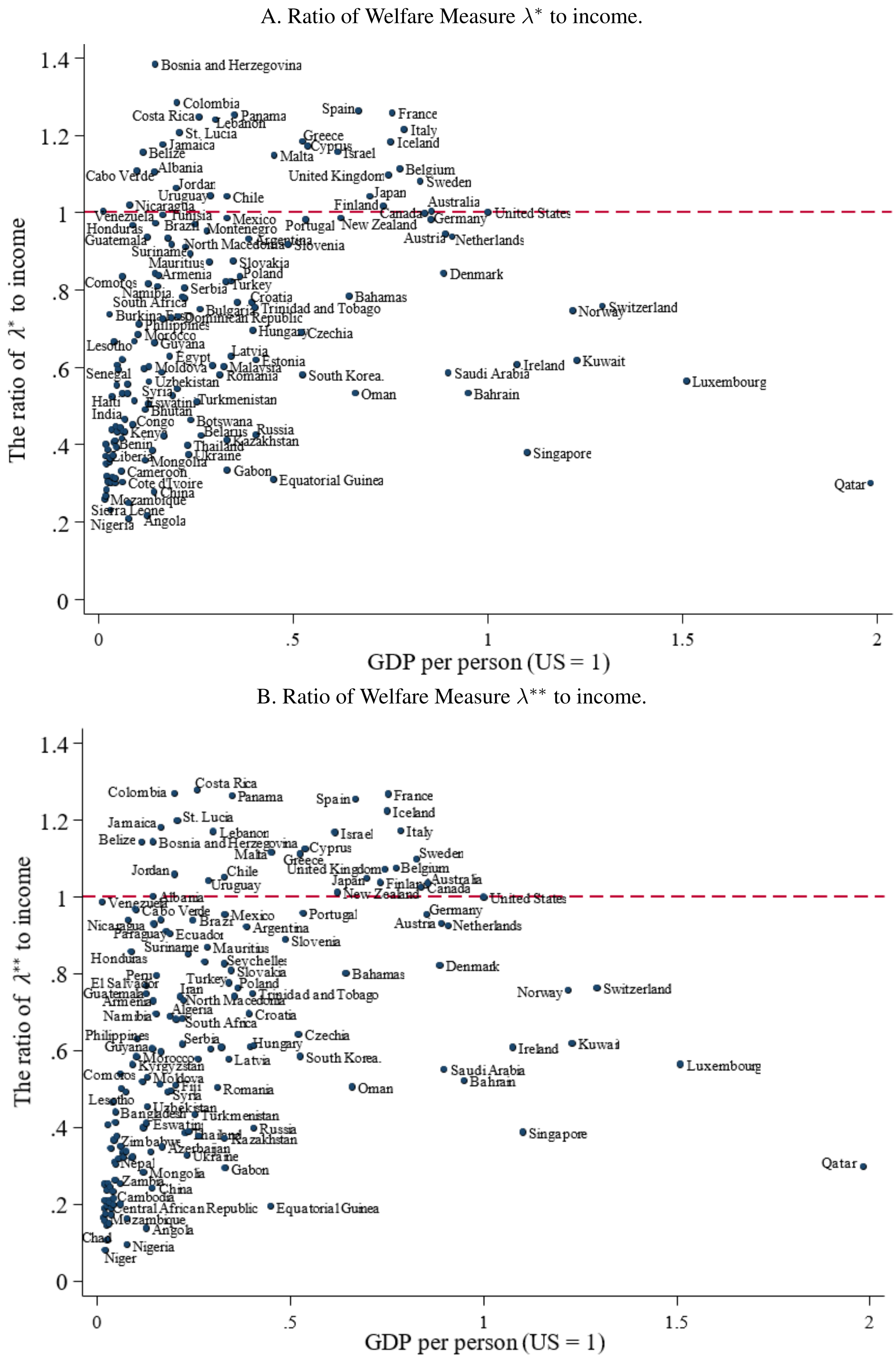


Figure 2.3: Welfare-Income Ratio and GDP per capita, (1990-2019 average)

In sum, adjusting welfare for environmentally health risks has a significant impact for a large number of countries worldwide, but this impact is especially pronounced for emerging market and developing economies. The poorest economies as a group appear to be the most affected by adjusting welfare for environmentally health risks, whereas the least affected are high-income OECD countries. This can be seen further by examining the economies who have the highest risk-adjusted welfare (Table 2.2) and those countries with the lowest welfare (Table 2.3).

Table 2.2 compares the measures of welfare and GDP per capita for the 25 countries with the highest levels of annual average welfare after adjusting for environmental health risks over 1990-2019. The United States is the top country, and all the other countries with the highest risk-adjusted welfare are high-income (advanced) economies and mostly members of the Organization for Economic Cooperation and Development (OECD). These countries appear to have experienced the same level of environmental health risks on average over 1990-2019. For example, the lower-bound probability from environmentally related morbidity ρ^* is, on average, 0.17% and the upper-bound probability ρ^{**} is 1.5% for all 25 economies in Table 2.2, which is approximately the same risk levels (0.16% and 1.4%, respectively) for the US. Finally, for these 25 countries, GDP per capita appears to be a relatively accurate proxy for risk-adjusted welfare, as the ratio $\lambda^*/\tilde{y}$ is nearly 94% and $\lambda^{**}/\tilde{y}$ is 93% for these economies over 1990-2019.

Nonetheless, adjusting welfare for environmental health risks is still important for comparing well-being across these 25 advanced economies. For many countries in Table 2.2, the ratios for λ^*/λ and λ^{**}/λ are over 100%. This occurs because the average individual in these countries faces a lower probability of losing life years due to environmentally related YLDs DALYs compared to the United States. Thus, adjusting for these risks boosts average annual welfare more than what occurs in the US. This outcome appears especially significant for a number of OECD countries, such as Australia, Canada, Iceland, Finland and New Zealand.

Table 2.2: Countries with Highest Risk-adjusted Welfare, 1990-2019

Country	$\tilde{y}$	λ^*	λ^{**}	ρ^*	ρ^{**}	λ^*/λ	λ^{**}/λ	$\lambda^*/\tilde{y}$	$\lambda^{**}/\tilde{y}$
United States	100.0	100.0	100.0	.0016	0.014	100.0	100.0	100.0	100.0
Switzerland	129.3	97.5 *(118.4,96.4)*	98.0 *(120.5,96.0)*	.0013	0.012	100.1	100.6	75.9	76.3
France	75.3	94.3 *(107.7,90.3)*	95.0 *(109.1,91.1)*	.0011	0.012	100.2	101.0	125.8	126.9
Italy	78.4	93.8 *(103.2,92.8)*	90.7 *(98.5,90.5)*	.0023	0.020	99.4	96.2	121.4	117.4
Norway	121.8	90.3 *(123.0,73.4)*	91.5 *(127.1,73.2)*	.0009	0.011	100.3	101.5	74.6	75.7
Sweden	82.5	89.2 *(114.3,85.1)*	90.6 *(117.9,85.6)*	.0009	0.010	100.3	101.9	108.1	109.8
Iceland	75.0	88.9 *(113.4,80.2)*	92.1 *(118.9,82.4)*	.0005	0.007	100.6	104.0	118.3	122.4
Belgium	77.3	85.9 *(93.7,87.3)*	83.0 *(90.3,84.4)*	.0020	0.020	99.7	96.3	111.3	107.5
Australia	85.4	85.7 *(108.3,72.6)*	88.6 *(113.3,74.2)*	.0008	0.007	100.4	103.6	100.3	103.6
Netherlands	90.8	85.0 *(91.5,91.6)*	83.9 *(90.4,90.4)*	.0016	0.016	99.9	98.7	93.8	92.6
Luxembourg	151.0	84.7 *(90.7,93.4)*	84.8 *(92.5,92.1)*	.0012	0.014	100.1	100.2	56.4	56.5
Austria	89.0	83.8 *(93.2,76.7)*	82.7 *(92.3,75.5)*	.0017	0.016	99.9	98.5	94.4	93.2
Spain	66.7	83.7 *(108.0,77.6)*	83.2 *(106.9,77.4)*	.0019	0.015	99.7	99.1	126.3	125.5
Germany	85.3	83.6 *(90.8,79.1)*	81.2 *(87.1,76.8)*	.0020	0.019	99.7	97.0	98.2	95.5
Canada	83.7	83.3 *(96.2,83.0)*	85.7 *(99.5,85.1)*	.0009	0.008	100.4	103.1	99.8	102.6
UK	74.4	81.5 *(87.0,73.8)*	79.6 *(85.7,71.2)*	.0015	0.019	100.0	97.6	109.7	107.2
Denmark	88.6	74.3 *(88.6,75.1)*	72.7 *(86.9,73.1)*	.0012	0.018	100.2	98.0	84.2	82.3
Finland	73.1	74.1 *(90.3,64.5)*	75.8 *(93.1,65.4)*	.0007	0.009	100.5	102.7	101.6	103.8
Japan	69.7	71.5 *(94.8,55.9)*	72.0 *(93.8,56.9)*	.0015	0.011	99.8	100.7	104.2	104.9
Israel	61.4	71.0 *(88.1,70.7)*	71.7 *(90.0,70.8)*	.0016	0.012	99.9	100.8	115.7	116.9
Kuwait	122.8	70.8 *(38.1,84.6)*	70.7 *(37.1,85.8)*	.0029	0.018	99.3	98.7	61.8	61.9
Ireland	107.5	64.2 *(79.8,54.5)*	64.5 *(81.2,53.9)*	.0009	0.013	100.3	100.7	60.7	60.9
Cyprus	53.7	62.6 *(72.6,54.9)*	60.2 *(68.6,53.3)*	.0024	0.022	99.4	95.6	117.1	112.6
New Zealand	62.1	61.4 *(77.1,58.5)*	63.0 *(79.7,59.7)*	.0007	0.008	100.5	103.1	98.6	101.2
Greece	52.4	61.2 *(64.9,60.1)*	57.6 *(58.1,58.3)*	.0022	0.024	99.5	93.7	118.4	111.2
Qatar	198.3	58.6 *(36.0,87.9)*	58.1 *(36.3,87.1)*	.0031	0.018	99.2	98.5	30.1	29.8
Saudi Arabia	89.7	52.6 *(40.5,68.6)*	49.5 *(36.2,65.0)*	.0032	0.029	99.2	93.2	58.6	55.1
Portugal	53.2	51.9 *(54.1,45.0)*	50.6 *(52.2,44.2)*	.0018	0.019	99.9	97.4	98.2	95.7
Malta	45.0	51.9 *(71.0,38.0)*	50.4 *(68.1,37.3)*	.0020	0.019	99.6	96.9	114.9	111.6
Bahamas	64.3	51.6 *(28.6,79.8)*	52.8 *(29.1,81.6)*	.0024	0.012	99.6	101.9	78.3	80.1
Bahrain	94.9	51.3 *(36.3,72.8)*	50.3 *(35.3,70.8)*	.0035	0.021	98.9	97.1	53.3	52.3
Average of 25	86.8	74.68	74.4	0.0017	0.015	99.9	93.7	93.87	93.32
Average of 163	30.8	24.38	23.5	0.0035	0.073	99.3	83.9	70.4	63.0

Notes: Ranking based on average annual λ^* over 1990-2019. All welfare and income values are denoted relative to the United States ($US = 100$). λ is welfare that is not adjusted by environmental health risks, λ^* is welfare adjusted for years of healthy life lost due to disability (YLDs) attributable to the environment, λ^{**} is welfare adjusted for years lost due to disability-adjusted life years (DALYs) attributable to the environment, and $\tilde{y}$ is GDP per capita relative to the United States. Italicized numbers in parentheses represent the value in 1990 and in 2019, respectively.

Table 2.3 compares risk-adjusted welfare measures and GDP per capita for the 30 countries with the lowest levels of average welfare over 1990-2019. These countries are either low-income of lower middle-income countries, and around half of them have risk-adjusted welfare (as measured by λ) less than or equal to one percent of the welfare of the United States. All but five – Myanmar, Cambodia, Laos, Haiti and Nepal – are in Sub-Saharan Africa.

Environmental health risks are significantly higher in the 30 low and lower middle-income countries of Table 2.3. For these economies, the probability that a representative individual will lose some life years from environmental health risks was, on average over 1990-2019, around 0.46% for the lower-bound estimate ρ^{*} and 19.5% for the upper-bound estimate ρ^{**}, which are both significantly higher than their averages for all 163 countries (0.35% and 7.3%, respectively). In addition, GDP per capita greatly overestimates risk-adjusted welfare for the economies of Table 3. The ratio $\lambda^{**}/\tilde{y}$ is only 35.7% and $\lambda^{**}/\tilde{y}$ is 21.5% for these 30 economies over 1990-2019.

Overall, our results suggest that, across all 163 countries over 1990-2019, countries with higher environmental health risks per capita experienced the largest declines in welfare relative to the United States. There are also stark differences between rich and poor economies. While welfare in advanced economies is close to that of the US, emerging market and developing economies generally faced greater environmental health risks per capita and have much lower welfare relative to the United States. This outcome is especially prominent among low and lower middle-income countries. In addition, the divergence between welfare adjusted for environmental health risks and GDP per capita is more substantial for poorer economies, whereas GDP per capita appears to be a reasonable proxy for risk-adjusted welfare in advanced economies.

Table 2.3: Countries with lowest risk-Adjusted Welfare, 1990-2019

Country	$\tilde{y}$	λ^*	λ^{**}	ρ^*	ρ^{**}	λ^*/λ	λ^{**}/λ	$\lambda^*/\tilde{y}$	$\lambda^{**}/\tilde{y}$
Mozambique	1.6	.37 *(.36,.47)*	.24 *(.24,.26)*	.0042	0.175	99.6	64.5	25.8	16.5
Burundi	1.7	.48 *(.21,.98)*	.29 *(.10,.62)*	.0046	0.186	99.3	57.0	26.7	15.8
Niger	1.9	.56 *(.31,.84)*	.16 *(.07,.24)*	.0048	0.418	99.2	27.4	28.4	8.0
Mali	2.3	.59 *(.46,.44)*	.27 *(.18,.21)*	.0055	0.261	99	45.3	30.4	14.5
Ethiopia	2.1	.62 *(.81,.81)*	.35 *(.52,.41)*	.0048	0.207	99.2	55.4	31.8	17.5
Liberia	1.8	.62 *(.46,1.08)*	.32 *(.31,.57)*	.0047	0.224	99.2	52.0	37.0	18.9
Chad	2.4	.68 *(.18,1.34)*	.23 *(.03,.52)*	.0053	0.360	99.2	30.6	30.2	10.6
Congo, Dem. Rep.	1.9	.71 *(.28,2.18)*	.44 *(.2,1.47)*	.0042	0.179	99.4	58.7	35.1	21.0
Malawi	1.8	.76 *(.45,1.19)*	.47 *(.30,.69)*	.0044	0.186	99.4	63.2	40.1	25.2
Sierra Leone	3.0	.77 *(.23,3.20)*	.50 *(.13,2.22)*	.0044	0.210	99.7	61.0	23.1	14.9
Tanzania	3.1	.91 *(.88,1.26)*	.61 *(.61,.78)*	.0037	0.144	99.6	67.3	30.2	20.4
Uganda	2.7	.92 *(.78,1.19)*	.66 *(.58,.83)*	.0038	0.127	99.7	71.6	35.4	25.5
Rwanda	2.4	.94 *(1.51,.46)*	.62 *(1.07,.31)*	.0042	0.196	99.5	64.1	36.7	23.7
Myanmar	4.2	1.00 *(1.25,.76)*	.69 *(.92,.42)*	.0062	0.126	98.2	66.9	30.1	19.9
Central African Rep.	2.3	1.04 *(.16,3.63)*	.54 *(.04,1.87)*	.0047	0.292	99.5	43.8	38.7	19.5
Togo	2.8	1.07 *(.59,2.31)*	.62 *(.32,1.35)*	.0044	0.187	99.3	55.5	36.5	21.0
Guinea-Bissau	3.5	1.17 *(.46,2.97)*	.65 *(.26,1.72)*	.0046	0.218	99.4	53.4	31.6	17.3
Cambodia	4.2	1.18 *(1.29,1.21)*	.83 *(.98,.67)*	.0051	0.122	98.7	69.9	31.2	21.5
Guinea	3.6	1.34 *(.62,2.32)*	.68 *(.29,1.14)*	.0048	0.223	99.2	50.0	37.2	18.9
Madagascar	3.2	1.48 *(.64,2.65)*	.83 *(.34,1.54)*	.0044	0.186	99.1	54.1	43.9	24.4
Nigeria	7.6	1.50 *(.37,3.16)*	.68 *(.15,1.51)*	.0042	0.287	99.7	42.3	20.8	9.4
Benin	3.9	1.55 *(1.02,2.18)*	.88 *(.56,1.18)*	.0041	0.176	99.3	56.2	40.5	23.3
Laos	7.6	1.78 *(2.16,1.45)*	1.19 *(1.59,.81)*	.0046	0.141	99.0	65.4	24.9	16.3
Zambia	4.5	1.81 *(1.55,4.55)*	1.21 *(1.08,2.96)*	.0038	0.161	99.7	67.2	39.3	26.4
Haiti	3.4	1.84 *(.76,3.23)*	1.22 *(.45,2.13)*	.0050	0.141	98.8	64.1	52.5	34.6
Cote d'Ivoire	6.0	1.84 *(1.07,4.13)*	1.21 *(.70,2.72)*	.0041	0.160	99.5	64.5	30.3	19.9
Nepal	4.3	1.86 *(1.51,1.86)*	1.3 *(1.05,1.09)*	.0067	0.122	97.8	68.0	44.7	31.1
Zimbabwe	4.2	1.86 *(.79,6.16)*	1.66 *(.56,5.62)*	.0041	0.079	99.6	83.8	41.0	36.7
Djibouti	4.7	1.89 *(2.25,3.19)*	1.31 *(1.49,2.22)*	.0032	0.109	99.5	69.5	43.4	30.4
Burkina Faso	2.7	1.91 *(.73,3.69)*	1.05 *(.25,2.07)*	.0050	0.254	99.2	49.8	73.7	40.8
Average of 30	3.4	1.17	0.72	0.0046	0.195	99.2	58.1	35.7	21.5
Average of 163	30.8	24.38	23.54	0.0035	0.073	99.3	83.9	70.4	63.0

Notes: Ranking based on average annual λ^* over 1990-2019. All welfare and income values are denoted relative to the United States ($US = 100$). λ is welfare that is not adjusted by environmental health risks, λ^* is welfare adjusted for years of healthy life lost due to disability (YLDs) attributable to the environment, λ^{**} is welfare adjusted for years lost due to disability-adjusted life years (DALYs) attributable to the environment, and $\tilde{y}$ is GDP per capita relative to the United States. Italicized numbers in parentheses represent the value in 1990 and in 2019, respectively.

2.5 Conclusion

This paper provides a measure of economic well-being that incorporates the effects of environmentally environmental health risks using macroeconomic and health data from 163 countries spanning the period of 1990 to 2019. Our approach extends the expected lifetime component of the welfare measure developed by Jones and Klenow (2016) to allow for the impacts of environmentally related mortality and morbidity for each country relative to the United States. For our lower-bound measure of environmental health risks, we use the Global Burden of Disease (GBD) estimates for the number of years of healthy life lost due to disability (YLDs) attributable to the environment. Our upper-bound estimate of environmental health risks is based on disability-adjusted life years (DALYs) from the GBD, which combines both YLDs and years of life lost due to premature mortality due to health factors. We then use our measure of welfare conditioned on environmental health risks to compare with GDP per capita and growth over 1990-2019 for all 163 countries.

Our results suggest that, for countries that face substantial environmental health risks, adjusting welfare for these risks can be significant when compared to income (GDP) per capita or to welfare that excludes these risks. This outcome is especially significant among emerging market and developing countries, who are disproportionately affected by environmental health risks and have much lower risk-adjusted welfare relative to the US. Even in advanced economies that display the highest welfare levels once environmental health risks are considered, adjusting for these risks boosts average annual welfare for many countries above that of the US. Whereas GDP per capita is relatively accurate approximation of risk-adjusted welfare in richer countries, it is a poor proxy in poorer economies.

Our finding that adjusting welfare for environmental health risks matters but is especially significant for poorer economies, has some important policy implications. First, the health risks posed by environmentally related mortality and morbidity are a considerable obstacle to improving the well-being of the average individual of the poorest economies of the world. For example, across all low-income economies, the probability that a person in country i will lose some life years due to environmentally related disability (i.e., morbidity) is around 0.5% on average over 1990-2019, whereas for the entire sample of 163 countries this probability is 0.3% and for high-income OECD countries it is 0.2%. The probability that the average person in country i will lose some life years due to environmentally related morbidity and mortality is 20% in low-income countries but only 7% across all 163 countries and 2% in OECD advanced economies. Even across our entire sample of 163 countries over 1990-2019, we find that countries with higher environmental health risks per capita experienced the largest declines in welfare relative to the US, and overall, low and lower-middle income countries generally faced greater environmental health risks per capita and also had the largest declines in welfare.

Second, low and lower middle-income economies can ill-afford the losses in human capital caused by greater environmental health risks. Accumulation of human capital, which consists of the skills, training and health embodied in a country's workforce, is essential to sustained economic development. However, if the average individual in the poorest countries of the world is sustaining substantial losses due to environmentally related DALYs, then the health risks posed by pollution, unsafe water and sanitation, climate change and other environmental causes are likely to remain a significant barrier to human capital accumulation, improvements in labor productivity, and long-run development.

Finally, we began this paper by citing recent economic criticisms of GDP per capita as a cross-country measure of economic welfare (Fleurbaey 2009; Fleurbaey and Blanchet 2013; Jorgenson 2018; Stiglitz et al. 2010). Our paper adds further evidence to support this view. Whereas GDP per capita appears to be a reasonable proxy for welfare adjusted for environmental health risks in many advanced economies, it is an inadequate measure of welfare in the poorest countries. Moving "beyond GDP" is perhaps more essential than ever, if we want to obtain a more accurate indicator of the development and well-being of many emerging market and developing countries, especially the least wealthy economies.

Because our measure of welfare adjusted for environmental risks relies on macroeconomic and health data for 163 countries over 1990-2019, data limitations prevent further refinement of our wealth measure. For example, the dataset of environmentally related mortality and morbidity from the Global Health Data Exchange (http://ghdx.healthdata.org/gbd-results-tool) that we employ to construct the probability that a random individual in year t will lose some life years due to environmental health risks does not disaggregate this data for different age groups within countries and over time. Once age-standardized data for environmental health risks (especially DALYs) become available across countries and for different years, it should be possible to extend our measure welfare to account for such varying risks across different age groups within each country. This is an important area for future research.

Chapter 3

Externalities from illegal trawling of Africa's Fisheries

3.1 Introduction

Two major problems that plague the marine fisheries in Africa are the ecosystem and crowding externalities due to the illegal trawling of small pelagic by-catch. Yet the true impacts of these externalities are ignored in many of Africa's fisheries.

Ecosystem externalities arise when harvesting activities of fishers affect the quantity and quality of the habitat underlying the biological productivity of the fish stock (Ryan, Holland and Herrera 2014). Specifically, the illegal trawling in shallow waters for by-catch reduces the complexity of the benthic structure, increasing the resuspension of benthic sediments, altering the trophic status of the ecosystem and impacting the complex bottom structure such as filamentous algae, seagrass beds, and oyster reefs (see, Johnson 2002). Such deleterious impacts on the marine ecosystem have been found to inhibit recruitment or reduce survival rate of juveniles by making them more susceptible to predators (see, Bishop et al. 2005; Kamenos, Moore, and Hall-Spencer 2004). In addition, trawling for by-catch may also compromise recruitment and food availability in the habitat. For example, Dwyer, Bailey, and Livingston (1987) found that trawling for by-catch reduces productivity of the Alaskan pollock fishery because Alaskan pollock are cannibal species which prey on its juveniles. Thus, a by-catch of juvenile pollock does not only remove individuals from recruitment, but can affect food availability within the pollock population.

Crowding externalities arise from the congestion of vessels in the fishery or fishing ground (Smith 1968; Ryan et al. 2014). Crowding impacts the fishery in two ways. First, the vessel congestion in the fishery influences the amount of vessel accidents per each fishing season (see, Jin et al., 2001, Jin and Thunberg, 2005, Perez-Labajos et al., 2006, Perez-Labajos et al., 2009, Roberts et al., 2010). For example, Jin and Thunberg (2005) found that the probability of fishing vessel accident was higher in summer than in winter, suggesting that vessel accidents are more likely in the busy fishing season when vessels are crowded in the fishery. Second, competition over a slow growing resources like the small pelagic stock creates external diseconomies in the fishery (Smith 1968), which lowers the catch per unit effort. Such reductions in the catch per unit effort of vessels implies that the cost of harvesting the same quantity of catch in current period will be higher when compared to previous periods when such crowding was absent. This forces some fishers out of the industry until a new profit-making equilibrium is established. This is consistent with the findings of Ávila-Foucat et al. (2013) who provided evidence that crowding negatively affects the probability of tourists returning for a whale watching trip.

Both externalities impact the productivity of the fishery and harvesting cost of coastal communities that depend on the resources. For developing coastal countries in Africa such as Ghana, the majority of these externalities results from illegal trawling activities in which trawlers illegally target small pelagic stocks and report them as by-catch. In 2017 alone, such by-catches were estimated to be about 10,000 metric tons representing, 40% of total artisanal catch and valued at around US$34-65million for Ghana (Hen Mpoano, 2018).

The purpose of this paper is to develop a bioeconomic model to analyze the optimal tax that will deter illegal targeting of by-catch, as well as analyze the optimal combination of by-catch and harvest of the small pelagic stock to ensure continuous productivity of the artisanal fishery. The model is empirically estimated for the case of small pelagic fishery in Ghana. The key motivation of the study is that the illegal trawling in shallow waters for small pelagic stock (1) impacts the biological growth of the stock; and (2) deprives income to artisanal fishers since the small pelagic stock is the legal target stock for artisanal fishers.

Several studies have explored ecosystem externalities in natural resource production and extraction. The first group of such studies is typified by Parks and Bonifaz (1994), Barbier and Strand (1998) and Barbier (2003) which linked mangrove ecosystems to shrimp productivity. Other studies explore the impacts of ecosystem quality on the productivity of the fishery. For example, Knowler, Barbier, and Strand (2002) found evidence that phosphorous concentration in the Black Sea impacts the recruitment of anchovy stocks. Nguyen, Ravn-Jonsen, and Vestergaard (2016) linked nitrogen concentration from eutrophication to the productivity of the Eastern Baltic Cod Fisheries. Compared to these studies, this chapter focuses on ecosystem externalities resulting from the illegal trawling of by-catch which has damaging impacts on the habitat while incorporating the general idea of crowding phenomena suggested by Smith (1968) and Ryan et al. (2014). Unlike the works of earlier authors where the crowding externalities are caused by congestion of agents in the same fishery, we model a situation where the crowding externalities comes from the illegal entrance of trawlers into the artisanal fishery. The congestion in the artisanal fishing ground reduces the efficiency of harvesting and thus increases the costs of fishing.

Investigating these issues is of great importance for the economic well-being of fishers in Africa's fishery for two reasons. First, the fisheries sector remains a critical source of dietary protein, creating about 35 million active jobs for fishing households in Africa (Belhabib, Sumaila, and Le Billon, 2019), contributing to agricultural GDP, non-traditional export revenues, and the local economy of developing coastal countries (see Béné et al. 2010; Boisrobert and Virdin, 2008; World Bank, 2004; Béné et al., 2007). Second, the marine fishery resources in Africa continue to be overexploited and about 50 percent of total catch constitute illegal, unreported and unregulated fishing (see. Doumbouya et. al. 2017; Belhabib, et al., 2019; OECD, 2012). For example, satellite monitoring and surface patrols in the West African waters reveal that 86% of licensed fishing vessels in 2013 and 60% in 2015 were engaged in serious infractions of targeted fisheries (World Bank, 2016) as well as illegal targeting of juvenile pelagic stocks and disguising them as by-catches to avoid taxes (Penney et al., 2017; Hen Mpoano, 2015). With overcapitalization in the sector and very limited capacity to conduct monitoring and surveillance within the exclusive economic zones, illegal fishing activities have escalated (Hen Mpoano, 2015).

This study contributes to the growing literature in economics that seeks to examine the welfare implications of externalities in resource harvesting. To analysis the key externalities described above, we develop a two sector bioeconomic model which treats the number of trawl vessels from the industrial fishery sector illegally entering the small pelagic fishery as the source of ecosystem and crowding externalities to the artisanal fishery sector. The number of trawl vessels is modeled into the biological growth function of the stock to capture the ecosystem externalities and into the cost function of the artisanal fishery to capture the crowding externalities as discussed in the introduction. The idea is that the amount of trawl vessels entering the fishery determines the level of ecosystem damage (hence the ecosystem externality). Here, ecosystem damage is loosely synonymous to ecosystem externaties as it includes damages to the benthic floor, tropic status of the ecosystem, recruitment and the biological productivity of the small pelagic stock. The model further incorporates the role of government, which is to impose taxes on revenue from by-catch, with the aim of regulating overexploitation of the small pelagic stock for by-catch. The steady state conditions from the artisanal fishery's problem are further incorporated into the solutions from the government's problem to produce the optimal combination of harvest and by-catch of small pelagic stock. Also, by comparing the decentralized equilibrium choice of number of trawl vessels entering the small pelagic fishery and government's choice of trawl vessels, we are able to solve for the optimal tax (see, Parks and Bonifaz, 1994).

Primarily, our model investigates the effect of illegal harvesting of by-catch by allowing the number of trawl vessels entering the artisanal fishery to affect the parameters that govern the biological system and economic structure of the fishery. We clarify and illustrate the difference between crowding and ecosystem externalities while exploring their collective impacts on the fishery. The model is developed in three stages. First, we describe the artisanal fishery outcome, where it is assumed that by-catch is determined exogenously by industrial trawlers. This allows us to specify a long-run equilibrium stock, effort and thus harvest in the fishery, for a given number of industrial trawlers operating illegally in the small pelagic fishery. When setting up the artisanal fishery's problem, we employ the general Gordon-Schaefer setup, where agents (ie. artisanal fishery, industrial fishery, and government) choose effort, which in turn affects the productivity of the fishery. It is assumed that the artisanal fishery's choice of effort produces a "healthy" harvest of small pelagic fish without any externalities. This allows us to assume away any negative stock effects that maybe come from the harvesting activities of artisanal fishers and focus only on externalities from the trawl vessels entering into the artisanal fishery. Next, we model the profit-maximizing decision of the industrial trawling fishery that determines the number of trawlers that enter the small pelagic fishery, given the equilibrium stock level of the artisanal fishery. The corresponding number of trawlers chosen by the industry to illegally enter the small pelagic stocks is a function of various parameters of the model but is also determined by the tax imposed by the government on illegal by-catch. Consequently, in the final stage, we show how the government derives an optimal tax on by-catch, and how this tax both reduces the number of illegal trawlers in the small pelagic fishery and increases harvest and thus revenues of the artisanal fishers.

Our theoretical results show that increases in the number of trawl vessels entering the small pelagic fishery will lead to a fall in both the steady state small pelagic harvest and revenue of the artisanal fishery. In response to the lost of revenue, effort will exit the artisanal fishery. Thus, the repercussion of illegal trawling of by-catch does not only affect the resources stock but creates hardship for local economies and poor artisanal fishers who rely heavily on the stock for livelihood and food. Empirically, we found that the effort level of the industrial fishing has being increasing since 2007, but with less than a proportionate increase in legal annual catch. This seems to have coincided with increases in by-catch, which averages about 93% of total artisanal catch since 2007. Between 1986 and 2013, by-catch ranges between 18 - 95% of total artisanal catch. The conjectured is that the extra increases in industrial fishing effort may have being move toward illegal trawling of by-catch, which may explain why effort is increasing with less than a proportionate increase in industrial fishery's annual landings. We estimated the optimal tax rate to be 11%. However, given the data challenges, we believe that the true optimal tax lies between 100% and 10% of revenue from by-catch.

The findings of our theoretical and empirical exercise have significant policy implications for developing coastal countries. For example, in the case study country (ie. Ghana), current tax on illegal by-catch is negligible and lacks proper enforcement. If government's goal is to increase the productivity of the artisanal fishery, current levels of by-catch should be reduced through monitoring and effective tax structures.

The rest of the chapter is organized as follows. Section 3.2 provides the setup and assumptions of the theoretical model, while Section 3.3 provides details of the case study country and highlights important aspects of the data. Section 3.4 provides the empirical strategy, empirical estimations and results. Section 3.5 concludes.

3.2 Model

The model that follows is an open access fishery problem, in which trawlers illegally target small pelagic stocks in shallow waters and report them as by-catch. Trawlers encroaching on the small pelagic fishing zone is not only illegal but also (1) raises the harvesting costs of artisanal fishers, and (2) damages the benthic floor which houses the ecosystems of food. We refer to the former as crowding externality and the latter as ecosystem externality.[15] Our model focuses on the situation where trawlers knowingly target adult and juvenile small pelagic stocks and pass them off as by-catch. The small pelagic stocks (like sardine, sardinella, mackerel and anchovy) are the target stock of the artisanal fishery sector in Africa. To illustrate this problem, we develop a bioeconomic model with two sectors: artisanal fishery sector (A) and industrial fishery sector or trawlers (I).

The model of this section is developed in three stages. First, we describe the artisanal fishery outcome, where it is assumed that by-catch is determined exogenously by industrial trawlers. This allows us to specify a long-run equilibrium stock, effort and thus harvest in the fishery, for a given number of industrial trawlers operating illegally in the small pelagic fishery. Next, we model the profit-maximizing decision of the industrial trawling fishery that determines the number of trawlers that enter the fishery, given the equilibrium stock level of the artisanal fishery. The corresponding number of trawlers chosen is a function of various parameters of the model, but also determined

[15] Noteworthy, reporting a small by-catch is expected since some small pelagic fishes could be accidentally captured while fishing for demersal fishes which trawlers are licensed to fish.

by the tax imposed by the government on illegal by-catch. Consequently, in the final stage, we show how the government derives an optimal tax on by-catch, and how this tax both reduces the number of illegal trawlers in the small pelagic fishery and increases harvest and thus revenues of the artisanal fishers.

3.2.1 Artisanal Fishery Problem

The artisanal fishery is managed as open access and their target stock is the small pelagic fishes, which are also illegally caught by trawlers as by-catch. The artisanal fishery has no control over the harvesting decision of the trawlers, so it takes the by-catch of trawlers, B, as exogenously given. However, it is assumed that the number of competing trawl vessels coming from the industry fishery into the small pelagic zone congests and reduces the efficiency of artisanal fishing effort, thereby increasing the cost of harvesting for the artisanal fishers.

Thus, artisanal fishers exploit the resource according to the following production function:

$$H[t] = H(S[t], E[t]), \qquad \frac{\partial H}{\partial E[t]} > 0, \frac{\partial H}{\partial S[t]} > 0 \tag{3.1}$$

where $H[t]$ is the total harvest by all artisanal fishers, $S[t]$ is the biomass of small pelagic stock and $E[t]$ is total effort which is defined as the total number of artisanal fishing boats employed in the artisanal fishery in period t. Since there is competition from trawlers to bring by-catch to the market, it is assumed that any changes in the volume of harvest will not impact the market price of small pelagic fish. The artisanal fishery, therefore, faces an instantaneous profit function of the form:

$$\pi^A[t] = PH(S[t], E[t]) - C(E[t], Z[t]), \qquad \frac{\partial C}{\partial E[t]} > 0, \frac{\partial C}{\partial Z[t]} > 0 \tag{3.2}$$

where $Z[t]$ is the number of trawling vessels illegally entering the small pelagic fishery, and P represents the landed fish price per unit harvested. $C(E[t], Z[t])$ is the total cost function of the artisanal fishery that increases with effort, and the crowding externality from trawlers illegally entering the small pelagic fishing ground, $Z[t]$.

As discussed earlier, Africa's small pelagic fisheries are open access. The standard assumption for an open access artisanal fishery is that the decision of fishers to enter the industry depends on the magnitude of profit. Thus, effort will adjust instantaneously in response to the profit or losses made in the current period. That is

$$\dot{E} = \sigma(PH(S[t], E[t]) - C(E[t], Z[t])) \tag{3.3}$$

where $\dot{E}$ represents the change in effort with respect to time and $\sigma > 0$ is the adjustment coefficient. The excess profit will continue to attract new boats until the profit disappears and an equilibrium is established in the fishery, leaving no further changes in effort. Conversely, in the case of loses, the effort in the fishery declines over time and becomes constant if there is no profit to be made.

As discussed above, the ecosystem externality resulting from the illegal catching of small pelagic stock by the trawlers impact the biological productivity of the stock by altering growth rate, recruitment and the mortality of the stock. We model this impact through the biological growth function of the stock with the assumption that the level of ecosystem damage depends on the number of trawl vessels illegally entering the small pelagic fishing ground. Thus, the biological growth function is defined as a function of the stock level $(S[t])$ and declines with the number of trawling vessels $Z[t]$ because of the ecological damage they cause. More formally, the biomass of small pelagic stock changes over time according to the follow equation:

$$\dot{S} = G(S[t], Z[t]) - H(S[t], E[t]), \qquad \frac{\partial G}{\partial Z[t]} < 0 \tag{3.4}$$

All the variables are time-dependent and for simplicity, we proceed by ignoring $[t]$. Using equations (3.3) and (3.4), we can characterize the equilibrium of the artisanal fishery in terms of the stock and effort levels, as well as the crowding and ecosystem externalities. In the long run, free entry and exit by fishers will eventually reduce any profits or losses, so in equation (3.3) total revenue equals total cost and effort is constant. For this to occur, the small pelagic fish stock must also be constant, thus equation (3.4) is also equal to zero in the steady state equilibrium for the fishery. For simplicity, let's denote the equations (3.3) and (3.4) by their counterparts: $\kappa(S, E, Z) = \dot{E}$ and $\chi(S, E, Z) = \dot{S}$ respectively.

Assume that the biological growth is logistic $G(S, Z) = rS(1 - S/K(Z))$ where r is the intrinsic growth rate and the carrying capacity $K(Z)$ is a decreasing function of Z. Adapting Barbier (2007)'s specification of the carrying capacity, let $K(Z) = \mu/\ln(\omega Z)$ where μ is the maximum viable size of the stock in the long run and ω is a parameter that translates the number of vessel into ecosystem externalities.[16] Noteworthy, there is a significant conceptual difference between our hypothesis and that of Barbier (2007). Barbier (2007) specified a positive relationship between mangrove and shrimp production, while we specify a negative relationship between invading trawlers and small pelagic fish production. Suppose the production function of small pelagic fish follows a Gordon-Schaefer specification so that $H(S, E) = q_1 SE$ with q_1 as the 'catchability' coefficient per unit effort in the artisanal fishery.[17] Because the presence of trawlers causes a crowding externality, the variable cost of harvesting by the aritsanal fishery is assumed to be a power function of the fishery's own effort and the number of trawlers.

$$C(E, Z) = cEZ^{\beta} \tag{3.5}$$

where c and β are parameters. This formulation allows for non-linear relationships to be investigated. Positive values of $\beta < 1$ indicates that Z is convex in $C(E, Z)$ while $\beta > 1$ indicates that Z is strictly increasing in $C(E, Z)$.

---

[16]The carrying capacity $K(Z) = \mu/\ln(\omega Z)$ is defined as the maximum amount of the stock population that can survive in its ecosystem. Based on the assumptions of the model, Z is a negative externality that increases the amount of by-catch B while decreasing the size of the stock through its impact on the marine ecosystem. The term $\left(1 - \frac{S}{\mu/\ln(\omega Z)}\right)$ slows growth rate linearly toward zero as fish stock approaches $K(Z)$. If S exceeds $K(Z)$, then the growth rate becomes negative, causing the stock population to decline monotonically toward $K(Z)$. The opposite is true.

[17]The catchability coefficient is the fraction of the biomass that is caught by unit of fishing effort. In other words, it tells the relationship between the catch per unit effort and the true population size (S).

With the specific functional forms, equations (3.3) and (3.4) yield the following long-run equilibrium for the artisanal fishery.

$$\kappa(S, E; Z) = \sigma[Pq_1SE - cEZ^\beta] = 0 \tag{3.6a}$$

$$\chi(S, E; Z) = rS\left(1 - \frac{S}{\mu/\ln(\omega Z)}\right) - q_1SE = 0 \tag{3.6b}$$

Equation (3.6a) shows that the growth of the small pelagic stock should equal harvest at the equilibrium. Equation (3.6b) shows that the long-run profit in the artisanal fishery is zero. Next, we use this system of equations to derive the equilibrium for the artisanal fishery. Equations (3.6a) and (3.6b) can be solved for the steady-state small pelagic stock, S^* and effort, E^*

$$S^* = \frac{cZ^\beta}{Pq_1} \tag{3.7a}$$

$$E^* = \frac{r\left(Pq_1\mu - cZ^\beta[\ln(\omega Z)]\right)}{Pq_1^2\mu} \tag{3.7b}$$

The above two steady-state conditions (S^*, E^*) ensure that there is a unique solution. Specifically, equations (3.6a) and (3.7a) show that there is a unique value for fish stock in the long-run regardless of the level of effort. This is shown by the vertical isocline curve, $\kappa(S, E, Z)$ in Figure 3.1. Equation (3.6b), on the other hand, shows the combinations of small pelagic stock and artisanal fishing effort that will lead to a constant level of small pelagic stock in the long-run. The associated slope of the $\chi(S, E, Z)$ isocline in (S, E) space is downward sloping, ie. $\dfrac{dE}{dS} = -\dfrac{r}{q_1\mu/\ln(\omega Z)}$. The unique steady-state equilibrium at the intersection of the two isoclines determines E^*, which is defined explicitly by equation (3.7b). Equations (3.7a) and (3.7b) can be solved for the biological and economic parameters in the model (see Chambers and Strand, 1986; Homans and Wilen, 1997).

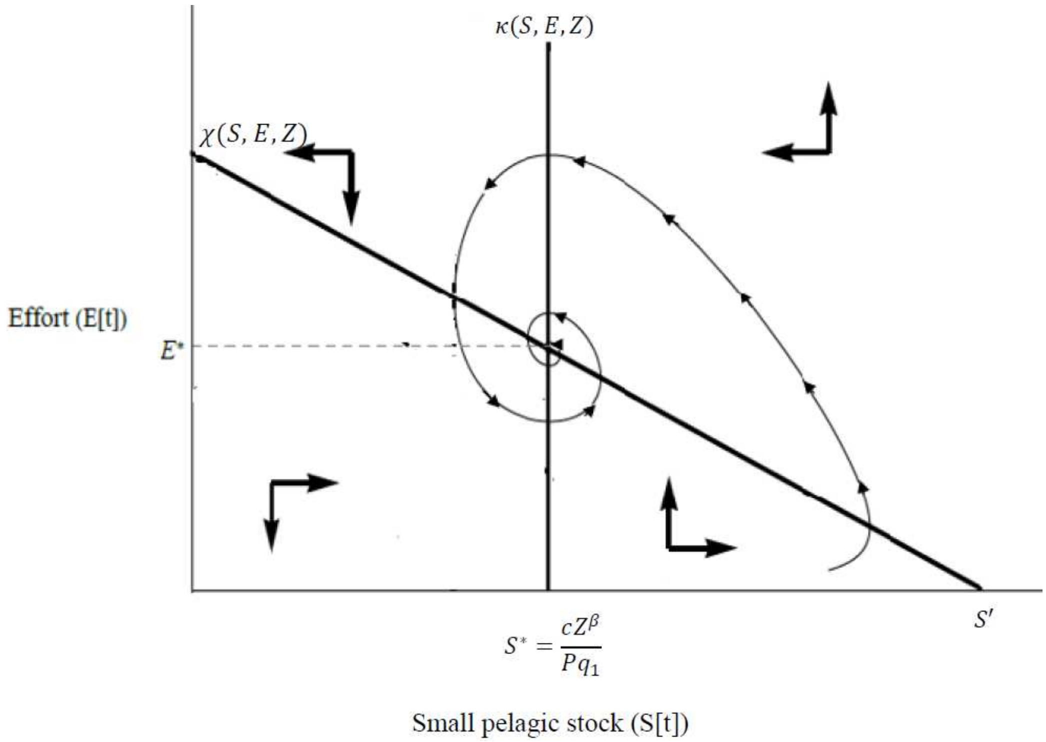


Figure 3.1: Equilibrium in the artisanal fishery.

Figure 3.1, depicts a graphical representation of the system and the equilibrium conditions in (S, E) space while assuming an initial stock level of S'. Both $\chi(S, E, Z)$ and $\kappa(S, E, Z)$ are the isoclines corresponding to the initial long-run equilibrium. Since the two-equation dynamic system has similar properties to that of Barbier and Strand (1998), as the latter have shown, a possible phase trajectory for small pelagic fish stocks and effort is a stable spiral to the steady-state equilibrium.

The analysis in Figure 3.1 assumes that the stock biomass, effort and the trawl vessels in the artisanal fishery are in equilibrium. However, any change in the number of trawl vessels will impact the long-run equilibrium of the fishery, altering the stock biomass and effort. To investigate the impact of such a change, we first need to examine the number of vessels that the industrial fishery illegally sends to the artisanal fishery.

3.2.2 Industrial Fishery (Trawler) Problem

It is assumed that the industrial fishery's "legal" profit from catching demersal fishes is already fully maximized and yet the industry dedicates additional efforts or vessels, Z, toward catching small pelagic stocks and passing them as by-catch. The profit maximizing trawler harvests without consideration for growth of the stock, crowding and ecosystem externalities that determine the evolution of the small pelagic stock. To discourage overfishing of by-catch, the government imposes a per-unit severance tax (τ) on by-catch. Naturally, the industry's production of by-catch depends on the amount of vessels Z and the stock biomass S in each time period. As in the case of the artisanal fishery, let's assume that by-catch production follows Gordon-Schaefer functional form. That is,

$$B = B(Z, S) = q_2 Z^\alpha S, \qquad \frac{\partial B}{\partial Z} \geq 0, \frac{\partial B}{\partial S} \geq 0 \tag{3.8}$$

where q_2 is the 'catchability' coefficient per trawl vessel illegally entering the artisanal fishery. Thus, the industry level by-catch, B, increases with the number of vessels at the rate $0 < \alpha < 1$. Like any externality, when regulations are lax, the perpetrators will catch as much as they can find in each period as long as there is positive profit to be made. Thus, the restricted industry's profit function is as follows:

$$\pi^I = (1 - \tau) P q_2 Z^\alpha S - vZ \tag{3.9}$$

where v is the per-unit cost of operating each vessel illegally in the artisanal fishing ground and τ is a per-unit tax on revenue from by-catch. Thus, the total cost of operating vessels illegally in the small pelagic fishing ground is vZ. The profit function of the industrial fishery sector (in equation 3.9) is considered a restricted profit function because it only captures the profit from by-catch and ignores all profits from legal catch.

The first order conditions associated with equation (3.9) is

$$(1 - \tau)\alpha P q_2 Z^{\alpha-1} S = v \tag{3.10}$$

Equation (3.10) shows that the value of marginal benefit from by-catch after tax equals the marginal cost of effort put towards illegal trawling of small pelagic fishes. As long as this condition holds, there is positive profit to be made from illegal catching of small pelagic stocks as by-catch. Since S is already determined in the artisanal fishery's problem, we solve for the equilibrium Z by substituting $S^* = cZ^\beta / Pq_1$ from equation (3.7a). That is

$$Z^* = \left(\frac{(1-\tau)\alpha c q_2}{q_1 v} \right)^{(\beta+\alpha-1)} \tag{3.11a}$$

and the associated by-catch is

$$B^* = \frac{cq_2}{Pq_1} \left(\frac{(1-\tau)\alpha c q_2}{q_1 v} \right)^{(\beta+\alpha)(\beta+\alpha-1)} \tag{3.11b}$$

Equation (3.11a) and (3.11b) are defined at the equilibrium stock of the artisanal fishery S^* as depicted by equation (3.7a). Both equations are determined by key parameters of the artisanal fishery model and two parameters from the industrial trawling problem, v and t. The latter tax rate is in turn determined by the government, which chooses t in order to control the number of trawlers illegally fishing the small pelagic stock. We next show how this optimal tax rate is determined.

3.2.3 Government's Problem

The government's aim is to reduce illegal trawling and overexploitation of small pelagic stocks as by-catch. In the absence of perfect monitoring and surveillance, there is information asymmetry and the only variable the government observes is the amount of by-catch that is brought to the shore, which is determined by the number of illegal trawling vessels Z. Thus, the government achieves its goal by prescribing the number of trawlers and imposing a per-unit severance tax on revenue from by-catch. Clearly, this policy choice may sound counterproductive comparative to the alternative of an outright ban on by-catch.

An outright ban on by-catch is not feasible because of the incidence of "accidental by-catch", which occurs small pelagic fishes are inadvertently caught while trawling for demersal fishes.[18] Some of the by-catch marketed at shore by industrial trawlers may therefore include small pelagic fish that are caught through their legal trawling operations, and not through illegal trawling in artisanal fisheries. Also, an outright ban on by-catch will encourage dumping of by-catch at sea. Aside being a waste of valuable resources, fish discarding has a significant detrimental impact on the marine environment (Barnes et al., 2022). Based on these reasons, the government should choose a tax rate rather than an outright ban on by-catch. The simplest mechanism to determining such a tax is for the government to choose the optimal number of trawl vessels and tax the industry for any extra vessels that illegally enter the small pelagic fishery subject to the impact of trawling on changes in the stock of fish.

In essence, the government chooses Z to maximize the present value of tax revenue

$$\max_{\{Z\}} \int_0^\infty \left[\tau P B(Z,S)\right] e^{-\delta t} dt \tag{3.12a}$$

subject to

$$\dot{S} = rS\left(1 - \frac{S}{\mu/\ln(\omega Z)}\right) - q_1 SE \tag{3.12b}$$

an initial condition S' and a terminal condition

$$\lim_{t\to\infty} e^{-\delta t} S(t) \geq 0 \tag{3.12c}$$

The current value Hamiltonian associated with equations (3.12a) and (3.12b) is

$$\mathcal{H} = \tau P q_2 S Z^\alpha + \lambda\left(rS\left[1 - \frac{S}{\mu/\ln(\omega Z)}\right] - q_1 SE\right) \tag{3.13}$$

[18] Under normal circumstances where trawlers use the right gear and fish for demersal fishes, the accidental by-catch should be negligible.

where λ is the current value shadow price on the marginal small pelagic fish. δ is the social discount rate or the return on all other assets in the economy. The associated first order conditions of equation (3.13) are

$$\frac{\partial \mathcal{H}}{\partial Z} = \tau \alpha P q_2 S Z^{\alpha-1} - \lambda \frac{rS^2}{Z\mu} = 0 \tag{3.14a}$$

$$\delta\lambda - \dot{\lambda} = \frac{\partial \mathcal{H}}{\partial S} = r\left[1 - \frac{2S}{\mu/\ln(\omega Z)}\right]\lambda - \lambda q_1 E + \tau P q_2 Z^{\alpha} \tag{3.14b}$$

The associated transversality condition is given by

$$\lim_{t\to\infty} e^{-\delta t}\lambda(t)S(t) = 0 \tag{3.14c}$$

Equations (3.15a) is from rearranging (3.14a). Equation (3.15C) is the other important dynamic equation of the model besides (3.15b). Thus, the system of equations that characterizes the long-run equilibrium of the government are

$$\frac{\mu\tau\alpha P q_2 Z^{\alpha}}{rS} = \lambda \tag{3.15a}$$

$$\frac{\dot{\lambda}}{\lambda} = \delta + q_1 E - r\left[1 - \frac{2S}{\mu/\ln(\omega Z)}\right] - \frac{\tau P q_2 Z^{\alpha}}{\lambda} \tag{3.15b}$$

$$\dot{S} = rS\left(1 - \frac{S}{\mu/\ln(\omega Z)}\right) - q_1 S E \tag{3.15c}$$

λ is the shadow price, and it also captures the scarcity value of the small pelagic stock. From equation (3.15a), the shadow price is expressed as the value of the average stock effect evaluated at the market price of small pelagic fish. Equation (3.15b) shows that the growth rate of the shadow price is equal to the exogenous rate of return on investments elsewhere in the economy, as represented by the social discount rate, minus the marginal net "bioeconomic" return for a unit of small pelagic fish left unharvested. Substituting equation (3.15a) into (3.15b) yields

$$\frac{\dot{\lambda}}{\lambda} = \delta + q_1 E - r\left[1 - \frac{2S}{\mu/\ln(\omega Z)}\right] - \frac{rS}{\alpha\mu}. \tag{3.16a}$$

The current form of equation (3.16a), is difficult to solve for a closed form equation for the optimal path over time for $\widetilde{Z}$. Thus, we solve equation (3.16a) by assuming that the fishery is in a long-run equilibrium as determined by $\dot{\lambda} = 0$ and $\dot{S} = 0$. Consequently, the amount of stock growth is equal to harvest at the equilibrium, so that the net growth after harvest is zero (ie. $\frac{\partial \dot{S}}{\partial S} = 0$). Since the residual from expression $q_1 E - r\left[1 - \frac{2S}{\mu/\ln(\omega Z)}\right]$ is the marginal net growth in the stock, then by definition, it should equal zero at the equilibrium.

$$\delta = \frac{rS}{\alpha\mu} \tag{3.16b}$$

which when evaluated at $S^* = cZ^\beta/Pq_1$ simplifies to

$$\widetilde{Z} = \left(\frac{rc}{\delta\alpha\mu P q_1}\right)^{\beta}. \tag{3.17a}$$

The corresponding socially optimal by-catch is

$$\widetilde{B} = \frac{cq_2}{Pq_1}\left(\frac{rc}{\delta\alpha\mu P q_1}\right)^{\beta(\beta+\alpha)} \tag{3.17b}$$

As expected, government's choice of effort and by-catch are much lower than the outcome from the decentralized equilibrium of the industrial fishery sector. We can explicitly verify this result by comparing either Z^* and $\widetilde{Z}$ or B^* and $\widetilde{B}$. That is

$$\widetilde{Z} < Z^* \Longrightarrow \left(\frac{rc}{\delta\alpha\mu P q_1}\right)^{\beta} < \left(\frac{(1-\tau)\alpha c q_2}{q_1 v}\right)^{(\beta+\alpha-1)} \tag{3.18a}$$

or

$$\widetilde{B} < B^* \Longrightarrow \frac{cq_2}{Pq_1}\left(\frac{rc}{\delta\alpha\mu P q_1}\right)^{\beta(\beta+\alpha)} < \frac{cq_2}{Pq_1}\left(\frac{(1-\tau)\alpha c q_2}{q_1 v}\right)^{(\beta+\alpha)(\beta+\alpha-1)} \tag{3.18b}$$

Dividing both sides of equation (3.18a) by $\left(\frac{c}{q_1}\right)^{\beta}$ and (3.18b) by $\frac{cq_2}{Pq_1}\left(\frac{rc}{q_1}\right)^{\beta(\beta+\alpha)}$, yields

$$\left(\frac{r}{\delta\alpha\mu P}\right)^{\beta} < \left(\frac{q_1}{c}\right)^{1-\alpha}\left(\frac{(1-\tau)\alpha q_2}{v}\right)^{(\beta+\alpha-1)}, \qquad \tau < \widetilde{\tau} \tag{3.18c}$$

where $\widetilde{\tau}$ is the optimal tax rate. Whether we compare Z^* and $\widetilde{Z}$ or B^* and $\widetilde{B}$, the expression in equation 3.18c holds true in every period during the entire fishing horizon for any tax rate lower than the optimal tax rate. At the optimal tax rate, both ratios should be equal and the decentralized equilibrium emerges as the social equilibrium.[19] The result shows that the number of trawling vessels illegally operating in the artisanal fishery will have to be reduced in order to achieve the socially optimal by-catch and increase the harvest of the small pelagic fishery.

Our analysis of the impact of illegal trawling of by-catch on the artisanal fishery proceeds by examining the effects of a change in the number of trawl vessels on the long-run equilibrium of the fishery. At first glance of the equilibrium stock, $S^* = cZ^{\beta}/Pq_1$, it seems that an increase in Z leads to an increase in the equilibrium stock. Mathematically, this is indeed the case from the perspective of the artisanal fishery. Because, as the cost of harvesting increases due to the crowding externality, artisanal fishers tend to exit the fishery, allowing the stock to recover. However, in reality, the exit of artisanal fishers does not necessarily lead to stock recovery because trawlers continue to fish, which eventually erodes the stock recovery leading to a decline in the stock. Hence, any recuperation that occurred as artisanal fishers exited is quickly erased.

Also, because the entrance of new trawl vessels affects the marine ecosystem and crowd out artisanal fishers, the resulting impact significantly changes the dynamics of the system. This is represented by the leftward shift of both isoclines to establish a new equilibrium at (S^A, E^A), where both the effort level and stock biomass are much lower. Understanding the ecosystem-fishery linkage is straightforward, as we expect that damages to the marine ecosystem or habitat (resulting

[19]Given that q_2 is the catchability coefficient of trawlers, v is the marginal cost of industrial fishery effort, τ is the tax rate, $0 < \alpha < 1$, c and β are constants, r is the intrinsic growth and μ is the maximum viable size of the stock in the long run, it is safe to conclude that $\lim_{\mu\to\infty}\left(\frac{r}{\delta\alpha\mu P}\right)^{\beta} \to 0$ but $\left(\frac{q_1}{c}\right)^{1-\alpha}\left(\frac{(1-\tau)\alpha q_2}{v}\right)^{(\beta+\alpha-1)} > 0$.

from the new entrance of trawl vessels) will compromise recruitment and food availability in the habitat, leading to a decline in the stock biomass. However, the associated fall in effort is less straightforward. Assuming there is a feasible trajectory to this new equilibrium given S', then it makes intuitive sense for the artisanal fishers to cut down on fishing effort, at least due to the high cost of harvesting. If the fishery follows this trajectory, there will be a stable spiral to the new steady-state equilibrium.

However, if the artisanal fishing effort does not instantaneously adjust to the new equilibrium (S^A, E^A) as depicted in Figure 3.2, there will be a second unstable trajectory that could lead to "near collapses" of the stock. In other words, if the artisanal fishery fails to reduce effort, this will put the fishery on a different trajectory that might lead to collapse of the small pelagic stock. As stated in the introduction, there is evidence that illegal trawling of by-catch is impacting the small pelagic stock, but the idea of "near collapses" scenario is currently unlikely. Therefore, we proceed with the analysis by assuming that the new steady state (S^A, E^A) is a feasible one.

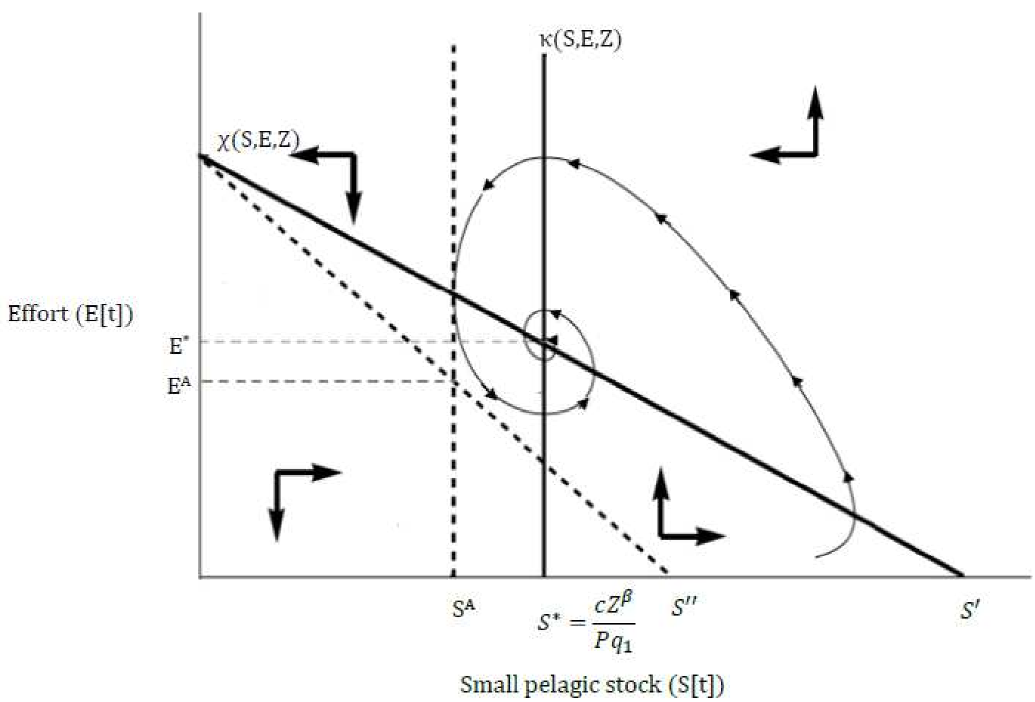


Figure 3.2: Equilibrium in the artisanal fishery as illegal trawling increases.

3.2.4 Comparative Statics of a Change in number of trawl vessels

Also, we can explicitly solve out the impact of a change in the number of trawl vessels illegally entering the small pelagic fishery by conducting a comparative statics analysis on (3.6a) and(3.6b). By totally differentiating equations (3.6a) and(3.6b), we can explicitly solve for the effect of a change in the number of trawl vessels on the equilibrium level of effort, E^* and stock biomass, S^*.

$$(Pq_1S - cZ^\beta)dE + Pq_1EdS - c\beta EZ^{\beta-1}dZ = 0 \tag{3.19a}$$

$$-q_1SdE + \left(r - \frac{2rS}{\mu/\ln(\omega Z)} - q_1E\right)dS - \frac{rS}{\mu Z}dZ = 0 \tag{3.19b}$$

As shown previously, the long-run equilibrium stock is defined by equation (3.7a), implying that $\left(r - \frac{2rS}{\mu/\ln(\omega Z)} - q_1E\right) = 0$. Thus, equations (3.19a) and (3.19b) yields the following matrix:

$$\begin{bmatrix} \left(Pq_1S - cZ^\beta\right) & Pq_1E \\ -q_1S & 0 \end{bmatrix} \begin{bmatrix} {}^{dE}/_{dZ} \\ {}^{dS}/_{dZ} \end{bmatrix} = \begin{bmatrix} c\beta EZ^{\beta-1} \\ {}^{rS}/_{\mu Z} \end{bmatrix} \tag{3.20}$$

with the determinant of the main 2×2 matrix being $q_1^2PSE > 0$. Using Cramer's rule, we can solve for the effect of a small change in Z on effort as

$$\frac{dE}{dZ} = -\frac{q_1rPSE/\mu Z}{q_1^2PSE} = -\frac{r}{q_1Z\mu} < 0. \tag{3.21}$$

Also, the effect of a small change in Z on the stock biomass is [20]

$$\frac{dS}{dZ} = -\frac{c\beta Z^{\beta-1}}{q_1P} < 0 \tag{3.22}$$

This corroborates our hypothesis that an increase in the number of trawl vessels in the small pelagic fishery will result in a lower level of effort and stock biomass in the long-run. The decline in fishing effort suggests that there will be a loss of harvest as well. We can explicitly solve out this

[20] That is $\frac{dS}{dZ} = \frac{{}^{rS}/_{\mu Z}\left(Pq_1S - cZ^\beta\right) - q_1Sc\beta EZ^{\beta-1}}{q_1^2PSE}$. Substitute $S^* = cZ^\beta/Pq_1$ into the resultant fraction obtain from dividing the determinant of the sub-matrix by the main matrix and solve.

impact on harvest by using equations (3.7a), (3.8) and the Gordon-Schaefer production function stated earlier, ie. $H(S, E) = q_1 SE$. Thus,

$$dH = q_1 S dE = -\frac{rcZ^{\beta-1}}{q_1^2 P\mu} dZ < 0 \tag{3.23}$$

with the resulting change in revenue give by

$$PdH = -\frac{rcZ^{\beta-1}}{q_1^2 \mu} dZ < 0. \tag{3.24}$$

An increase in the number of trawl vessels in the small pelagic fishery will therefore result in a fall in the steady state small pelagic harvest and revenue of the artisanal fishery. In response to the lost of revenue, effort will exit the artisanal fishery. In effect, the illegal trawling of by-catch displaces some artisanal fishers out of the fishery. Thus, the repercussion of illegal trawling of by-catch does not only affect the resources stock but creates hardship for local economies and poor artisanal fishers who rely heavily on the stock for livelihood and food. The dynamics of the system in response to changes in illegal trawling is illustrated in Figure 3.2.

3.2.5 Optimal Tax Policy

Following similar approach as Parks and Bonifaz (1994), the optimal tax expression is the difference between Z^* and $\widetilde{Z}$. That is

$$\left(\frac{(1-\tau)\alpha c q_2}{q_1 v}\right)^{(\beta+\alpha-1)} - \left(\frac{rc}{\delta\alpha\mu P q_1}\right)^{\beta} = 0 \tag{3.25}$$

$$\widetilde{\tau} = 1 - \frac{q_1 v}{\alpha c q_2}\left(\frac{rc}{\delta\alpha\mu P q_1}\right)^{\frac{\beta}{(\beta+\alpha-1)}} \tag{3.26}$$

The same expression will be obtained when we use the difference between B^* and $\widetilde{B}$. The tax expression in (3.26) does not depend on time. This implies that the optimal tax rate that government chooses is constant throughout the entire fishing horizon. Since the $\lim_{\mu\to\infty} \frac{rc}{\delta\alpha\mu P q_2} \to 0$ and $\frac{q_1 v}{\alpha c q_2}\left(\frac{rc}{\delta\alpha\mu P q_1}\right)^{\frac{\beta}{(\beta+\alpha-1)}} < 1$, it is safe to conclude that the optimal tax rate must be $0 < \tau < 1$.

Next, we analyze the comparative static effects of the optimal tax with respect to parameters of interest, such as the intrinsic growth rate, market price of small pelagic fish and the discount rate.

Equation (3.27) shows a negative relationship between the tax rate and the intrinsic growth of the small pelagic stock. Thus, the tax rate tends to increase with decreases in the intrinsic growth rate of the small pelagic fish. A fall in the intrinsic growth of the stock implies a decline in stock recruitment level. As a result, the tax rate ought to be increased till the stock returns to equilibrium.

$$\frac{\partial\widetilde{\tau}}{\partial r} = -\frac{\beta}{(\beta+\alpha-1)}\frac{q_1 v}{\alpha c q_2 r}\left(\frac{rc}{\delta\alpha\mu P q_1}\right)^{\frac{\beta}{(\beta+\alpha-1)}} < 0 \tag{3.27}$$

$$\frac{\partial\widetilde{\tau}}{\partial P} = \frac{\beta}{(\beta+\alpha-1)}\frac{q_1 v}{\alpha c q_2 P}\left(\frac{rc}{\delta\alpha\mu P q_1}\right)^{\frac{\beta}{(\beta+\alpha-1)}} > 0 \tag{3.28}$$

Also, an analyses of the effect of the market prices of small pelagic fish shows a positive relationship (see, 3.28). Thus, the tax rate turns to increase with increases in the market price of small pelagic fish. This is because price increases will induce more illegal targeting of by-catch. As such, it makes intuitive sense to increase the tax rate to mitigate the illegal trawling activities.

$$\frac{\partial\widetilde{\tau}}{\partial \delta} = \frac{\beta}{(\beta+\alpha-1)}\frac{q_1 v}{\alpha c q_2 \delta}\left(\frac{rc}{\delta\alpha\mu P q_1}\right)^{\frac{\beta}{(\beta+\alpha-1)}} > 0 \tag{3.29}$$

$$\frac{\partial\widetilde{\tau}}{\partial q_2} = \frac{q_1 v}{\alpha c q_2^2}\left(\frac{rc}{\delta\alpha\mu P q_1}\right)^{\frac{\beta}{(\beta+\alpha-1)}} > 0 \tag{3.30}$$

$$\frac{\partial\widetilde{\tau}}{\partial q_1} = \frac{\beta}{(\beta+\alpha-1)}\frac{v}{\alpha c q_2 q_1}\left(\frac{rc}{\delta\alpha\mu P q_1}\right)^{\frac{\beta}{(\beta+\alpha-1)}} - \frac{v}{\alpha c q_2}\left(\frac{rc}{\delta\alpha\mu P q_1}\right)^{\frac{\beta}{(\beta+\alpha-1)}} < 0 \tag{3.31}$$

Next, we found a positive relationship between the optimal tax rate and the social rate of discount (δ), as shown in equation (3.29). This implies that the tax rate increases with higher discount rates. Similarly, we found a positive relationship between the tax rate and catchability coefficient of trawl vessels, as shown in equation (3.30) and a negative relationship between the tax rate and catchability coefficient of the artisanal fishery as shown in equation (3.31). These results have significant intuitive appeal. Given the effort level, for the catchability coefficient of the artisanal fishery to increase, it must be true that the stock biomass has increased. This is possible if illegal trawling is declining. As such, it makes sense for the government to reduce the tax.

3.3 Application of the model to the Case of Ghana

The capture fisheries sector in Ghana employs about 20 percent of the active labor force (Atta-Mills et al., 2004), contributes to about 5 percent of national GDP and is a critical source of about 60 percent of animal protein requirements in the economy (Hen Mpoano, 2015). As is the story throughout coastal African countries, the fish stock in Ghana is also biologically overfished and illegal, unreported and unregulated (IUU) fishing activities have escalated in recent years (Penny et al., 2015; Atta-Mills et al., 2004). The sardinella stock, which is a critical target stock for artisanal fishers, is near collapse, with landings falling from over 200,000 metric tons in 1995 to 17,000 metric tons in 2014 (Hen Mpoano, 2015). These stock declines are attributable to the huge destructive and illegal fishing practices and overcapitalization within the waters of Ghana.

Artisanal fishery is typically managed as open access with gear restrictions while industrial fishers (trawlers) are managed through licensing for demersal fishes in deep waters (Hen Mpoano, 2015) , yet these trawlers illegally and actively target juvenile pelagic stocks in shallow waters, destroying the benthic floors as well as underreporting catches in order to avoid taxes (Akpalu and Bitew, 2014; Penney et al., 2017). The illegal by-catch fishing by trawl vessels is locally known as "saiko" fishing in Ghana.

Saiko fishing is a coordinated fishing crime between owners of trawl vessels and a few artisanal fishers who engage in illegal transshipment of illegal by-catch, mostly small pelagic stocks, for economic gains. These illegal activities cause serious damage to the ecosystem of the inshore exclusive zone, degrading the environmental carrying capacity of the resource. The Saiko are typically frozen into rectangular slabs and transshipped illegally to fishing boats for retailing at the shore (Hen Mpoano, 2015; Penny et al., 2017). Despite negative impact of these activities on the resource stock, inadequate monitoring and surveillance creates the perfect environment for saiko fishing to flourish among most trawlers in Ghana. Currently, more than 100 boats are engaged in saiko fishing in the Western and Central Regions of Ghana, with vessel capacity up to 44 metric tons of fish per a fishing trip (Hen Mpoano, 2018). Saiko landings, in 2017 alone, was estimated at 10,000 metric tons, representing 40% of total artisanal catch and valued at around US$34-65million (Hen Mpoano, 2018).

3.3.1 Data

In this section, the functions and parameters from the model above are estimated and calibrated using available data on Ghana. Table 3.1 depicts the artisanal fishery's annual landings of small pelagic fishes, the effort level and the catch per unit effort (CPUE) in the artisanal fishery. Because data on the level of by-catch is unavailable, we draw inference from the available data on the industrial fishery's legal annual landings of demersal fishes, the effort level and the catch per unit effort (CPUE) as shown in Table 3.1. The data in Table 3.1 is plotted in Figure 3.3A and 3.3B. From Figure 3.3A, artisanal fishing effort is fairly constant within the 1990s but soar in the early 2000s. However, annual landings seem not to be increasing with the rate of increase in effort. In contrast, the industrial fishery's annual landings appear to be increasing with the increase in effort, except after 2006 when large increases in industrial fishing effort resulted in less than a proportionate increase in catch when compared to the previous years (see Figure 3.3B).

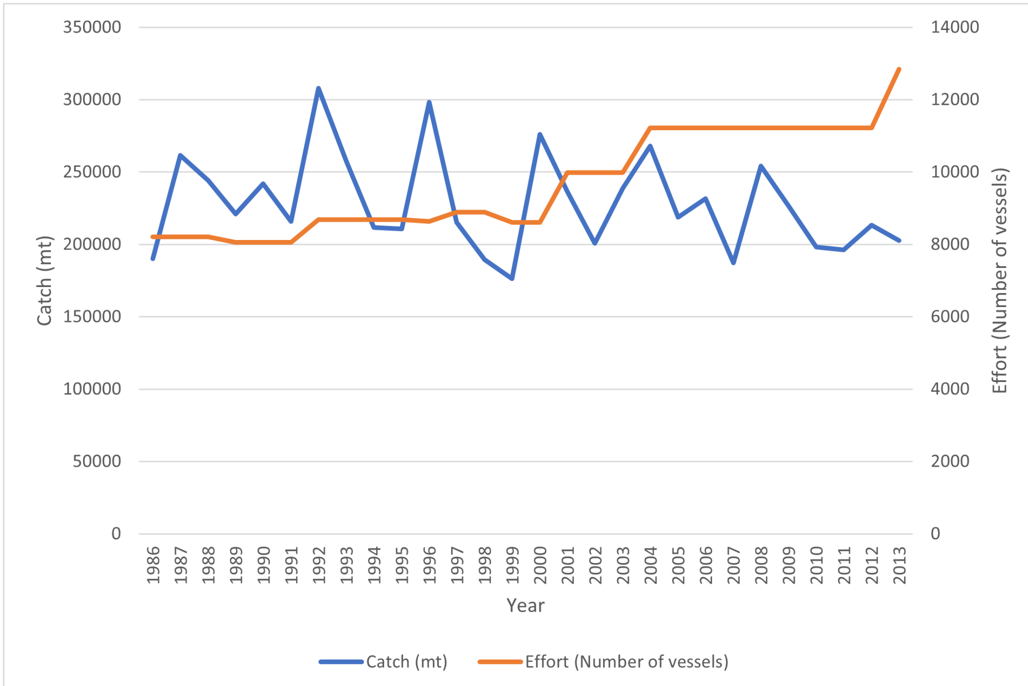
The conjecture is that as industrial fishing efforts increase without a proportionate increase in legal annual landings of demersal fishes, it maybe true that some of these efforts are directed toward illegal trawling of small pelagic fishes as by-catch. Such by-catches are unreported. As a result, there is no available data on by-catch for the case study country, Ghana. The task is to use the available data to estimate and calibrate the stock biomass and by-catch.

Table 3.1: Catch and Effort in the Artisanal and Industrial Fishery, 1986 - 2013.

	Artisanal fishery			Industrial Fishery		
Year	Catch (Metric ton)	Effort (No. of vessel)	Catch per unit effort (CPUE)	Catch (Metric ton)	Effort (No. of vessel)	Catch per unit effort (CPUE)
1986	190197	8214	23155	8091	58	139500
1987	261451	8214	31830	8768	47	186553
1988	244042	8214	29710	4344	47	92426
1989	220878	8052	27431	7851	34	230912
1990	242020	8052	30057	18060	43	420000
1991	215847	8052	26807	22078	44	501773
1992	307931	8688	35443	16366	38	430684
1993	257237	8688	29608	14921	36	414472
1994	211747	8688	24372	19026	49	388286
1995	210659	8688	24247	15298	50	305960
1996	298249	8641	34516	25104	62	404903
1997	215125	8895	24185	17528	56	313000
1998	189459	8895	21299	16847	50	336940
1999	176237	8610	20469	13945	50	278900
2000	275965	8610	32052	15455	55	281000
2001	236355	9981	23680	19644	55	357164
2002	200824	9981	20121	13900	54	257407
2003	238861	9981	23932	9943	67	148403
2004	267910	11219	23880	14010	71	197324
2005	218871	11219	19509	12494	53	235736
2006	231681	11219	20651	17419	88	197943
2007	187088	11219	16676	19892	91	218593
2008	254133	11219	22652	18289	119	153689
2009	226755	11219	20212	20837	89	234124
2010	198152	11219	17662	18859	101	186723
2011	196200	11219	17488	19597	116	168940
2012	213451	11219	19026	19763	116	170371
2013	202602	12847	15770	19406	115	168748

Source: Ministry of food and agriculture (2016). Fisheries management plan of Ghana: A national policy for the management of the marine fisheries sector (2015-2019). Available at https://www.mofad.gov.gh/wp-content/uploads/2016/07/FISHERIES-MANAGEMENT-PLAN-OF-GHANA.pdf

A. Artisanal Fishery



B. Industrial Fishery

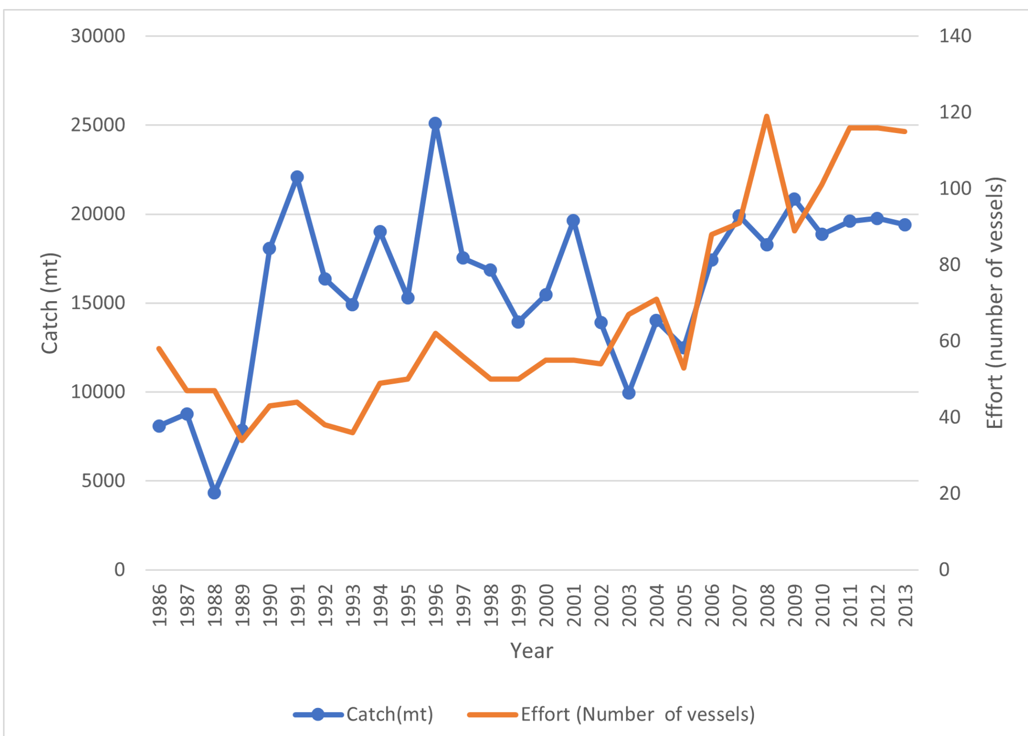


Figure 3.3: Catch and Effort, 1986 - 2013

Source: Author's illustration based on data from Ministry of food and agriculture (2016). Fisheries management plan of Ghana: A national policy for the management of the marine fisheries sector (2015-2019). Available at https://www.mofad.gov.gh/wp-content/uploads/2016/07/FISHERIES-MANAGEMENT-PLAN-OF-GHANA.pdf

3.4 Empirical Strategy

Estimating the model developed above requires data on parameters associated with the stock dynamics such as catchability coefficient, natural mortality rate or the net growth and the recruitment relationships among others. Data on these parameters are currently lacking for developing countries contest like Ghana. However, using the observed data on catch and effort or CPUE as shown in Table 3.1, we can estimate the unknown biomass of the small pelagic stock using a CPUE analysis and proceed to calibrate other parameters of interest.

Generally, the goal of an empirical exercise is to estimate the impact of independent variables on the dependent variable, but our analysis of the catch-effort-stock relationship, presents an interesting challenge in regards to the data. Catch and effort are generally known but the stock biomass and other biological parameters such as the intrinsic growth are unknown. This asymmetry presents a conundrum which is generally resolved through a "classical calibration" of expected values of the known parameters to obtain the unknown using the ordinary least squares regression (Lancia et al, 1996). Following a similar approach, we proceed to estimate the systems of equations that govern our model (ie. equation 3.6a and 3.6b).

3.4.1 Estimating equation (3.6a)

First, let's write equation (3.6a) in a standard discrete time format:

$$E_{it} = a_0 + a_1 H_{it-1} + a_2 E_{it-1} + \eta_{it-1} \tag{3.32}$$

where i is the observation, $t-1$ = 1 , ..., 28 years (1986 - 2013), a_0 is the constant of regression and η_{it-1} is the error term. For simplicity and lack of data on cost and market price, we transform the profit function $[Pq_1SE - cEZ^{\beta}]$ in equation (3.6a) into mH_{it-1}, which is simply some net price or markup (m) times harvest from year $t-1$.[21] In that case, the coefficient $a_1 = m\sigma$. The intuition is that after subtracting the per-unit cost of harvest (which includes the crowding cost)

[21] This follows the standard way of specifying profit function in terms of output, price and marginal cost. For example, $profit = (price - marginal\ cost)output$. Here we call $(price - marginal\ cost)$ the net price or markup.

from the per-unit selling price in each year, there is some markup or net price left. Multiplying that net price by total harvest yields the total profit of the artisanal fishery in each year. Off course, in the long-run, this net price is zero. All other variables, including σ and r, carry their original definitions as stated above. Both E_t and H_{it} are predetermined and for the case of Ghana, we have 28 years worth of data. Therefore, we proceed to estimate equation (3.32) as reported in Table 3.2.

Table 3.2: OLS Estimates of Equation (3.32) for artisanal fishery in Ghana

Parameter	Value
a_0	-792.427
	[738.888]
a_1	0.003
	[0.002]
a_2	1.038***
	[0.071]
Observations	27
R-squared	0.893

Dependent variable is current year's effort (E_{it}). Standard errors in brackets are robust to heteroscedasticity. $***p < 0.01, **p < 0.05, *p < 0.1$.

The result shows a statistically significant positive relationship between effort in the previous year and current effort. The associated coefficient is 1.038 suggesting that, by bringing one more artisanal fishing boat into the fishery in the previous year, the total size of effort in the current period increases by approximately one. The estimates of a_0 and a_1 are statistically insignificant. It is, however, important to acknowledge that our estimates suffer from omitted variable bias due to lack of data on important variables.

Next we proceed to estimate equation (3.6b). Estimating equation (3.6b) is particularly difficult because of the lack of data on the stock biomass. So, we first attempt to estimate the stock biomass from the catch-effort relationship. Details of the approach for estimating the stock biomass are shown in the following section.

3.4.2 Estimating the stock biomass from catch - effort relationship

As previously discussed, the harvesting in our model follows the Gordon-Schaefer production specification $H(S, E) = q_1 SE$. The ratio of harvest (or catch) over effort produces CPUE. CPUE is the most common information used in literature to assess the stock biomass and relative abundance of stocks (Arreguín-Sánchez, 1996; Lancia et al, 1996; Bishir and Lancia, 1996; Allen et al., 2020). This is because the CPUE presents a symmetric relationship between catch-effort ratio and stock biomass (Allen et al., 2020). That is

$$\text{CPUE} = q_1 S, \qquad \text{or} \qquad \text{CPUE} = \frac{\text{H}}{E}. \tag{3.33}$$

All variables and parameters are as defined above. Taking the natural logarithm of both side of equation (3.33) yields $\ln \text{CPUE} = \ln H - \ln E$, which simplifies to

$$\ln H = \ln(q_1 S) + \ln E \tag{3.34}$$

Equation (3.34) shows a log linear relationship between catch (ie.$\ln H$) and effort (ie.$\ln E$) relationship. Since S and q_1 are unknown, the term $\ln(q_1 S)$ will be estimated as the intercept of equation (3.34). However, the symmetric relationship between CPUE and catch-effort ratio present a challenge for the ordinary least squares (OLS) estimator, which also requires that independent variables are measured without error, while the dependent variable is modeled as having uncertainty. If measurements of both independent and dependent have error (as is the case of reported data from developing countries such as Ghana), this could lead to a violation of the underlying least-squares regression assumptions.

Other researchers have addressed the measurement errors and symmetric relationship bias by using the reduced major axis (RMA) regression, which is based on the maximum likelihood technique designed to handle errors in both independent and dependent the variables and to describe the true relationship between both variables (Warton et al., 2006). Also, the RMA regression has a unique ability to establish a confidence interval for the intercept using profile-likelihood techniques while the OLS uses Taylor series expansion and the normality assumption to establish confidence intervals (Lancia et al, 1996). This statistical property of RMA makes it a superior estimated over the OLS in cases such as ours, where there are potential measurement errors and lack of data on other important explanatory variables. This alternative to the least squares gained its notoriety from the works of Bishir and Lancia (1996) who modeled the RMA and showed how the stock abundance of animal species can be estimated using information only information on harvest and effort. Since then, the least square method and RMA have been generally used to analyze CPUE and stock abundance (Lancia et al, 1996; Erisman et al. 2011; Ward et al. 2013). For example, Allen et al., (2020) used the RMA regression and 21 years of data on effort and harvest for bobcat in Wisconsin to estimate the bobcat population from 1993 to 2013.

Following literature, we estimate equation (3.34) using the RMA regression while using the OLS estimator as a robustness check. The results are shown in Table 3.3 and plotted in Figure 3.4, along with the corresponding confidence interval.[22]

Table 3.3: Estimating the Catch-Effort and Stock Relationship

Variables	Ordinary Least Squares (OLS)	Reduced Major Axis (RMA)
Intercept	14.193***	21.412***
	[1.526]	[1.526]
ln (artisanal fishing effort)	-0.203	-0.991***
	[0.165]	[0.165]
Observations	28	28
R-squared	0.042	0.042

Note: The lmodel2 function in R was use to computes simple linear regressions using the following methods: reduced major axis (RMA) and ordinary least squares (OLS). Parametric 95% confidence intervals are also computed for the slope and intercept parameters. The dependent variable is natural log(ln) of annual catch or harvest. Standard errors in brackets are robust to heteroscedasticity. $***p < 0.01, **p < 0.05, *p < 0.1$. Both the univariate OLS and RMA have the same assumptions concerning the residuals, such as independency, normality and homogeneous variance. As a result, the R^2 and standard errors of coefficients of both the univariate OLS and RMA turns to be identical (see. Warton et al. 2006).

[22] Note: RMA is best fitted for estimating the true relationship between two variables that have symmetric relationship while the OLS is for predicting the direct impact of the independent variable on the dependent variable. As such, coefficient from the RMA should be interpreted with caution. The coefficients should not be interpreted as direct elasticity, as in the case of OLS.

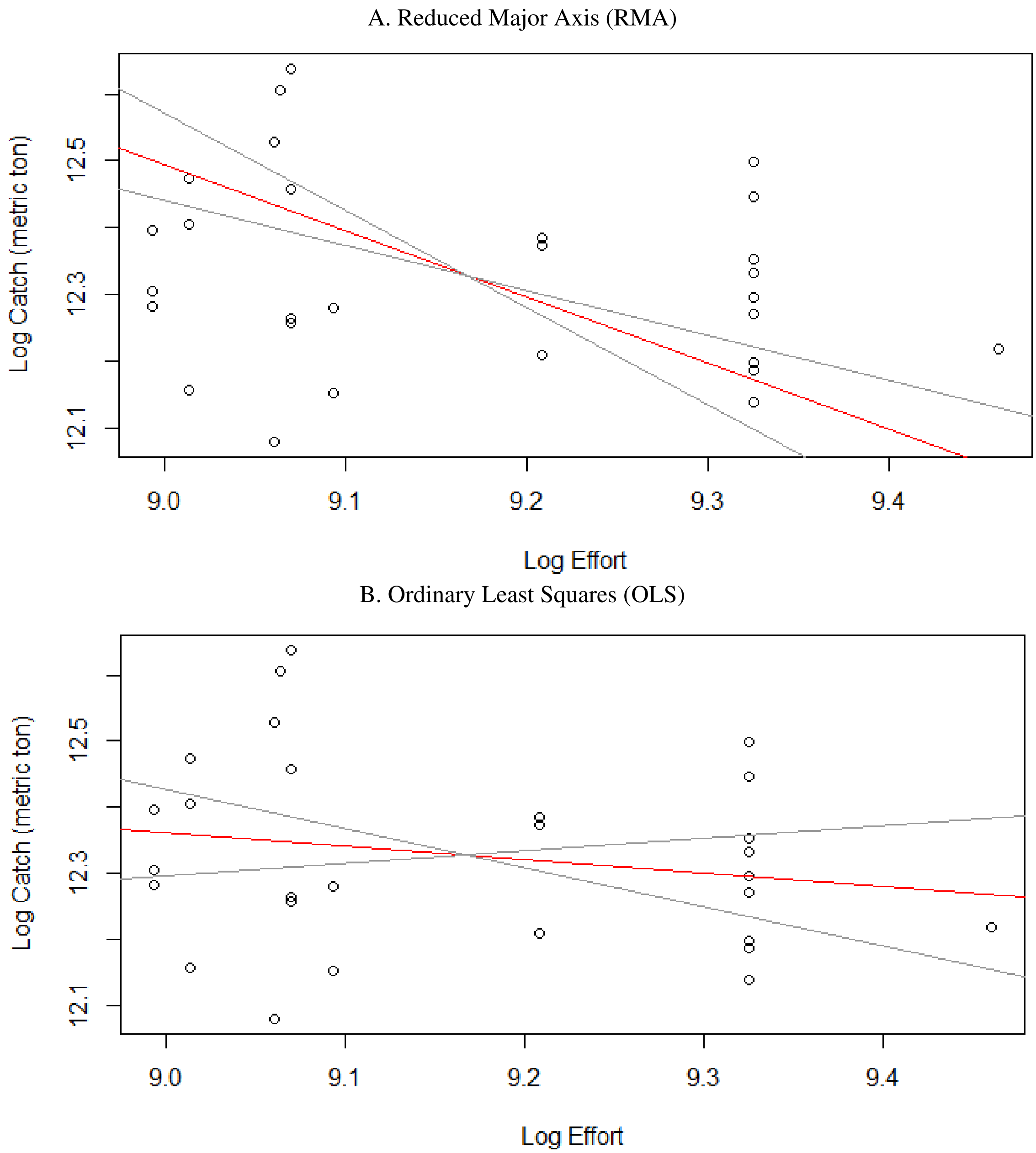


Figure 3.4: Estimating of Catch-Effort and Stock Relationship

Figure 3.4, shows the regression line of the RMA model reported in Table 3.3. The red lines are the regression lines and the 95% confidence interval are gray. The RMA regression shows a negative relationship between effort and harvest, with the corresponding slope coefficient of -0.991 at the 1% significant level. This suggest, that harvest is decreasing with increases in effort. This is consistent with the observed data plotted in Figure 3.3A. From the OLS regression, we found that the effort does not significantly explain harvest. While the OLS regression provides useful insight about the catch- effort relationship, the coefficient estimates are bias and tend to understate the catch values. However, the RMA regression provides less biased parameter estimates because it is specifically designed to handle errors in both the dependent and independent variables.

Using the estimates from RMA regression, Equation (3.34) becomes

$$\ln H = 21.412 - 0.991 \ln E. \tag{3.35}$$

we can proceed to calibrate the stock biomass. But, first, we analyze the consistency of our estimates to the actual reported data on catch and CPUE. We pluck the artisanal fishing effort for each year into equation (3.35) to estimate the catch from 1986 to 2013. The estimated catch and actual catch are plotted in Figure 3.5 and the estimated CPUE and the actual CPUE are plotted in Figure 3.6. The results show that our estimates are good approximations of the reported data.

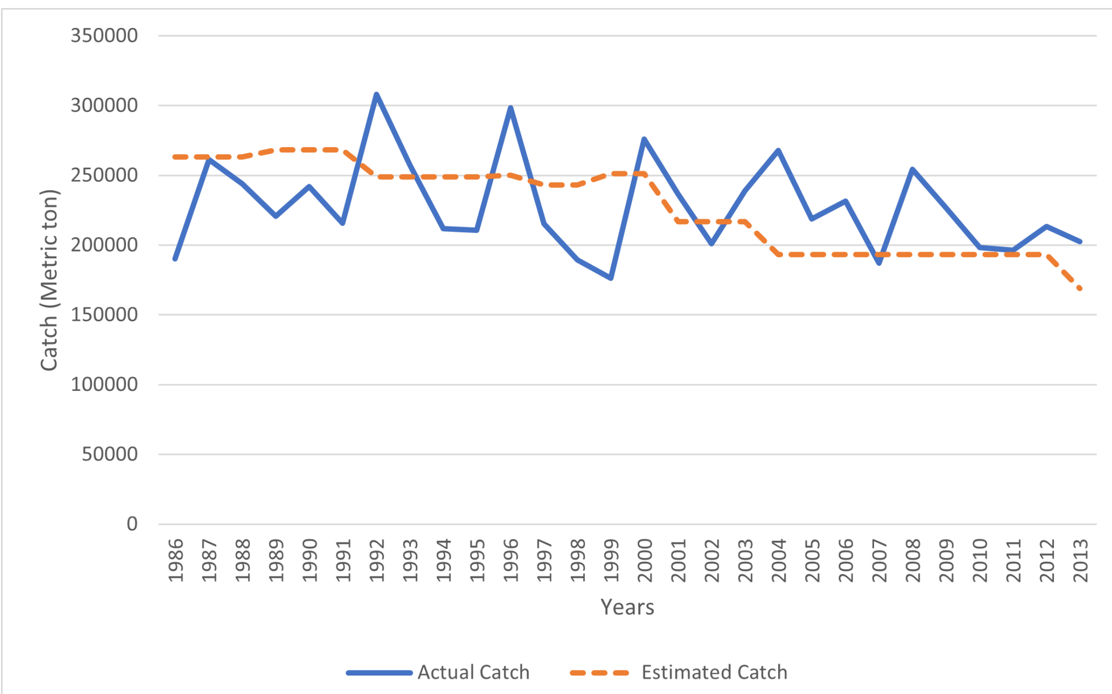


Figure 3.5: Actual Catch vs. Estimated Catch Based on RMA Regression

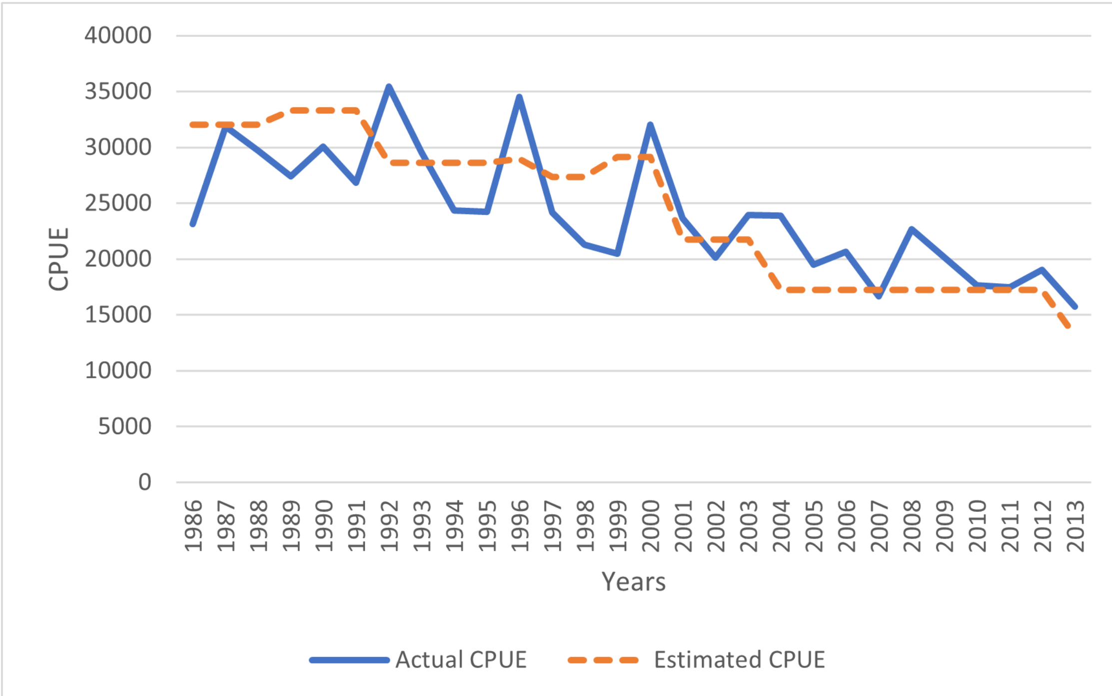


Figure 3.6: Actual CPUE vs. Estimated CPUE Based on RMA Regression

3.4.3 Stock Biomass and By-catch

The stock biomass is estimated using the estimated catch-effort relationship and the resulting intercept from equation (3.34). The intercept $e^{21.41157} = 1,990,337,382$ metric ton is the average harvest when effort is zero. Intuitively, when effort is zero, there can be no catch. Thus, we can infer that the intercept is the highest catch if all the stock were to be harvested at the beginning of the fishing horizon. This also means that the catchability coefficient at the intercept is one (ie. $q_1 = 1$). As a result, the intercept is the initial stock. Using the initial stock, we can calculate the catchability coefficient of 1986 by dividing the CPUE of the industrial fishery in 1986 by the initial stock. For the rest of the years, we calibrate catchability coefficient for both the artisanal and industrial fishery by dividing each year's CPUE by the stock biomass at the beginning of the year.

To calibrate the by-catch, it is assumed that the industrial fishery dedicates only 1% of its effort in each period to illegal trawling of by-catch. So that $Z = 0.01\times$industrial fishing effort or vessels.[23] Based on this data, we calculate the by-catch from 1986 to 2013 as follows:

$$\begin{aligned}
\text{By-catch in 1986} = &\text{catchability coefficient of 1986} \\
&\times 0.01 \times \text{industrial fishing effort or vessels in 1986} \\
&\times \text{initial stock biomass.} \\
&\vdots \\
\text{By-catch in 2013} = &\text{catchability coefficient of 2013} \\
&\times 0.01 \times \text{industrial fishing effort or vessels in 2013} \\
&\times \text{stock biomass in 2012.}
\end{aligned}$$

Next, we calculate the stock biomass as:

$$\begin{aligned}
\text{Stock biomass in 1986} = &\text{initial stock biomass} - \text{estimated catch in 1986} \\
&- \text{estimated by-catch in 1986.} \\
&\vdots \\
\text{Stock biomass in 2013} = &\text{stock biomass in 2012} - \text{estimated catch in 2013} \\
&- \text{estimated by-catch in 2013}
\end{aligned}$$

By this formulation, we are implicitly assuming that all harvests and by-catches are extracted one time at the end of each year. Thus, the current stock biomass minus harvest and by-catch becomes

[23]Naturally, we should be able to explicitly estimate Z from equation (3.15) ie. $Z^* = \left(\frac{(1-\tau)c}{q_1 v}\right)^\beta$. However, because of lack of data on economic parameters such as the marginal cost of harvest, we had to make an assumption to estimate Z in a more conservative way (ie. $Z = 0.01 \times$ industrial fishing effort). It is worth nothing that we explore a number of assumptions to numerically estimate Z. In the case where the industrial fishery dedicates more than 1% of it effort to illegal trawling, by-catch far outweighs the actual reported catch of the artisanal fishery. This is because the catchability coefficient of the industrial fishery is much higher than that of the artisanal fishery in every period (see, Table 3.3).

the stock biomass at the beginning of the next year. We calibrate each subsequent by-catch from 1987 to 2013 using the biomass at the beginning of each period.

Importantly, the assumption that industrial fishery dedicates 1% of it effort to illegal trawling makes it such that by-catch ranges between 18% - 95% of total artisanal catch, except for 1991, 2007, and 2011 which maybe outliers (see. Table 3.4). These results are consistent with Hen Mpoano (2018) who estimated by-catch in 2017 to be about 10,000 metric tons representing, 40% of total artisanal catch and valued at around US$34-65million for Ghana. The results also show a significant increase in by-catch since 2007, which averages about 93% of total artisanal catch since 2007. These increases in by-catch seem to have coincided with increases in industrial fishery effort, which is not commensurate with the increases in annual industrial fishery's catch. The conjectured is that the extra increases in industrial fishing effort may have being move toward illegal trawling of by-catch, which may explain why effort is increasing with less than a proportionate increase in industrial fishery's annual landings.

With the right data and under appropriate assumptions regarding market price of small pelagic stock, intrinsic growth rate, marginal cost and the social discount rate, we can estimate the tax rate (ie. $\tau = 1 - \frac{rv}{\delta\mu P}$) and other economics variables of interest such as net revenue after tax. The information that 10,000 metric tons was valued at around US$34-65million in 2017 (see Hen Mpoano, 2018) allows us to infer that the market price of one metric ton of small pelagic fish is between $3400 - 6500. However, we still don't have information on the intrinsic growth rate, marginal cost and the social discount rate. Estimating the other economic variables and parameters should be an area of further research when more data becomes available. However, for the purpose of this study, we attempt to estimate some of the parameters of interest by estimating equation (3.6b), as we did for equation (3.6a) above.

Table 3.4: Calibrating the Stock Biomass and By-catch in the Artisanal Fishery

Year	Artisanal Fishery				Estimated Stock	Catchability Coefficient of Artisanal (q_1)	Catchability Coefficient of Trawlers (q_2)	$Z = 0.01 * vessels$	By-catch ($B = q_2 ZS$)	By-catch as % of Actual Catch
	Actual Catch	Estimated Catch	Actual CPUE	Estimated CPUE						
1986	190197	263140	23155	32036	1990066275	0.000012	0.000070	0.58	80910	43
1987	261451	263140	31830	32036	1989717144	0.000016	0.000094	0.47	87680	34
1988	244042	263140	29710	32036	1989429662	0.000015	0.000046	0.47	43440	18
1989	220878	268386	27431	33332	1989130274	0.000014	0.000116	0.34	78510	36
1990	242020	268386	30057	33332	1988707654	0.000015	0.000211	0.43	180600	75
1991	215847	268386	26807	33332	1988271027	0.000013	0.000252	0.44	220780	102
1992	307931	248912	35443	28650	1987799436	0.000018	0.000217	0.38	163660	53
1993	257237	248912	29608	28650	1987392989	0.000015	0.000209	0.36	149210	58
1994	211747	248912	24372	28650	1986990982	0.000012	0.000195	0.49	190260	90
1995	210659	248912	24247	28650	1986627343	0.000012	0.000154	0.50	152980	73
1996	298249	250253	34516	28961	1986078054	0.000017	0.000204	0.62	251040	84
1997	215125	243171	24185	27338	1985687649	0.000012	0.000158	0.56	175280	81
1998	189459	243171	21299	27338	1985329720	0.000011	0.000170	0.50	168470	89
1999	176237	251146	20469	29169	1985014033	0.000010	0.000140	0.50	139450	79
2000	275965	251146	32052	29169	1984583518	0.000016	0.000142	0.55	154550	56
2001	236355	216941	23680	21735	1984150723	0.000012	0.000180	0.55	196440	83
2002	200824	216941	20121	21735	1983810899	0.000010	0.000130	0.54	139000	69
2003	238861	216941	23932	21735	1983472608	0.000012	0.000075	0.67	99430	42
2004	267910	193209	23880	17222	1983064598	0.000012	0.000099	0.71	140100	52
2005	218871	193209	19509	17222	1982720787	0.000010	0.000119	0.53	124940	57
2006	231681	193209	20651	17222	1982314916	0.000010	0.000100	0.88	174190	75
2007	187088	193209	16676	17222	1981928908	0.000008	0.000110	0.91	198920	106
2008	254133	193209	22652	17222	1981491885	0.000011	0.000078	1.19	182890	72
2009	226755	193209	20212	17222	1981056760	0.000010	0.000118	0.89	208370	92
2010	198152	193209	17662	17222	1980670018	0.000009	0.000094	1.01	188590	95
2011	196200	193209	17488	17222	1980277847	0.000009	0.000085	1.16	195970	100
2012	213451	193209	19026	17222	1979866766	0.000010	0.000086	1.16	197630	93
2013	202602	168934	15770	13150	1979470104	0.000008	0.000085	1.15	194060	96
Intercept					1990337382					

Note: B is calibrated under the assumption that the industrial fishery devote only 1% of its effort(or vessels) to the illegal trawling of by-catch. Thus, $Z = 0.01 \times$ Industrial fishing effort or vessels. If they dedicate more than 1%, by-catch will far outweigh artisanal catch in every period. The actual catch, estimated catch and estimated stock are in metric ton.

3.4.4 Estimating equation (3.6b)

Having estimated the stock biomass, we proceed to estimate equation (3.6b). As before, let's write equations (3.6b) in standard discrete time format: [24]

$$S_{it} = b_0 + b_1 S_{it-1} + b_2 S_{it}^2 + b_3 H_{it} + \eta_{it-1} \tag{3.36}$$

where i is the observation, $t-1$ = 1 , ..., 28 years (1986 - 2013), b_0 is the constant of regression and η_{it-1} is the error term. $b_1 = \dfrac{1}{(1-r)}$, $b_2 = -\dfrac{r}{(1-r)K(Z)}$ and $b_3 = -\dfrac{1}{(1-r)}$. The term $b_2 S_{it}^2$ represents the amount of biological stock decline due to natural factors and ecosystem externalities, while the coefficient $\dfrac{1}{(1-r)}$ functions as a discount factor for discounting all the variables of interest to obtain the current biomass. Thus, equation (3.36) describes current stock as a function of previous year's stock minus amount of biological stock lost minus current harvest. All other variables, including σ and r, carry their original definitions as stated above. We proceed to estimate equation (3.36) using the OLS estimator as reported in Table 3.5.

Table 3.5: OLS Estimates of Equation (3.36) for artisanal fishery in Ghana

Parameter	Value
b_0	980.9 million***
	[5.75 million]
b_1	0.012*
	[0.006]
b_2	0.000***
	[0.000]
b_3	0.007
	[0.013]
Observations	27
R-squared	1.000

Dependent variable is current year's stock (S_{it}). Standard errors in brackets are robust to heteroscedasticity. $***p < 0.01, **p < 0.05, *p < 0.1$. The coefficient of b_2 is 0.000000000249

[24] $S_{it} - rS_{it} = S_{it-1} - \left(\frac{r}{K(Z)}\right) S_{it}^2 - H_{it} + \eta_{it-1}$

As expected, we found a positive relationship between the lag term of stock biomass and current stock, with a corresponding coefficient of 0.012. This implies that stock biomass from previous year significantly influences the amount of stock available in the current year. The result also shows that artisanal harvest of small pelagic fish does not significantly impact the stock. However, we see that ecosystem externalities captured by the coefficient $b_2 = 0.000000000249$ is statistically significant in determining the current level of stock. This implies that the health of the marine ecosystem is influential in determining the stock biomass.

3.4.5 Estimated Tax Rate, trawl vessel and By-catch

To estimate the parameters of interest, we use values and expressions from the regression results of equations (3.32) and (3.36) reported in Tables 3.2 and 3.5 respectively. Using $b_1 = 0.012 = \frac{1}{(1-r)}$, we calculate r to be -82.333. This shows that the small pelagic stock has a negative intrinsic growth rate, suggesting that the stock is in decline. Using our earlier assumption concerning Z, let $Z = 1.01$ which is equivalent to the projected Z for year 2010 (see Table 3.4). From $b_2 = 0.000000000249 = -\frac{r}{(1-r)K(Z)}$, we can calculate $K(Z) = 3967871486$, so that $\mu = 3967871486 \times lnZ = 39481634.07$. To calculate the net price (m) from $a_1 = 0.003 = m\sigma$, let $\sigma = 0.00004$ as estimated by Barbier (2007) so that $m = 0.003/0.00004 = 75$. The parameters are tabulated in Table 3.6 below. [25]

For simplicity, let's assume that the constant c in the artisanal fishery's problem is equal to the marginal cost of the industrial and $\alpha = 0.5$. Also, let's assume a quadratic relationship for the impact of Z in the cost function (ie. $C(E, Z) = cEZ^2$) so that $\beta = 2$.

[25] "In 2023, the approximate price range for US Mackerel is between US$ 1.64 and US$ 1.47 per kilogram or between US$ 0.74 and US$ 0.67 per pound(lb). The average price for a tonne is US$ 1640.76 in New York and Washington." Retrieve from Selina Wamucii Insights on 4/22/2023. Available on https://www.selinawamucii.com/insights/prices/united-states-of-america/mackerel/

Table 3.6: Parameter values of interest

Parameter	Value
Intrinsic growth rate (r)	-82.333
Net price (m)	75
Selling price per ton (P)	\$1640.76
Marginal cost per trawl vessel(v)	\$1565.76
c	\$1565.76
β	2
α	0.5
Discount rate (δ)	0.1
Maximum viable size of the stock($\mu = lnZK(Z)$)	39481634.07 metric ton
Catchability coefficient of trawlers ($\bar{q_2}$)	0.000133
Catchability coefficient of artisanal fishers ($\bar{q_1}$)	0.000012

Note: The value for $\bar{q_2}$ and $\bar{q_1}$ are the corresponding average catchability coefficient from 1986 to 2013. See Table 3.5 for the full list of values.

Optimal tax rate

Substituting the parameter values from Table 3.6 into the tax expression of equation (3.26) yields

$$\begin{aligned} \widetilde{\tau} &= 1 - \frac{q_1 v}{\alpha c q_2}\left(\frac{rc}{\delta\alpha\mu P q_1}\right)^{\frac{\beta}{(\beta+\alpha-1)}} \\ &= 1 - \frac{0.000012}{0.5 \times 0.000133}\left(\frac{82.33 \times 1565.76}{0.1 \times 0.5 \times 39481634.07 \times 1640.76 \times 0.000012}\right)^{\frac{2}{1.5}} = 0.107 \end{aligned} \tag{3.37}$$

This result shows that the optimal tax rate to be imposed by the government on revenue from by-catch is 10.7%. Given the lack of data on important parameters, it is safe to assume that the true optimal tax lies somewhere between 100% and 10% of revenue from by-catch.

Decentralized Equilibrium vs Socially Optimal Vessel

By substituting the parameters into Equations (3.11a) and (3.17a), we can compute the corresponding number of vessels that the trawlers and government chooses, as shown in equations (3.38b) and (3.38c). Consequently, when we evaluate Z^* and $\widetilde{Z}$ at the optimal tax, the number of vessels chosen by the industry fishery in the decentralized equilibrium is identical to the number chosen by the government. This shows that the tax rate of 10.7% is the tax rate under which the decentralized equilibrium merges with the social equilibrium.

$$Z^* = \left(\frac{(1-\tau)\alpha c q_2}{q_1 v}\right)^{(\beta+\alpha-1)} = \left(\frac{(1-0.107)\times 0.5 \times 0.000133}{0.000012}\right)^{1.5} = 11 \tag{3.38a}$$

And if $\tau = 0$

$$Z^* = \left(\frac{c\alpha q_2}{q_1 v}\right)^{\beta} = \left(\frac{0.5 \times 0.000133}{0.000012}\right)^{1.5} = 30.7 \tag{3.38b}$$

$$\widetilde{Z} = \left(\frac{rc}{\delta\alpha\mu P q_1}\right)^{\beta} = \frac{82.33 \times 1565.76}{0.1 \times 0.5 \times 39481634.07 \times 1640.76 \times 0.000012} = 11. \tag{3.38c}$$

For comparison, when the tax rate is zero, $Z^* = 30.7$ and $\widetilde{Z} = 11$. The average number of vessels in the industrial fishery between 1986 and 2013 is 66 (see Table 3.1). Our estimate of Z^* shows that, on the average, the industrial fishery uses about $1/2$ of their vessels for illegal trawling of small pelagic fish, if tax is zero.

Decentralized equilibrium vs Socially Optimal By-catch

Again, by substituting the parameters into equations (3.11b) and (3.17b), we can compute the corresponding by-catch that the trawlers and government chooses. As before, when we evaluate B^* and $\widetilde{B}$ at the optimal tax, the amount of by-catch chosen by the industry fishery in the decentralized equilibrium is identical to the amount chosen by the government.

$$\begin{aligned} B^* &= \frac{cq_2}{Pq_1}\left(\frac{(1-\tau)\alpha c q_2}{q_1 v}\right)^{(\beta+\alpha)(\beta+\alpha-1)} \\ &= \frac{1565.76 \times 0.000133}{1640.76 \times 0.000012}\left(\frac{(1-0.107)\times 0.5 \times 0.000133}{0.000012}\right)^{2.5*1.5} \\ &= 4244.34 \quad \text{metric tonnes} \end{aligned} \tag{3.39a}$$

And if $\tau = 0$

$$B^* = \frac{cq_2}{Pq_1}\left(\frac{\alpha c q_2}{q_1 v}\right)^{(\beta+\alpha)(\beta+\alpha-1)} = \frac{1565.76 \times 0.000133}{1640.76 \times 0.000012}\left(\frac{0.5 \times 0.000133}{0.000012}\right)^{2.5*1.5}$$
$$= 55278.03 \quad \text{metric tonnes} \tag{3.39b}$$

$$\widetilde{B} = \frac{cq_2}{Pq_1}\left(\frac{rc}{\delta\alpha\mu P q_1}\right)^{\beta(\beta+\alpha)}$$
$$= \frac{1565.76 \times 0.000133}{1640.76 \times 0.000012}\left(\frac{82.33 \times 1565.76}{0.1 \times 0.5 \times 39481634.07 \times 1640.76 \times 0.000012}\right)^{2*2.5} \tag{3.39c}$$
$$= 4244.34 \quad \text{metric tonnes}$$

The findings pertaining to Z^* and $\widetilde{Z}$ as well as B^* and $\widetilde{B}$ suggest that, when optimal tax rate is applied, the industrial fishery will chose to cooperate with fishery regulations and avoid illegal trawling of small pelagic fishes. As a result cooperation with fishing laws emerge as the Nash equilibrium.

3.5 Conclusion

The capture fisheries sector is a critical source of food and livelihood for fishing households in Africa. Yet, illegal targeting of impropriety species has escalated in recent decades due to limited capacity of the regulatory bodies, inadequate enforcement of fishing regulations and the lack of resource-centered policies. For our consideration, in the case of Ghana, these illegal targeting of impropriety species is done by trawlers who are licensed to trawl for demersal fishes, yet they encroach into the small pelagic zone to illegally trawl for small pelagic fishes and pass them as by-catch. Trawling in the small pelagic zone is not only illegal, it raises the harvesting costs of artisanal fishers, and damages the benthic floor which houses the ecosystems of food for the fishes. We refer to the former as crowding externality and the latter as ecosystem externality.

In this paper, we introduce a general approach on how to analyze the impact of crowding and ecosystem externalities on the artisanal fishery by developing a bioeconomic model and empirically estimating the model for the case of Ghana. We demonstrate that both externalities impact the productivity and profitability of the artisanal fishery, whose legal target stock is the small pelagic fishes. Our empirical results show that, between 1986 and 2013, by-catch ranges from 18% - 95% of total artisanal catch except for some extreme outliers. We also found that industrial fishing effort has being increasing since 2007 but with less than a proportionate increase in legal annual catch, when compared to previous years. This seems to have coincided with increases in by-catch, which averages about 93% of total artisanal catch since 2007. The conjectured is that the extra increases in industrial fishing effort may have being moved toward illegal trawling of by-catch. This may explain why effort is increasing with less than a proportionate increase in industrial fishery's annual landings.

We estimated the optimal tax rate to be approximately 11%. However, given the data challenges, we believe that the true optimal tax lies between 100% and 10% of revenue from by-catch. Consequently, when the optimal tax rate is applied, the amount of by-catch chosen by the industry fishery in the decentralized equilibrium is identical to the amount chosen by the government.

Our results have important policy implications. If government's goal is to increase the productivity of the artisanal fishery, the current level of by-catch should be reduced through monitoring and effective tax structures.

Bibliography

Allen ML, Roberts NM, Bauder JM (2020) Relationships of catch-per-unit-effort metrics with abundance vary depending on sampling method and population trajectory. *PLOS ONE* 15(5): e0233444. https://doi.org/10.1371/journal.pone.0233444

Arreguín-Sánchez, F. (1996). Catchability: a key parameter for fish stock assessment. *Reviews in fish biology and fisheries*, 6, 221-242.

Ávila-Foucat, V. S., Vargas, A. S., Jordan, A. F., and Flores, O. R. (2013). The impact of vessel crowding on the probability of tourists returning to whale watching in Banderas Bay, Mexico. *Ocean and coastal management*, 78, 12-17.

Banerjee, A.V., and E. Duflo (2003). Inequality and Growth: What Can the Data Say? *Journal of Economic Growth*, 8(3): 267–99. https://doi.org/10.1023/A:1026205114860

Barbier, E. B. (2003). Habitat–Fishery Linkages and Mangrove Loss in Thailand. *Contemporary Economic Policy*, 21(1):59–77.

Barbier, E. B. (2007). Valuing ecosystem services as productive inputs. *Economic policy*, 22(49), 178-229.

Barbier, E.B., and J.P. Hochard (2018). Poverty, Rural Population Distribution and Climate Change. *Environment and Development Economics*, 23(3): 234–56. https://doi.org/10.1017/S1355770X17000353

Barbier, E., and I. Strand. (1998). Valuing Mangrove–Fishery Linkages. *Environmental and Resource Economics*, 12:151–66.

Barnes, T. C., Candy, S. G., Morris, S., and Johnson, D. D. (2022). Understanding discarding in trawl fisheries: A model based demersal case study with implications for mitigating and assessing impacts. *Plos one*, 17(2), e0264055.

Barro, R.J. (1991). Economic Growth in a Cross Section of Countries. *The Quarterly Journal of Economics*, 106(2): 407–43. https://doi.org/10.2307/2937943

Belhabib, D., Sumaila, U. R., & Le Billon, P. (2019). The fisheries of Africa: Exploitation, policy, and maritime security trends. *Marine Policy*, 101, 80-92.

Bénabou, R. (1996). Inequality and Growth. *NBER Macroeconomics Annual*, 11: 11–74. https://doi.org/10.3386/w5658

Béné, C., Belal, E., Ousman Baba, M., Ovie, S., Raji, A., Malasha, I., Njaya, F., Na Andi, M., Russel, A., Neiland, A., (2010). Struggle, dispute and alliance over the new power: analyzing 'democratic' decentralization of natural resources through the lenses of Africa inland fisheries. *World Development* 37 (12), 1935-1950.

Béné, C., Macfadyen, G., Allison, E., (2007). Increasing the Contribution of Small-Scale Fisheries to Poverty Alleviation and Food Security. FAO, Rome, Italy.

Bishir, J., and Lancia, R. A. (1996). On catch-effort methods of estimating animal abundance. *Biometrics*, 1457-1466.

Bishop, M. J., C. H. Peterson, H. C. Summerson, and D. Gaskill. 2005. Effects of Harvesting Methods on Sustainability of a Bay Scallop Fishery: Dredging Uproots Seagrass and Displaces Recruits. *Fishery Bulletin* 103(4):712–19.

Bricelj, V. M., R. E. Malouf, and C. Boisrobert, C., & Virdin, J. (2008). The Importance of Africa's coastal and marine ecosystems. *Environment Matters*.

Carleton, T.A., Jina, A., Delgado, M.T., Greenstone, M., Houser, T., Hsiang, S.M., Hultgren, A., Kopp, R.E., McCusker, K.E., Nath, I.B. and Rising, J., et al. (2020). Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits (No. w27599). *National Bureau of Economic Research*.

Chambers, R. G., and Strand Jr, I. E. (1986). Estimating parameters of a renewable resource model without population data. Marine resource economics, 2(3), 263-274.

Chen, S., and M. Ravallion (2001). How Did the Worlds Poorest Fare in the 1990s? *Review of Income and Wealth*, 47: 283–300. https://doi.org/10.1111/1475-4991.00018

Clark CW (1990) Mathematical bioeconomics: the optimal management of renewable resources. Wiley- Interscience Publication, New York.

Clark, R. (2011). World Health Inequality: Convergence, Divergence, and Development. *Social Science and Medicine*, 72(4): 617–24. https://doi.org/10.1016/j.socscimed.2010.12.008

Decerf, B., Ferreira, F.H., Mahler, D.G. and Sterck, O., 2021. Lives and livelihoods: estimates of the global mortality and poverty effects of the Covid-19 pandemic. *World Development*, 146, p.105561.

Deininger, K., and L. Squire (1996). A New Data Set Measuring Income “inequality. *The World Bank Economic Review*, 10(3): 565–91. https://doi.org/10.1093/wber/10.3.565

Doumbouya, A., Camara, O. T., Mamie, J., Intchama, J. F., Jarra, A., Ceesay, S., ... & Belhabib, D. (2017). Assessing the effectiveness of monitoring control and surveillance of illegal fishing: The case of West Africa. *Frontiers in Marine Science*, 50.

Durlauf, S.N., P.A. Johnson, and J.R. Temple (2005). *Growth Econometrics: Handbook of Economic Growth*, 1: 555–677. https://doi.org/10.1016/S1574-0684(05)01008-7

Dwyer, D. A., K. M. Bailey, and P. A. Livingston. 1987. Feeding Habitats and Daily Ration of Walleye Pollock (Theragra chalcogramma) in the Eastern Bering Sea, with Special Reference to Cannibalism. *Canadian Journal of Fisheries and Aquatic Sciences*, 44(11):1972–84.

Erisman, B. E., L. G. Allen, J. T. Claisse, D. J. Pondella, E. F. Miller, J. H. Murray, and C. Walters. (2011). The illusion of plenty: hyperstability masks collapses in two recreational fisheries that target fish spawning aggregations. *Canadian Journal of Fisheries and Aquatic Sciences*, 68: 1705–1716.

Fleurbaey, M. (2009). Beyond GDP: The quest for a measure of social welfare. *Journal of Economic Literature*, 47(4):1029-75.

Fleurbaey, M. and Blanchet, D. 2013. *Beyond GDP: Measuring welfare and assessing sustainability*. Oxford University Press.

Fuller, R., P.J. Landrigan, K,Balakrishnan, G. Bathan, S. Bose-OReilly, M. Brauer, J. Caravanos, T. Chiles, A. Cohen, L. Corra, M. Cropper. G. Ferraro, J. Hanna, D. Hanrahan, H. Hu, D. Hunter, G. Janata, R. Kupka, B. Lanphear, M. Lichtveld, K. Martin, A. Mustapha, E. Sanchez-Triana, K. Sandilya, L Schaefli, J. Shaw, J. Seddon, William Suk, M.M. Téllez-Rojo, and C. Yan (2022). Pollution and Health: A Progress Update. *Lancet Planet Health*, 6(6): E535–47. https://doi.org/10.1016/S2542-5196(22)00090-0

Gastwirth, J.L. (1971). A General Definition of the Lorenz Curve. *Econometrica*, 39(6): 1037–39. https://doi.org/10.2307/1909675

GHDx (2019). Environmentally Related DALYs and Deaths. Washington, DC: Institute for Health Metrics and Evaluation. Available at: http://ghdx.healthdata.org/gbd-results-tool (accessed 20 November 2021).

Gradín, C. (2021). Trends in Global Inequality using a New Integrated Dataset. WIDER Working Paper 2021/61. Helsinki: UNU-WIDER. Available at: www.wider.unu.edu/sites/default/files/Publications/Working-paper/PDF/wp2021-61-trends-global-inequality.pdf (accessed 28 October, 2021). https://doi.org/10.35188/UNU-WIDER/2021/999-0

Gronau, R. (1977). Leisure, home production, and work–the theory of the allocation of time revisited. *Journal of political economy*, 85(6), 1099-1123.

Hall, R.E., Jones, C.I. and Klenow, P.J., 2020. Trading off consumption and covid-19 deaths (No. w27340). *National Bureau of Economic Research*.

Homans, F. R., and Wilen, J. E. (1997). A model of regulated open access resource use. Journal of Environmental Economics and Management, 32(1), 1-21.

Jagger, C., van Oyen, H. and Robine, J.M... (2014). Health Expectancy Calculation by the Sullivan Method: A Practical Guide. Euro-REVES project and Institute for Ageing, Newcastle University, UK. Available at http://reves.site.ined.fr/en/resources/computation_online/sullivan/

Jin, D., Kite-Powell, H., and Talley, W. (2001). The safety of commercial fishing: determinants of vessel total losses and injuries. *Journal of Safety Research*, 32(2), 209-228.

Jin, D., and Thunberg, E. (2005). An analysis of fishing vessel accidents in fishing areas off the northeastern United States. *Safety Science*, 43(8), 523-540.

Johnson, K. A. (2002). A Review of National and International Literature on the Effects of Fishing on Benthic Habitats. NOAA Technical Memorandum NMFS-F/SPO-57. http://www.nmfs.noaa.gov/habitat/habitatprotection/essentialfishhabitat10.htm.

Johnson, P., and C. Papageorgiou (2020). What Remains of Cross-Country Convergence? *Journal of Economic Literature*, 58(1): 129–75. https://doi.org/10.1257/jel.20181207

Jones, C.I. and Klenow, P.J. 2016. Beyond GDP? Welfare across Countries and Time. *American Economic Review*, 106(9):2426-2457.

Jorgenson, D.W. 2018. Production and welfare: progress in economic measurement. *Journal of Economic Literature*, 56(3):867-919.

Kaiser, M. J., J. S. Collie, S. J. Hall, S. Jennings, and I. R. Poiner. (2002). Modification of Marine Habitats by Trawling Activities: Prognosis and Solutions. *Fish and Fisheries*, 3(2):114–36.

Kamenos, N. A., P. G. Moore, and J. M. Hall-Spencer. (2004). Nursery Area Function of Maerl Grounds for Juvenile Queen Scallops Aequipecten opercularis and Other Invertebrates. *Marine Ecology Progress Series* 274:183–89.

Knowler, D., E. B. Barbier, and I. Strand. (2002). An Open-Access Model of Fisheries and Nutrient Enrichment in the Black Sea. *Marine Resource Economics*, 16(3):195–217.

Kremer, M., J. Willis, and Y. You (2022). Converging to Convergence. *NBER Macroeconomics Annual*, 36(1): 337–412. https://doi.org/10.1086/718672

Lancia, R. A., Bishir, J. W., Conner, M. C., and Rosenberry, C. S. (1996). Use of catch-effort to estimate population size. *Wildlife Society Bulletin*, 731-737.

Landrigan, P.J., Fuller, R., Acosta, N.J., Adeyi, O., Arnold, R., Baldé, A.B., Bertollini, R., Bose-O'Reilly, S., Boufford, J.I., Breysse, P.N., Chiles, T. et al., (2018). The Lancet Commission on pollution and health. *The Lancet*, 391(10119):462-512.

LeSage, J., Christina, L., (2012). The impact of migration on social capital: do migrantstake their bowling balls with them? *Growth and Change* 43, 1–26.

Mankiw, N.G., D. Romer, and D.N. Weil (1992). A Contribution to the Empirics of Economic Growth. *Quarterly Journal of Economics*, 107(2): 407–37. https://doi.org/10.2307/2118477

Milanovic, B., P.H. Lindert, and J.G. Williamson (2011). Pre-industrial Inequality. *Economic Journal*, 121(551): 255–72. https://doi.org/10.1111/j.1468-0297.2010.02403.x

Miller, R. and Bairoliya. 2021. Health, Longevity, and Welfare Inequality of Older Americans. *Review of Economics and Statistics*. Accepted September 2021 https://doi.org/10.1162/rest_a_01103

Molla, M.T., Madans, J.H., Wagener, D.K. and Crimmins, E.M.. 2003. Summary Measures of Population Health: Report of Findings on Methodologic and Data Issues. National Center for Health Statistics, Hyattsville , MD. Available at http://www.cdc.gov/nchs/data/misc/pophealth.pdf

Mpoano, H (2015), Addressing illegal fishing through Education and Sensitization for Sustainable Fisheries Management in Ghana: Rapid Assessment of IUU fishing in three coastal communities in the Central and Western Region of Ghana. Hen Mpoano and BUSAC. 38pp.

Mpoano, H. (2018). VSLA Financial Literacy Training Report. The USAID/Ghana Sustainable Fisheries Management Project (SFMP). Narragansett, RI: Coastal Resources Center, Graduate School of Oceanography, University of Rhode Island and Hen Mpoano. GH2014_ACT184_HM.

Nansai, K., S. Tohno, S. Chatani, K. Kanemoto, S. Kagawa, Y. Kondo, W. Takayanagi, and M. Lenzen (2021). Consumption in the G20 Nations Causes Particulate Air Pollution resulting in Two Million Premature Deaths Annually. *Nature Communications*, 12(1): 1–12. https://doi.org/10.1038/s41467-021-26348-y

Nguyen, T. V., Ravn-Jonsen, L., & Vestergaard, N. (2016). Marginal damage cost of nutrient enrichment: the case of the Baltic Sea. *Environmental and Resource Economics*, 64(1), 109-129.

Ortiz-Ospina, E. 2017. “Life Expectancy” – What does this actually mean? Our World in Data August 28, 2017. https://ourworldindata.org/life-expectancy-how-is-it-calculated-and-how-should-it-be-interpreted

Pande, R., and N.T. Enevoldsen (2021). Comment on “Converging to Convergence”. *National Bureau of Economic Research Macroeconomics Annual*, 36: 413–24. https://doi.org/10.1086/718673

Parks, P. J., and Bonifaz, M. (1994). Nonsustainable use of renewable resources: mangrove deforestation and mariculture in Ecuador. *Marine Resource Economics*, 9(1), 1-18.

Penney, R., Wilson, G., & Rodwell, L. (2017), Managing sino-ghanaian fishery relations: A political ecology approach. *Marine Policy*, 79, 46-53.

Perez-Labajos, C., Azofra, M., Blanco, B., Achutegui, J., and Gonzalez, J. (2006). Analysis of accident inequality of the Spanish fishing fleet. *Accident Analysis and Prevention*, 38(6), 1168-1175.

Pérez-Labajos, C. A., Blanco, B., Azofra, M., Achútegui, J. J., and Eguia, E. (2009). Injury and loss concentration by sinkings in fishing fleets. *Safety science*, 47(2), 277-284.

Peters, D. H., Garg, A., Bloom, G., Walker, D. G., Brieger, W. R., & Hafizur Rahman, M. (2008). Poverty and access to health care in developing countries. *Annals of the new York Academy of Sciences*, 1136(1), 161-171.

Prüss-Üstün, A., J. Wolf, C. Corvalán, R. Bos, and M. Neira (2016). Preventing Disease through Healthy Environments: A Global Assessment of the Burden of Disease from Environmental Risks. Geneva: WHO.

Ravallion, M. (1997). Can High-Inequality Developing Countries Escape Absolute Poverty? *Economics Letters*, 56(1): 51–57. https://doi.org/10.1016/S0165-1765(97)00117-1

Ravallion, M. (2001). Growth, Inequality and Poverty: Looking beyond Averages. *World Development*, 29(11): 1803–15. https://doi.org/10.1016/S0305-750X(01)00072-9

Ravallion, M. (2003). Inequality Convergence. *Economics Letters*, 80(3): 351–56. https://doi.org/10.1016/S0165-1765(03)00141-1

Ravallion, M. (2012). Why Dont we See Poverty Convergence? *American Economic Review*, 102(1): 504–23. https://doi.org/10.1257/aer.102.1.504

Ravallion, M. (2014). Income Inequality in the Developing World. *Science*, 344(6186): 851–55. https://doi.org/10.1126/science.1251875

Ravallion, M. (2018). Inequality and Globalization: A Review Essay. *Journal of Economic Literature*, 56(2): 620–42. https://doi.org/10.1257/jel.20171419

Roberts, S. E., Jaremin, B., and Marlow, P. B. (2010). Human and fishing vessel losses in sea accidents in the UK fishing industry from 1948 to 2008. *International maritime health*, 62(3), 143-153.

Romer, P.M. (1990). Endogenous Technological Change. *Journal of Political Economy*, 98(5, Part 2), S71-S102. https://doi.org/10.1086/261725

Ryan, R. W., Holland, D. S., and Herrera, G. E. (2014). Ecosystem externalities in fisheries. *Marine Resource Economics*, 29(1), 39-53.

Smith, V. L. (1968). Economics of Production from Natural Resources. American Economic Review 58 (3):409–31.

Smith, V.K. and Zhao, M.Q. 2020. Economy-Wide Modeling, Environmental Macroeconomics, and Benefit-Cost Analysis. *Land Economics*, 96(3):305-332.

Stiefel, M.C., Perla, R.J. and Zell, B.L. 2010. A healthy bottom line: healthy life expectancy as an outcome measure for health improvement efforts. *The Milbank Quarterly*, 88(1):30-53.

Stiglitz, J.E., Sen, A. and Fitoussi, J.P., 2010. Mismeasuring our lives: Why GDP doesn't add up. *The New Press*.

UNU-WIDER (2021). World Income Inequality Database (WIID) Companion Dataset (wiidcountry and/or wiidglobal). Version 31 May 2021. Helsinki: UNU-WIDER. https://doi.org/10.35188/UNUWIDER/WIIDcomp-310521

Viscusi, W.K., (2021). Economic lessons for COVID-19 pandemic policies. *Southern Economic Journal*, 87(4):1064-1089.

Ward, H. G., P. J. Askey, J. R. Post, and K. Rose. (2013). A mechanistic understanding of hyperstability in catch per unit effort and density-dependent catchability in a multistock recreational fishery. *Canadian Journal of Fisheries and Aquatic Sciences*, 70:1542–1550.

Warton, D. I., Wright, I. J., Falster, D. S., and Westoby, M. (2006). Bivariate line-fitting methods for allometry. *Biological reviews*, 81(2), 259-291.

World Bank (n.d.). World Bank Country and Lending Groups Available at: https://datahelpdesk.worldbank.org/knowledgebase/articles/906519 (accessed 9 May 2022).

World Bank, (2004). *Saving Fish and Fishers: Toward Sustainable and Equitable Governance of the Global Fishing Sector*. World Bank, Agriculture and Rural Development Department, Washington D.C: World Bank

World Bank (2016). *West Africa Regional Fisheries Program (P106063). Implementation Status and Results Report*. Washington, DC: World Bank

World Health Organization (WHO), (2020a). *WHO Global Strategy on Health, Environment and Climate Change: The Transformation Needed to Improve Lives and Wellbeing Sustainably through Healthy Environments*. Geneva: WHO.

World Health Organization (WHO), (2020b). WHO methods and data sources for global burden of disease estimates 2000-2019. Department of Data and Analytics, Division of Data, Analytics and Delivery for Impact. WHO, Geneva. December 2020. https://cdn.who.int/media/docs/default-source/gho-documents/global-health-estimates/ghe2019_daly-methods.pdf

Appendix A

Chapter 1: Additional results and figures

Figure A.1: World Gini coefficient and environmentally related deaths.

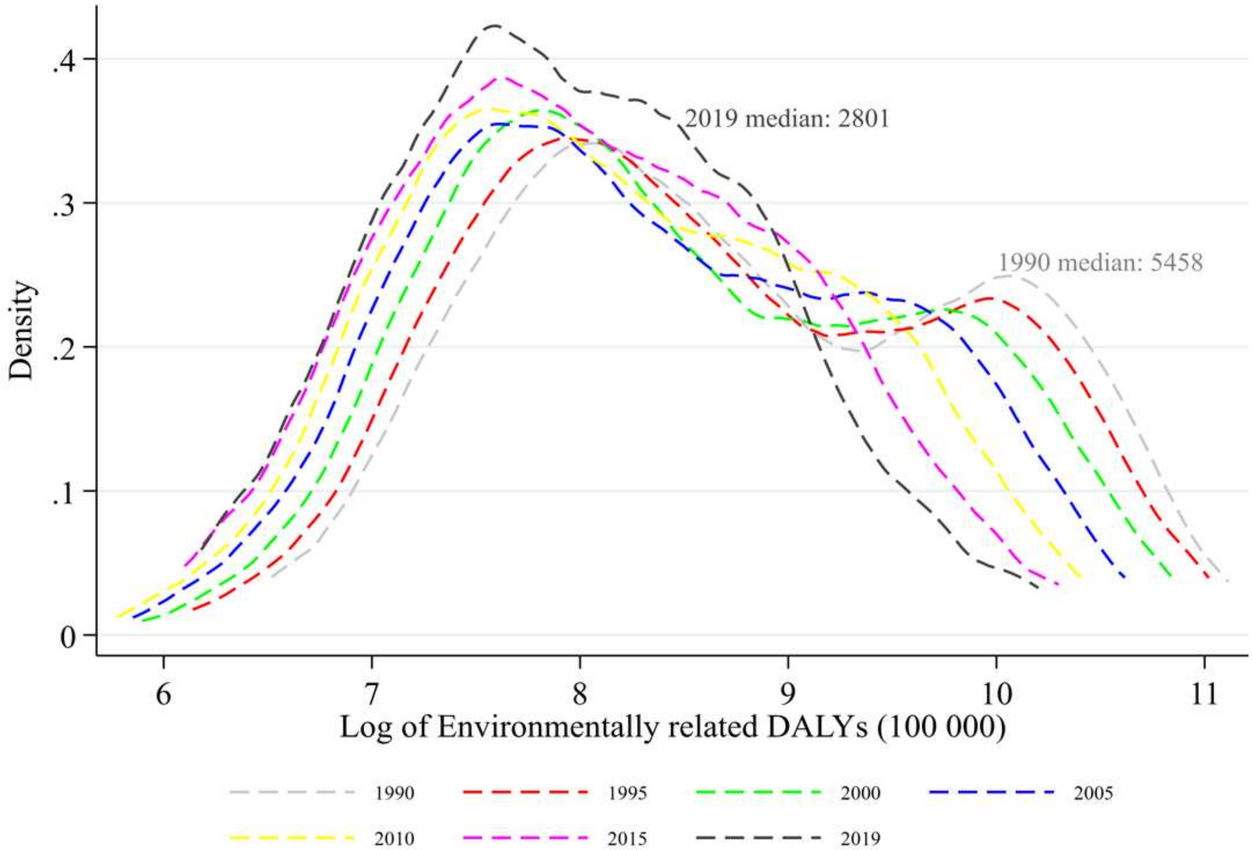


Figure A.2: Cross-country Distribution of log Environmentally related DALYs (1990, 2019)

Table A.1: 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				
Constant	2.09*	-7.33	-10.96	2.45	1.26	2.35	4.04
	[1.249]	[5.346]	[12.161]	[2.582]	[9.349]	[1.856]	[3.667]
Log of Gini index, initial year 1990, $\ln(g_{it-\tau})$	-4.58†	-3.70†	-3.24**	-8.34**	-22.08		
	[1.232]	[1.382]	[1.620]	[3.675]	[21.257]		
Log of Gini index, initial year 2000, $\ln(g_{it-\tau})$						-5.30†	-10.30**
						[1.621]	[4.879]
Log incidence of EIH, initial year 1990, $\ln(\sigma_{it-\tau})$	1.72†	2.22**	2.82	3.29*	9.34		
	[0.545]	[0.948]	[2.147]	[1.684]	[9.827]		
Log incidence of EIH, initial year 2000, $\ln(\sigma_{it-\tau})$						2.06†	4.09**
						[0.652]	[2.049]
Observations	178	73	105	178	178	179	179

the dependent variable is the annualized change in the log Gini index; the list of instruments for the Gini index includes 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 of less than 1% level, suggesting that initial EIH incidence and initial inequality are not exogenous to each other; estimates are for 179 countries for which EIH is available; heteroscedasticity-consistent robust standard errors (White) in parentheses; † significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A.2: 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 A3 for list of countries; heteroscedasticity-consistent robust standard errors (White) in parentheses; † significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A.3: List of 179 countries used for the empirical estimations

High income	Code	Upper middle income	Code	Lower middle income	Code	Low income	Code
Australia	AUS	Albania	ALB	Algeria	DZA	Burkina Faso	BFA
Austria	AUT	Argentina	ARG	Angola	AGO	Burundi	BDI
Bahamas, The	BHS	Armenia	ARM	Bangladesh	BGD	Central African Republic	CAF
Bahrain	BHR	Azerbaijan	AZE	Belize	BLZ	Chad	TCD
Barbados	BRB	Belarus	BLR	Benin	BEN	D.R. Congo	COD
Belgium	BEL	Bosnia and Herzegovina	BIH	Bhutan	BTN	Ethiopia	ETH
Canada	CAN	Botswana	BWA	Bolivia	BOL	Gambia, The	GMB
Chile	CHL	Brazil	BRA	Cabo Verde	CPV	Guinea	GIN
Croatia	HRV	Bulgaria	BGR	Cambodia	KHM	Guinea-Bissau	GNB
Cyprus	CYP	China	CHN	Cameroon	CMR	Liberia	LBR
Czechia	CZE	Colombia	COL	Comoros	COM	Madagascar	MDG
Denmark	DNK	Costa Rica	CRI	Congo, Rep.	COG	Malawi	MWI
Estonia	EST	Dominican Republic	DOM	Côte d'Ivoire	CIV	Mali	MLI
Finland	FIN	Ecuador	ECU	Djibouti	DJI	Mozambique	MOZ
France	FRA	Equatorial Guinea	GNQ	Egypt	EGY	Niger	NER
Germany	DEU	Fiji	FJI	El Salvador	SLV	Rwanda	RWA
Greece	GRC	Gabon	GAB	Eswatini	SWZ	Sierra Leone	SLE
Hungary	HUN	Georgia	GEO	Ghana	GHA	Sudan	SDN
Iceland	ISL	Guatemala	GTM	Haiti	HTI	Syria	SYR
Ireland	IRL	Guyana	GUY	Honduras	HND	Togo	TGO
Israel	ISR	Iraq	IRQ	India	IND	Uganda	UGA
Italy	ITA	Jamaica	JAM	Indonesia	IDN	Yemen	YEM
Japan	JPN	Jordan	JOR	Iran	IRN		
Korea, Rep.	KOR	Kazakhstan	KAZ	Kenya	KEN		
Kuwait	KWT	Lebanon	LBN	Kyrgyzstan	KGZ		
Latvia	LVA	Malaysia	MYS	Laos	LAO		
Lithuania	LTU	Maldives	MDV	Lesotho	LSO		
Luxembourg	LUX	Mauritius	MUS	Mauritania	MRT		
Malta	MLT	Mexico	MEX	Mongolia	MNG		
Netherlands	NLD	Moldova	MDA	Morocco	MAR		
New Zealand	NZL	Montenegro	MNE	Myanmar	MMR		
Norway	NOR	Namibia	NAM	Nepal	NPL		
Oman	OMN	North Macedonia	MKD	Nicaragua	NIC		
Poland	POL	Panama	PAN	Nigeria	NGA		
Portugal	PRT	Paraguay	PRY	Pakistan	PAK		
Qatar	QAT	Peru	PER	Philippines	PHL		
Saudi Arabia	SAU	Romania	ROU	Sâo Tomé and Príncipe	STP		
Seychelles	SYC	Russia	RUS	Senegal	SEN		
Singapore	SGP	Serbia	SRB	Sri Lanka	LKA		
Slovakia	SVK	South Africa	ZAF	Tajikistan	TJK		
Slovenia	SVN	St Lucia	LCA	Tanzania	TZA		
Spain	ESP	Suriname	SUR	Tunisia	TUN		
Sweden	SWE	Thailand	THA	Ukraine	UKR		
Switzerland	CHE	Turkey	TUR	Uzbekistan	UZB		
Trinidad and Tobago	TTO	Turkmenistan	TKM	Vietnam	VNM		
United Kingdom	GBR			Zambia	ZMB		
United States	USA			Zimbabwe	ZWE		
Uruguay	URY						

Appendix B

Chapter 2: Online Appendix

B.1 Introduction

This appendix provides further details of our modification of the macroeconomic welfare measure derived by Jones and Klenow (2016), who express economic well-being of a representative individual, in a country, as a function of consumption, leisure, inequality and mortality. Our aim here is to further extend the Jones-Klenow cross-country welfare to include the impacts of environmentally related deaths and disabilities on the life expectancy and thus welfare of the individual in current year t.

To do this, we draw on health and macroeconomic data for 163 countries, over 1990 -2019, from four databases: (1) average life expectancy at birth from the World Bank's World Development Indicators (https://databank.worldbank.org/source/world-development-indicators); (2) Penn World Table 10.0 (https://www.rug.nl/ggdc/productivity/pwt/?lang=en) for income (GDP), consumption, employment, population and hours worked; (3) Gini coefficients from the UNU-WIDER World Income Inequality Database (https://www.wider.unu.edu/project/wiid-%E2%80%93-world-income-inequality-database); and (4) the Global Burden of Disease (GBD) dataset of environmentally related mortality and burden of disease across163 countries over 1990-2019, available from the Global Health Data Exchange (GHDx, http://ghdx.healthdata.org/gbd-results-tool).

As with any macro-level empirical estimations, the model's predictability is limited to a representative individual or the average person in any given country. Individual specific dynamics that potentially influence individuals' welfare may not be fully capture by our welfare index, which is built on macro indicators. For example, the dataset of environmentally related mortality and morbidity from the Global Health Data Exchange (http://ghdx.healthdata.org/gbd-results-tool) that we employ to construct the probability that a random individual in year t will lose some life years due to environmental health risks does not disaggregate this data for different age groups within countries and over time. Because of this data constraint, the model implicitly assumes that a given country is populated by many people who are identical in all regards including consumption, leisure, exposure to environmental risks and life expectancy. It assumes a common incidence of environmentally related mortality and morbidity at each age. Similarly, growth of consumption, leisure and mortality at each age is fixed. These assumptions are necessary to smooth out the lifetime utility of the representative individual. Should life expectancy, consumption, leisure, or environmental risk exhibit any trend or vary with age, then lifetime utility will be difficult to pin down and could differ significantly for each age group.

The lack of high-quality data on the average hours per worker for some countries constitutes another source of limitations. Many low and lower middle-income countries do not have consistent time series data on hours worked. However, we notice a high correlation between the income group classification of countries and the average hours of work per worker. Thus, to remedy the situation, we replace the missing values with their respective income group mean hours per worker.

B.2 Variable Definitions

B.2.1 Environmental health risk

As explained in the main text, our approach to adjusting the expected lifetime component of the Jones-Klenow macroeconomic welfare requires an estimate of the probability ρ_i that an individual living in country i will lose some life years in year t due to environmental health risks. To estimate this parameter, we use the Global Burden of Disease (GBD) dataset of environmentally related mortality and morbidity across163 countries over 1990-2019, available from the Global Health Data Exchange (http://ghdx.healthdata.org/gbd-results-tool). We use these data from the GBD to compute a lower and upper-bound estimate of ρ_i.

For our lower-bound estimate, from the GBD we aggregate the total number of years of healthy life lost due to disability (YLDs) attributable to the environment for any given country. The YLDs were computed by summing up data from four Global Health Data Exchange (GHDx) codes (82, 85, 89, and 331) which correspond to disease burdens attributable to the environment. These

GBD codes are, respectively, (82) unsafe water, sanitation, and handwashing; (85) air pollution including particulate matter pollution, ambient particulate matter pollution, household air pollution from solid fuels, and ambient ozone pollution; (89) other environmental risks including residential radon and lead exposure; (331) suboptimal temperature including both low and high temperature.

The GBD estimates YLDs from these causes as the number of environmentally related incidents cases at year t multiplied by average duration of diseases and a weight factor that accounts for the severity of the disease on a scale of zero to one, where 0 is perfect health and 1 is death (WHO 2020). That is

$$YLD(a, z, t) = I(z, t) \times DW(a, z) \times L(a, z, t)$$

where $I(a, z, t)$ is the number of incident cases from environmental causes at a given age a and in year t, $DW(a, z)$ is the disability weight for environmental causes at age a and $L(a, z, t)$ is the average duration of case (in years) until remission. In addition, the GBD uses a discount factor and non-uniform age weights that give less weight to years lost at young and older ages but more weight to young adults (Murray 1996).

Our upper-bound estimate of environmental health risks is based on disability-adjusted life years (DALYs), which combines both YLDs and years of life lost due to premature mortality due to health factors (WHO 2020). From the GBD, we aggregate disability adjusted life years (DALYs) attributable to the environment for any given country, also by summing up data from four Global Health Data Exchange (GHDx) codes (82, 85, 89, and 331) which correspond to disease burdens attributable to the environment.

In the GBD, total environmentally related DALYs in country i at year t is defined as the sum of the life years lost due to environmentally related premature mortality (YLLs) and the number of years of healthy life lost due to disability (YLDs) by the portion of the population living in states of less than good health resulting from environmental causes (Murray 1996; WHO 2020). That is,

$$DALY(z,t) = YLL(a,z,t) + YLD(a,z,t)$$

where a is age and z is the sum of all environmentally related diseases burdens. In aggregating across age groups, the GBD again uses a discount factor and non-uniform age weights that give less weight to years lost at young and older ages but more weight to young adults (Murray 1996). For example, based on the time discounting and age weights, the GBD estimates that one infant death from any disease causes for 2011 represents 33 $DALYs$ while deaths between the ages 5–20 years is approximately 36 $DALYs$.

Probability: $\rho_i^*, \rho_i^{**}; \rho_{us}^*, \rho_{us}^{**}$

As defined in the main text, ρ are the probabilities that a random individual, living in country i and the United States respectively in any given year, loses some life years due to environmental health risks. Specifically, we calculate two probabilities for country i and United States (subscripted by us) base on environmentally related YLDs (ie. ρ_i^*, ρ_{us}^*) and YLDs (ie. $\rho^* *_i, \rho_{us}^{**}$). We calculate each of the probabilities by using the total DALYs or YLDs due to environmental causes divided by the size of population in each country for a given year.

For example, with a population of 3,286,070 in 1990, Albania recorded 12531.35 environmentally related YLDs and 166,961 environmentally related DALYs. It follows that the probability (ρ^*, ρ^{**}) for Albania in 1990 are

$$\rho_i^* = \frac{\text{environmentally related YLDs}}{population} = \frac{12531.35}{3,286,070} = 0.0038$$

$$\rho_i^* = \frac{\text{environmentally related DALYs}}{population} = \frac{166,961}{3,286,070} = 0.0508$$

That is, for Albania in 1990, 5 life years were lost from every 100 people due to environmental causes.

With these probabilities estimated for each country i, the coefficient for adjusting life expectancy for that country in any given year is simply $1 - \rho_i$. Similarly, for the US, the coefficient is $1 - \rho_{us}$. The next section explains how we arrived at this method of adjustment.

For simplicity, both probabilities for both country i and United States will simply be refer to as ρ_i and ρ_{us}

B.2.2 Adjusted Life Expectancy

The statistical *life expectancy at birth* as found in the World Development Indicators (WDI) and other secondary sources is the average number of years a newborn is expected to live if mortality and morbidity patterns at the time of its birth remains constant in the future (Ortiz-Ospina 2017; Suzuki and Neil, 2013). In essence, it looks at the number of people of different ages in a specific year and provides snapshot of the overall "mortality characteristics" for the population for that year, based on past patterns of death from previous years, and does not account for the number of years lost due to ill-health, disability or premature deaths (i.e. disability-adjusted life years or DALYs) from that year onwards. Typically, the computation of life expectancy at birth uses a period life table, which applies age-specific death rates based on past years to a hypothetical cohort of 100,000 newborns. For each cohort in a given year, the age-specific death rates are transformed into the probability of dying for that age group. Based on the values from the life table, life expectancy for the entire population is derived. However, this calculation is made without taking into account or correcting for the number of years that may be lost over the course of the life of each cohort due to changing exogenous factors, such as any environmental conditions that may impact the quality of life, morbidity, and mortality of a cohort.

In sum, although life expectancy at birth aims to project how long a representative individual of a population born in the current year t is expected to live, this estimation is based on past patterns of mortality and morbidity in the population from previous years up to year t that are assumed to remain the same throughout the individual's life. Thus, an estimate of life expectancy does not correct for the number of years potentially lost in year t due to changes in environmental quality that impact the quality of life, morbidity, and mortality of the average individual.

Specifically, total life expectancy at each age e_x is computed by summing up the total number of years that a cohort is expected to live from age x onward and dividing by the number of people in the cohort surviving to that age x (Jagger et al. 2014). That is,

$$e_x = \frac{1}{\ell_x} \sum_{a=x}^{\omega} L_a \tag{B.1}$$

where ℓ_x is the number of people in a cohort surviving to a specific age $x = 0, ..., \omega$, which is typically fixed at 100,000 for age 0 (i.e. birth). For subsequent ages, this number is multiplied by the probability of survival. For example, with a probability of death of 0.003606 at age 0, the number of people surviving to age 1 will be $100000 * (1 - 0.0036) = 99640$. L_a is the number of person-years for each cohort from any specific age $x = 0, ..., \omega$, with each person contributing one year. That is, a cohort of 100,000 people would have 100,000 person-years at every age, if nobody dies. Of course, there is a probability of death from birth onwards, so it follows that the total number of person-years for each cohort La is just below 100,000 at age 0 and continues to decrease as the cohort lives to the final age ω.

Using formula (B.1), Jagger et al. (2014) estimate female life expectancy at birth in Belgium for 2004. By assumption, ℓ_0 is 100,000, and L0 is calculated to be 99,711.50. The total number of person-years that the cohort is expected to live from age 0 to age 85+ years is estimated to be 8,141,517.37. It follows that $e_0 = \frac{8{,}141{,}517.37}{100{,}000} = 81.4$. The life expectancy at birth for a female in Belgium in 2004 is 81.4 years.

However, as noted previously, such estimations of life expectancy at birth are made without taking into account or correcting for the number of years that may be lost over the course of the life of each cohort due to changing environmental conditions. Adjusting life expectancy for the risks posed by environmental health risks could have implications when comparing life expectancy across countries. A representative individual living in country i with larger susceptibility to environmental health risks in current year t will have lower "adjusted" life expectancy compared to their counterparts in the United States. As such, it makes sense to adjust life expectancy for the risk of environmental health risks.

The approach we adopt is similar to calculating health-adjusted life expectancy (HALE), which combines both mortality and morbidity data of a country to estimate the expected number of years an average person spends in good health from a particular year, typically from birth. HALE is essentially life expectancy adjusted using a variety of measures of health such as disabilities, disease status and self-perceived health (Stiefel et al. 2010). Several measures of HALE have been advanced in the literature (Jagger et al. 2014; Molla et al. 2003) but the Sullivan method is, by far, the most used. This method adjusts life expectancy by the percentage of years spent in less than full health, using the conditional probabilities of deaths and proportion of population with disabilities (Sullivan 1971). While the Sullivan method draws inference about longitudinal HALE based on current cross-sectional or prevalence data, an alternative technique called the multistate method directly measures incidence of HALE from a longitudinal perspective.

Using the Sullivan method as an approximation of the multistate estimation of HALE leads to the hypothesis that the number of person-years that a cohort is expected to live from age a onward in any country i, including years with disabilities, $L_{ai}(D)$ is directly proportional to the total number of person years lived by a cohort at each specific age L_{ai} adjusted by the level of disability prevalence (Jagger et al. 2014). That is,

$$L_{ai}(D) = \pi_{ai} L_{ai}, \quad a = 0, ..., \omega \quad i = 1, ..., n \tag{B.2}$$

where π_{ai} is the prevalence of disability at age a for country i. Then, for a specific age $a = 0, ..., \omega$, the HALE and life expectancy with disability (DLE) at age x are defined by

$$HALE_x = \frac{1}{\ell_x} \sum_{a=x}^{\omega} (1 - \pi_{ai}) L_{ai} \tag{B.3}$$

$$DLE_x = \frac{1}{\ell_x} \sum_{a=x}^{\omega} \pi_{ai} L_{ai} \tag{B.4}$$

Limiting the scope of disabilities to those related to the environment, we respecify HALE in terms of environmental health risks for the purpose of our research, which is to isolate the impact of environmental health risks and its ramifications for welfare. Let $\rho_i(< \pi_i)$ be the probability of losing some life years due to environmental health risks in country i, as defined previously in Section B.1. Then, the environmental health adjusted life expectancy is

$$HALE_x = \frac{1}{\ell_x} \sum_{a=x}^{\omega} (1 - \rho_{ai}) L_{ai} \tag{B.5}$$

where ρ_{ai} is the probability of environmental health risks occurring at age a. As noted in our paper, we follow the special case adopted by Jones and Klenow (2016), who assume that each country is populated by people who are identical in all regards including consumption, leisure and exposure to uncertainty ($\beta^a = 1$). The corollary to this is that the people must also be identical in facing the same level of risk in terms of environmental health risks. If this is the case, then the probability of losing some life years due to environmental causes will be the same for each cohort at every age a. Then, environmental-health adjusted life expectancy simplifies to

$$HALE_x = (1 - \rho_{ai}) \frac{1}{\ell_x} \sum_{a=x}^{\omega} L_{ai} \tag{B.6}$$

It follows from (B.1) that the environmental health adjusted life expectancy for country i is

$$HALE_x = (1 - \rho_i) e_i \tag{B.7}$$

where e_i and e_{us} are the statistical life expectancy in each country i and the United States respectively, and ρ_i and ρ_{us} are the corresponding probabilities of losing some life years due to environmental health risks. In our paper, equation (B.7) is used to adjust expected lifetime utility of the representative individual, as indicated in equation (5).

B.3 Steps of Baseline model

It is useful to recall the basic setup of the baseline model. From equation (5) of the paper, we define expected lifetime utility for the average person in each country of analysis as environmental-health adjusted life expectancy multiplied by how much a year of life is worth:

$$U_i = (1-\rho_i)e_i u(C_i, l_i) = (1-\rho_i)e_i \left(\bar{u} + \log c_i + v(l_i) - \frac{\sigma_i^2}{2}\right) \tag{B.8}$$

That is, life expectancy at birth weighted by a flow of utility in country i while adjusting for the risk of losing some life years due to environmental health risks. The primary assumption here is that individual preferences over commodity consumption and leisure are expressed by an additively separable utility function. Next, the consumption that representative individual is assumed to be log-normally distributed, as well as independent of age and mortality. Then the expected lifetime utility in the United States is as follows:

$$U_{us}(\lambda_i) = (1-\rho_{us})e_{us} u(\lambda_i C_{us}, l_{us}) = (1-\rho_{us})e_{us} \left(\bar{u} + \log(\lambda_i c_{us}) + v(l_{us}) - \frac{\sigma_{us}^2}{2}\right) \tag{B.9}$$

is the expected lifetime utility of an average person in the United State adjusted to be equivalent to that of a person in country i. All things being equal, $\lambda_i(\rho_i)$ adjust consumption in the US in such away that individuals are indifferent between living in the United States or in country i. If such factor exist, then

$$U_{us}(\lambda) = U_i(1), \quad \text{holds for all } i \tag{B.10}$$

Equation (B.10) is the consumption-equivalent welfare condition. Suppose further that the utility of an average person in the United States can be defined in terms of the utility there in country i' according to the following expression:

$$u(C_{us}, l_{us}) = u(C_i, l_i) + [u(C_{us}, l_{us}) - u(C_i, l_i)] \tag{B.11}$$

That is the expected lifetime utility of an average person in the US will be the mean expected lifetime utility in country i plus the deviation. Equation (B.11) simplifies to the following:

$$
\begin{aligned}
U_{us} &= (1-\rho_{us})e_{us}\left(\bar{u} + \log c_{us} + v(l_{us}) - \frac{\sigma_{us}^2}{2}\right) \\
&= (1-\rho_{us})e_{us}\left(\bar{u} + \log c_i + v(l_i) - \frac{\sigma_i^2}{2}\right) \\
&+ (1-\rho_{us})e_{us}(\log c_{us} - \log c_i) \\
&+ (1-\rho_{us})e_{us}(v(l_{us}) - v(l_i)) \\
&- (1-\rho_{us})e_{us}\frac{1}{2}(\sigma_{us}^2 - \sigma_i^2)
\end{aligned} \tag{B.12}
$$

It is important to point out that this current adjustment to the formula (in Equation (B.12)) is not the application of the consumption-equivalent variation. This is just simply expressing expected lifetime utility in the US in terms of that of country i. By introducing the consumption adjustment factor $\lambda_i(\rho_i)$ and invoking the consumption-equivalent welfare condition, $U_{us}(\lambda) = U_i(1)$, we obtain the following:

$$(1-\rho_{us})e_{us}u(\lambda_i C_{us}, l_{us}) = U_{us}(1)$$

$$(1-\rho_{us})e_{us}\left(\bar{u} + \log(\lambda_i c_{us}) + v(l_{us}) - \frac{\sigma_{us}^2}{2}\right) = U_i(1)$$

$$\log \lambda_i(1-\rho_{us})e_{us} + (1-\rho_{us})e_{us}\left(\bar{u} + \log(\lambda_i c_{us}) + v(l_{us}) - \frac{\sigma_{us}^2}{2}\right) = U_i(1) \tag{B.13}$$

Notice that the second term on the left-hand side of equation (B.13) the same as U_{us} in equation (B.8). As such we can replace the second term in equation (A13) with equation (B.8) and substitute

(B.7) in place of $U_i(1)$. This simplifies to

$$\log \lambda_i(\rho_i) = \overbrace{\frac{(1-\rho_i)e_i - (1-\rho_{us})e_{us}}{(1-\rho_{us})e_{us}}}^{\text{\% difference in adjusted life expectancy}} \overbrace{\left(\bar{u} + \log c_i + v(l_i) - \frac{\sigma_i^2}{2}\right)}^{\text{worth of one life year in utility flows}}$$

$$+ (\log c_i - \log c_{us}), \qquad \text{Consumption Difference}$$

$$+ (v(l_i) - v(l_{us})), \qquad \text{Liesure Difference}$$

$$- \frac{1}{2}(\sigma_i^2 - \sigma_{us}^2), \qquad \text{Inequality Difference}$$

$\lambda_i(\rho_i)$ is the factor by which we can adjust the consumption of an average person to make him indifferent between living his life as a random person in the United States and living in some other country i. Dividing $\lambda_i(\rho_i)$ with relative GDP per capita ($\tilde{y}$) , as shown in equation (B.14), allow us to look at consumption as a share of income. All things being equal, countries with lower consumption share compared to the United States will have lower welfare relative to income. Under these assumptions, our baseline model is:

$$\left[\log \frac{\lambda_i(\rho_i)}{\bar{y}}\right] = \frac{(1-\rho_i)e_i - (1-\rho_{us})e_{us}}{(1-\rho_{us})e_{us}} \left(\bar{u} + \log c_i + v(l_i) - \frac{\sigma_i^2}{2}\right)$$
$$+ (\log c_i - \log c_{us}) + (v(l_i) - v(l_{us})) - \frac{1}{2}(\sigma_i^2 - \sigma_{us}^2) \quad \text{(B.14)}$$

B.4 Parameterization of the Welfare Measure

Calibration of this welfare measure requires parameterizing the labor supply function and utility function, as well as utility from leisure and home production. We consider economies populated with many identical, finitely lived individuals whose preference are expressed over commodity consumption and leisure. The utility function that represents those preference for the average person in country i is assumed to be additively separable, with consumption being log-normally distributed across individuals at each point in time and independent of age and mortality. Since we are using macro level data, the amount of leisure hour is assumed constant across ages within a particular year.

These assumptions are particularly important because we are working with macro level data (such as life expectancy, per capita GDP, etc.) which are generally the means of their distributions. It is possible that these aggregate data could mask substantial variations in predictors that are necessary in explaining welfare at the individual level. As such, results should be cautiously interpretated for the average person in each country. Notwithstanding, the macro level data still provides a useful snapshot of determinants of well-being such as consumption, leisure, inequality, morbidity and mortality across countries.

B.4.1 Labor Supply

We define labor supply as the number of hours spent on market work. The challenge is how to measure home production in the common sense of the term. Home production and leisure are practically difficult to distinguish especially in macro-level aggregated data (Mincer 1962). However, there may be no need to separate them. Both react similarly to changes in the socioeconomic environment and thus satisfy the conditions for comprising a composite input (Gronau 1977). We therefore aggregate leisure and home production into one entity, nonmarket hours, which we loosely called “leisure”. To obtain the total number of work hours in a year, we make the following assumptions.

Table B.1: Average hours worked per worker/person

Income groups of countries	Hours worked per worker				Hours worked per person			
	mean	sd	min	max	mean	sd	min	max
Low	2204.1	0	2204.1	2204.1	790.9	157.5	390.4	1141.8
Lower middle	2201.3	83.9	1733.9	2597.7	794.7	172.2	410.9	1323.1
Upper middle	2021.7	136.5	1551.6	2643.7	759.8	187.3	87.3	1387.6
High	1791.8	220.0	1380.6	2674.1	822.9	145.2	484.7	1567.5
United States	1786.5	31.8	1728.6	1844.9	852.8	32.4	790.1	907.9

Suppose that the average person has 8 hours of sleep, 16 waking hours per day and 365 days per year. The total number of available waking hours per year is $5840 = 365 days * 16$ waking hours per day. Knowing the number of waking hours and the number of hours worked by person, we can easily derive the amount of leisure hours. It is however important to distinguish between annual number of hours worked by person ($avhp$) and the annual hours worked per worker (avh). While avh is publicly available on Penn World Table Version 10.0, there are no comprehensive survey that provides data on $avhp$. Following Jones and Klenow (2016), we compute $avhp$ as avh multiplied by the employment-to-population ratio (ie. $avhp = avh \times \frac{\text{employed}}{\text{population}}$). By this computation, we attempt to spread the reported number of hours worked per the employed population over the whole population. What this does is to readjust the hours worked by the employed population to obtain some quasi-average hours worked per person for people of all ages in the whole population. The justification for this computation is: (a) the welfare index is a snapshot of the whole population and so should the indicators used to construct it; and (b) income and taxes from the employed are redistributed in some fashion to the unemployed, disabled, children and elderly. This form of income and tax redistribution can be seen as a redistribution of hours worked. Accordingly, we define the share of leisure hours as

$$leisure(l_i) = \frac{5840 - \text{annual hours worked per person}}{5840} \tag{B.15}$$

Generally, avh is highest among low and lower middle-income countries (see Table B.4). Their high levels of hours worked do not necessarily imply a higher welfare index because (a) higher hours worked implies low levels of leisure hours as well as a higher tendency for disutility from work; (b) countries with lower employment to population ratio experience much lower $avhp$ compared to the United States. All things being equal, a country or regions with a lower employment to population ratio and lower leisure hours may experience lower welfare index.

With l_i as the share of leisure hours, which is the proportion of total hours that a representative individual does not work in a year, labor supply is defined as $(1 - l_i)$. This tells us the proportion of total hours in a year that the individual is engage in paid employment. The implication of this supply relationship is that labor hours and leisure are substitutes, as increases in leisure decrease the amount of labor hours.

B.4.2 Utility function

We follow Jones and Klenow (2016) and assume that the individual's preferences are defined over commodity consumption and leisure and that the utility function that represents those preferences is additively separable. Consumption is log-normally distributed across individuals at a point in time and is independent of individual characteristics such as age and mortality. As indicated in (B.15), this leads to the following expression for the flow of utility for one year of life of the representation individual.

$$u(C_i, l_i) = \bar{u} + \log c_i + v(l_i) - \frac{\sigma_i^2}{2} \tag{B.16}$$

$\bar{u}$: Intercept in the utility function

This is the part of the utility function that does not directly depend on income, consumption or hours worked. We follow Jones and Klenow (2016) and approximate with the value of statistical life (VSL). One of the earliest analyses done by the US Environmental Protection Agency (EPA) estimates VSL for the United States to be $4.6 million in 2001 prices (EPA 1984). Later studies recommend values in the range of $5.5 to $7.5 million (Viscusi and Aldy 2003; Murphy and Topel 2006). Jones and Klenow (2016) use $5 million for VSL in the United States, and more recently, Viscusi (2018) estimates it to be between $9 and $10million. See Table B.2 below for the estimates we use and the sources.

c_i: Consumption as a share of GDP in country i

This component of utility is expressed as the share of real household and government consumption in national GDP. Using data from Penn World Table Version 10.0, we compute $c_i/y_i = (\text{real consumption})/(\text{real GDP})$. Since our welfare index is a relative measure of economic well-being, expressing consumption as a share of GDP allow us to compare consumption inequalities across countries.

$v(l_i)$: Utility from leisure and home production

The component $v(l_i)$ translates leisure and home production l_i into utility. Recall that all the hours that the representative individual is not engaged in paid work are loosely refer to as leisure, and the proportion of total hours that she is not undertaking work is the leisure ratio l_i. As labor supply and leisure are assumed to be perfect substitutes, one does not have to estimate directly the value of leisure. Instead, we focus on the disutility from work. All things being equal, higher supply of labor hours reduces leisure thereby increasing the amount of disutility associated with paid work. If the weight of that disutility is denoted by θ , we can then derive the value of the disutility associated with labor supply.

With consumption as the numeraire, the conventional first-order condition from the utility function for the labor-leisure decision implies that the marginal rate of substitution of leisure for consumption should equal the real wage w . That is

$$\frac{u_i}{u_c} = w(1-\tau) \tag{B.17}$$

where τ is the marginal tax rate on labor income. Following Jones and Klenow (2016), we assume a constant Frisch elasticity of labor supply (i.e., holding the marginal utility of consumption fixed, the elasticity of labor supply with respect to the wage is constant). The weight of the disutility in the welfare function is therefore

$$\theta = \frac{w(1-\tau)(1-l)^{-1/\epsilon}}{c} \tag{B.18}$$

As before, c is the share of real consumption in national GDP, and $w(1-\tau)(1-l)^{-1/\epsilon}$ is the market value of total annual labor supply by a representative individual. Thus, θ is the price of each unit of consumption in utility terms or the shadow price of disutility from work. Consequently, we can parameterize the functional form of $v(l)$ as

$$v(l) = -\frac{\theta\epsilon}{1+\epsilon}(1-l)^{\frac{1+\epsilon}{\epsilon}} \tag{B.19}$$

where ϵ is the Frisch elasticity. By setting $\epsilon = 1$,

$$v(l) = -\frac{\theta}{2}(1-l)^2 \tag{B.20}$$

This is the welfare cost associated with foregone leisure hours. The fundamental premise of this function is that leisure is welfare improving and market work that deny adequate leisure worsens welfare. As a numerical example of calculating (B.20), suppose that the marginal tax rate in the United States is 0.353, the real wage is $10.24 and c is 0.824. If the leisure ratio l is 0.656, then the shadow price or weight of disutility from market work is as follows

$$\theta = \frac{w(1-\tau)(1-l)^{-1/\epsilon}}{c} = \frac{10.24(1-0.353)(1-0.656)^(-1)}{0.824} = 23.373 \tag{B.21}$$

$$v(l) = -\frac{23.373}{2}(1-l)^2 = -11.6865(1-l)^2 \tag{B.22}$$

A complete guide to deriving each of the components of the utility function is presented in Table B.5.

$\log c_i - \log c_{us}$: Consumption difference

This term is simply the difference between log consumption of the average person in country i and that of the average person in the United States. It's a measure of absolute consumption gap. Consequently, comparing consumption in each country to that of the United States gives an indication of ordinal ranking of utility derived from consumption.

$\log c_i - \log c_{us}$: Leisure difference

Using the functional form (B.20), the difference between utility derived from leisure (disutility from work) in country i and that of the United States is

$$v(l_i) - v(l_{us}) = -\frac{\theta}{2}\left((1-l_i)^2 - (1-l_i)^2\right) \tag{B.23}$$

$\frac{1}{2}(\sigma_i^2 - \sigma_{us}^2)$: Inequality difference

While consumption difference is the measure of absolute consumption gap between each country and the United States, $\sigma_i^2/2$ and $\sigma_{us}^2/2$ are the corresponding measures of within-country consumption inequality. Thus, the difference between $\sigma_i^2/2$ and $\sigma_{us}^2/2$ is the absolute inequality gap.

The terms $\sigma_i^2/2$ and $\sigma_{us}^2/2$ are the variances of the log consumption in country i and the US respectively. The variance is simply the absolute consumption inequality index of the population share weighted over subgroups. This is not the same as the Gini coefficient. While $\sigma_i^2/2$ and $\sigma_{us}^2/2$ are measures of consumption inequality, the Gini coefficient is a measure of income inequality. Unlike the Gini coefficient, which is theoretically bounded on 0 and 1, consumption inequality can be more than 1. Just like the Gini coefficient $\sigma_i^2/2$, $\sigma_{us}^2/2 = 0$ implies perfect the absence of consumption inequality, and $\sigma_i^2/2$, $\sigma_{us}^2/2 > 0$ implies extreme within-country consumption inequality.

Note that $\sigma_i^2/2$ and $\sigma_{us}^2/2$ are random variables who are assumed to have standard normal distributions. It follows that the standard deviation of the distribution in each country is one and the distribution is centered on zero. The task is to determine the mean of the random variable σ_i^2 or σ_{us}^2 . Since the Gini coefficient is the overall measure of economic activities and provides a snapshot of the state of consumption, we proxy the mean of the random variable with the Gini coefficient $gini/100$. This scaling down of the Gini coefficient by 100 is necessary as the source of the Gini coefficient data from the WIDER World Income Inequality Database is multiplied by a hundred.

The cumulative distribution function (CDF) of the random variable $\sigma_i^2/2$ and $\sigma_{us}^2/2$ evaluated at $gini/100$ is the probability function that the value σ_i^2 or σ_{us}^2 will be less than or equal to $gini/100$. This has an intuitive appeal to our welfare index since we expect consumption inequality to be less than income inequality in richer countries due to the prevalence of welfare programs, income support, active credit markets and similar institutions in the latter countries.

To estimate σ for all countries (including the US) from the various Gini index data per country and over time from the UNU-WIDER World Income Inequality Database (https://www.wider.unu.edu/project/wiid-%E2%80%93-world-income-inequality-database) we used in the MATLAB "norminv" procedure in the following manner.

Let X be the consumption inequality of a country. The syntax $X = norminv(P, \mu, \sigma)$ in MATLAB computes the inverse of the normal cumulative distribution function of any random variable using the parameters of mean (μ), standard deviation at the corresponding probabilities in P. The vector or matrix of P, μ and σ must all have similar sizes which is why we scale back the Gini index by 100. The parameters of σ must be positive and the values in P must lie within the interval $[0, 1]$. Then for any $x \in X$, the inverse of the continuously differentiable cumulative distribution function $F(x) = P(X \leq x)$ is

$$x = F^{-1}(p|\mu, \sigma) = \{x : F(x|\mu, \sigma) = p\} \tag{B.24}$$

where $F(x)$ gives the “accumulative” probability up to and

$$p = F(x|\mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{x} e^{\frac{-(t-\mu)^2}{2\sigma^2}} dt \tag{B.25}$$

The result, x, is the solution to the above equation. From the baseline model, consumption inequality is defined as $X = \frac{1}{2}\sigma_i^2$, so that

$$\sigma_i = \sqrt{2} * \sqrt{X} \tag{B.26}$$

Since consumption inequality, X , is assumed to be normally distributed with a standard deviation of 1, we can obtain any $x \in X$ by summing the standard deviation and the mean of consumption which we proxy as $gini/100$. Hence the result of equation (B.24) is

$$x = F^{-1}(p|\mu, \sigma) = 1 + \frac{gini}{100} \tag{B.27}$$

After computing the value of x for each country and for each year, we can proceed to integrate over the entire range of X up to x according to the following cumulative distribution function.

$$F(X) = P\left(X \leq 1 + \frac{gini}{100}\right) \tag{B.28}$$

With the CDF in equation (B.28), we can calculate the actual values of X. To do this, we use the command "norminv" in MATLAB, which returns the inverse of the normal CDF

$$X = norminvP\left(X \leq 1 + \frac{gini}{100}\right) \tag{B.29}$$

Substituting equation (B.29) into the above expression $\sigma_i = \sqrt{2} * \sqrt{X}$, we have

$$\sigma_i = \left(norminvP\left(X \leq 1 + \frac{gini}{100}\right)\right)^{\frac{1}{2}} \tag{B.30}$$

Equation (B.30) is symmetric and applies to σ_{us} as well. It tells us the proportion of the observations from the normal distribution of consumption inequality that falls within one standard deviation from the mean. Recall that $\sigma_i, \sigma_{us} = 0$ implies the absence of consumption inequality within that specific country. Therefore, any observation of $\sigma_i, \sigma_{us} > 1$ suggests extreme within-group consumption inequality in the country.

Table B.2: Computation of the weight of disutility from work

Year	VSL (million)	Average hours per worker (avh)	Average hours per person ($avhp$)	c/y	$leisure\ per\ person\ (l) = \frac{5840 - avhp}{5840}$	real wage (w)	marginal tax rate (τ)	$\theta = \frac{w(1-\tau)(1-l)^{-1/\epsilon}}{c}$
1990	4.5	1795.568	876.318	0.827	0.850	7.5	0.28	43.539
1991	4.5	1787.338	853.626	0.831	0.854	7.5	0.31	42.607
1992	4.5	1774.883	841.180	0.827	0.856	7.5	0.31	43.456
1993	4.5	1789.955	849.145	0.827	0.855	7.5	0.396	37.679
1994	4.5	1807.827	866.476	0.820	0.852	7.5	0.396	37.218
1995	4.5	1817.474	873.650	0.818	0.850	7.5	0.396	37.001
1996	4.5	1823.521	879.074	0.812	0.849	7.5	0.396	37.084
1997	5	1828.488	890.730	0.804	0.847	7.5	0.396	36.958
1998	5	1839.196	898.967	0.805	0.846	7.5	0.396	36.551
1999	5	1841.334	904.024	0.806	0.845	7.5	0.396	36.328
2000	5	1844.854	907.893	0.808	0.845	7.5	0.396	36.066
2001	6	1823.659	888.396	0.821	0.848	7.3	0.391	35.583
2002	6	1806.691	868.834	0.830	0.851	7.2	0.35	37.921
2003	6	1790.842	857.005	0.830	0.853	7	0.35	37.358
2004	6	1789.528	858.606	0.826	0.853	6.9	0.35	36.916
2005	6	1787.014	863.197	0.823	0.852	6.6	0.35	35.275
2006	6.6	1787.351	870.953	0.822	0.851	6.4	0.35	33.952
2007	6.6	1785.884	869.722	0.823	0.851	6.6	0.35	34.984
2008	7.4	1765.766	850.798	0.827	0.854	7.2	0.35	38.867
2009	7.4	1728.608	796.962	0.846	0.864	8	0.35	45.040
2010	7.4	1735.011	790.068	0.837	0.865	8.4	0.35	48.242
2011	7.4	1744.908	796.043	0.831	0.864	8.1	0.35	46.461
2012	9.1	1746.859	804.269	0.821	0.862	7.9	0.35	45.434
2013	9.2	1752.533	808.570	0.812	0.862	7.8	0.396	41.880
2014	9.4	1758.269	817.802	0.811	0.860	7.7	0.396	40.976
2015	9.6	1770.023	828.798	0.813	0.858	7.7	0.396	40.301
2016	9.9	1766.744	833.539	0.820	0.857	7.6	0.396	39.214
2017	10.2	1763.727	839.165	0.820	0.856	7.4	0.396	37.946
2018	10.5	1774.704	850.066	0.816	0.854	7.3	0.37	38.727
2019	10.9	1765.346	849.236	0.817	0.855	7.3	0.37	38.704

Value of statistical life (VSL) sourced from U.S. Department of Transportation, accessed from www.transportation.gov/office-policy/transportation-policy/revised-departmental-guidance-on-valuation-of-a-statistical-life-in-economic-analysis; United States Environmental Protection Agency, accessed from www.epa.gov/environmental-economics/mortality-risk-valuation. Marginal tax rate sourced from Tax Policy Center, accessed from www.taxpolicycenter.org/statistics/historical-highest-marginal-income-tax-rate/ Real minimum wage sourced from Statista Research Department, accessed from www.statista.com/statistics/637626/united-states-minimum-wage-2000-2015/. c/y (real consumption/real GDP) and average hours per worker/person are based on authors' estimates using data from Penn Word Table 10.0.

B.5 Reference

Gronau, R. 1977. Leisure, home production, and work–the theory of the allocation of time revisited. Journal of Political Economy 85(6):1099-1123.

Jagger, C., van Oyen, H. and Robine, J.-M.. 2014. "Health Expectancy Calculation by the Sullivan Method: A Practical Guide." Euro-REVES project and Institute for Ageing, Newcastle University, UK. Available at http://reves.site.ined.fr/en/resources/computation_online/sullivan/ (accessed November 25, 2021).

Jones, C.I. and Klenow, P.J. 2016. Beyond GDP? Welfare across Countries and Time. American Economic Review 106(9):2426-2457.

Mincer, J. 1962. Labor force participation of married women: A study of labor supply. In Aspects of labor economics (pp. 63-105). Princeton University Press.

Molla, M.T., Madans, J.H., Wagener, D.K. and Crimmins, E.M.. 2003. Summary Measures of Population Health: Report of Findings on Methodologic and Data Issues. National Center for Health Statistics, Hyattsville , MD. Available at http://www.cdc.gov/nchs/data/misc/pophealth.pdf (accessed November 25, 2021).

Murphy, K. M. and Topel, R. H. 2006. The value of health and longevity. Journal of Political Economy 114(5):871-904.

Appendix C

Chapter 2: Supplementary Results

Table C.1: λ Summary Statistics, 1990-2019

				Decomposition				
	λ	Per capita income ($\tilde{y}$)	Log ratio	Life exp.	C/Y	Leisure	Cons. Ineq.	$\lambda/\tilde{y}$
Average	24.48	30.79	-0.50	-0.63	-0.02	0.04	0.11	70.86
Median	12.88	19.25	-0.41	-0.44	0.01	0.06	0.05	66.45
Standard deviation	28.23	34.05	0.60	0.70	0.25	0.17	0.23	36.90
Min	0.16	0.37	-3.04	-3.26	-1.68	-1.15	-0.26	4.77
Max	142.59	221.31	1.02	0.70	1.13	0.43	1.20	277.1
Income groups								
Low income	1.63	3.68	-1.06	-1.54	0.13	0.05	0.30	39.51
Lower middle income	5.21	8.93	-0.74	-1.01	0.04	0.03	0.20	55.87
Upper middle income	16.76	22.32	-0.35	-0.50	-0.03	0.07	0.12	79.73
High income	58.28	69.45	-0.17	-0.01	-0.12	0.02	-0.06	90.41
Non-OECD	45.34	72.54	-0.33	-0.12	-0.20	-0.01	0.01	84.13
OECD	62.71	68.39	-0.11	0.03	-0.10	0.03	-0.08	92.57

Notes: All welfare and income values are denoted relative to the United States ($US = 100$). Log ratio $\log \lambda_i/\tilde{y}$ is as defined in equation (2.8), and it is the sum of life expectancy multiplied by utility flow (Life exp.), differences in consumption share of income (C/Y), leisure and home production (Leisure) and consumption inequality (Cons. Inequality). ρ is the probability that a person in country i will lose some life years due to environmentally related deaths and morbidity, which is used to derive λ^* in equation (2.7b). $\lambda^*/\tilde{y}$ is the ratio (%) of this welfare measure to per capita GDP, and λ^*/λ is the ratio (%) of the two welfare measures. Regional income groups are based on the World Bank's Country and Lending Groups classification (https://datahelpdesk.worldbank.org/knowledgebase/articles/906519). OECD is Organization for Economic Cooperation and Development.

Table C.2: λ^* Summary Statistics, 1990-2019

	λ^*	Per capita income ($\tilde{y}$)	Log ratio	Decomposition: Life exp.	C/Y	Leisure	Cons. Ineq.	ρ^*	λ^*/λ	$\lambda^*/\tilde{y}$
Average	24.38	30.79	-0.51	-0.64	-0.02	0.04	0.11	0.0035	99.26	70.39
Median	12.76	19.25	-0.42	-0.45	0.01	0.06	0.05	0.0036	99.43	65.88
Standard deviation	28.23	34.05	0.60	0.70	0.25	0.17	0.23	0.0013	0.77	36.72
Min	0.16	0.37	-3.05	-3.27	-1.68	-1.15	-0.26	0.0005	95.11	4.73
Max	142.55	221.31	1.02	0.69	1.13	0.43	1.20	0.0075	100.79	276.98
Income groups										
Low income	1.62	3.68	-1.07	-1.55	0.13	0.05	0.30	0.0046	99.22	39.24
Lower middle income	5.15	8.93	-0.75	-1.02	0.04	0.03	0.20	0.0043	99.04	55.36
Upper middle income	16.61	22.32	-0.36	-0.51	-0.03	0.07	0.12	0.0036	99.08	79.00
High income	58.16	69.45	-0.17	-0.01	-0.12	0.02	-0.06	0.0022	99.63	90.11
Non-OECD	45.04	72.54	-0.34	-0.13	-0.20	-0.01	0.01	0.0028	99.32	83.52
OECD	62.64	68.39	-0.12	0.03	-0.10	0.03	-0.08	0.0020	99.74	92.36

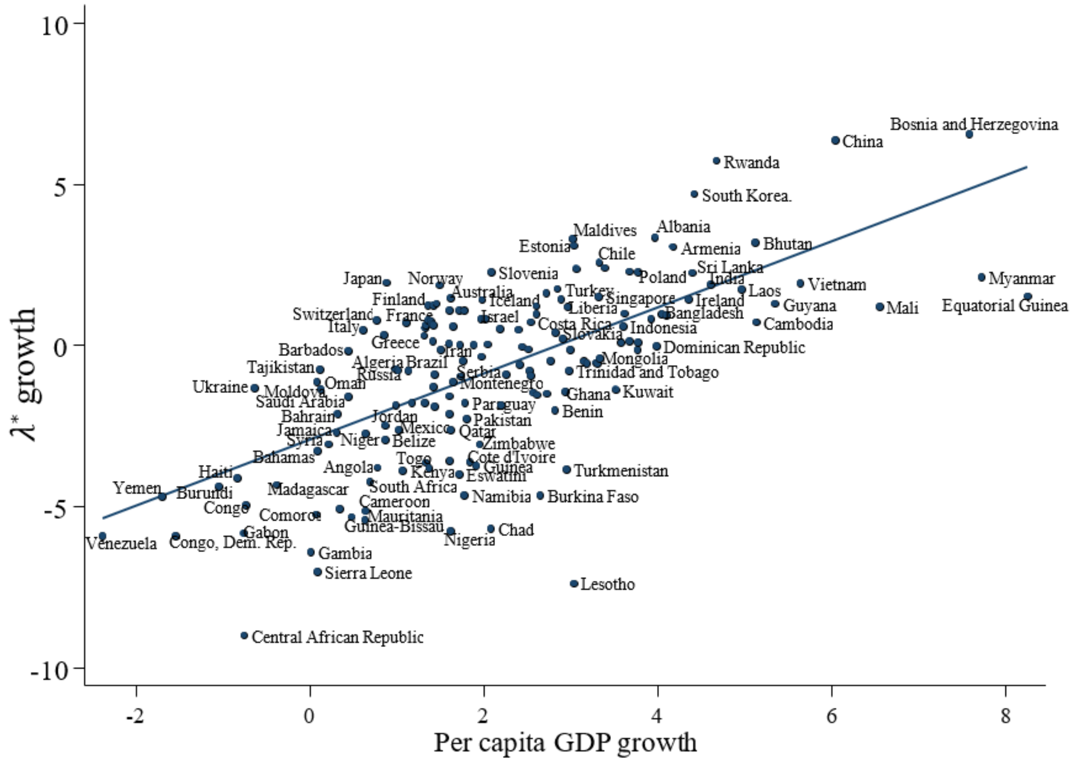
Notes: All welfare and income values are denoted relative to the United States ($US = 100$). Log ratio $\log \lambda_i/\tilde{y}$ is as defined in equation (2.7a), and it is the sum of life expectancy multiplied by utility flow (Life exp.), differences in consumption share of income (C/Y), leisure and home production (Leisure) and consumption inequality (Cons. Inequality). ρ is the probability that a person in country i will lose some life years due to environmentally related deaths and morbidity, which is used to derive λ^* in equation (2.7a). $\lambda^*/\tilde{y}$ is the ratio (%) of this welfare measure to per capita GDP, and λ^*/λ is the ratio (%) of the two welfare measures. Regional income groups are based on the World Bank's Country and Lending Groups classification (https://datahelpdesk.worldbank.org/knowledgebase/articles/906519). OECD is Organization for Economic Cooperation and Development.

Table C.3: λ^{**} Summary Statistics, 1990-2019

	λ^{**}	Per capita income ($\tilde{y}$)	Log ratio	Decomposition: Life exp.	Decomposition: C/Y	Decomposition: Leisure	Decomposition: Cons. Ineq.	ρ^{**}	λ^{**}/λ	$\lambda^{**}/\tilde{y}$	λ^{**}/λ^{*}
Average	23.54	30.79	-0.70	-0.84	-0.02	0.04	0.11	0.07	83.98	63.00	84.58
Median	11.43	19.25	-0.54	-0.55	0.01	0.06	0.05	0.04	89.64	58.17	90.63
Standard deviation	28.46	34.05	0.77	0.91	0.25	0.17	0.23	0.08	17.11	38.55	17.05
Min	0.03	0.37	-4.26	-4.69	-1.68	-1.15	-0.26	0.00	19.26	1.41	19.61
Max	146.12	221.31	1.04	0.68	1.13	0.43	1.20	0.67	105.7	283.9	104.87
Income groups											
Low income	1.13	3.68	-1.65	-2.13	0.13	0.05	0.30	0.20	57.73	23.82	58.17
Lower middle income	4.28	8.93	-1.04	-1.31	0.04	0.03	0.20	0.10	75.56	44.14	76.30
Upper middle income	15.34	22.32	-0.45	-0.61	-0.03	0.07	0.12	0.04	90.36	72.77	91.17
High income	57.56	69.45	-0.19	-0.03	-0.12	0.02	-0.06	0.02	97.82	88.72	98.16
Non-OECD	44.06	72.54	-0.36	-0.15	-0.20	-0.01	0.01	0.02	97.09	81.72	97.75
OECD	62.17	68.39	-0.13	0.01	-0.10	0.03	-0.08	0.02	98.07	91.11	98.30

Notes: All welfare and income values are denoted relative to the United States ($US = 100$). Log ratio $\log \lambda_i/\tilde{y}$ is as defined in equation (2.8), and it is the sum of life expectancy multiplied by utility flow (Life exp.), differences in consumption share of income (C/Y), leisure and home production (Leisure) and consumption inequality (Cons. Inequality). ρ is the probability that a person in country i will lose some life years due to environmentally related deaths and morbidity, which is used to derive λ^* in equation (2.7a). $\lambda^*/\tilde{y}$ is the ratio (%) of this welfare measure to per capita GDP, and λ^*/λ is the ratio (%) of the two welfare measures. Regional income groups are based on the World Bank's Country and Lending Groups classification (https://datahelpdesk.worldbank.org/knowledgebase/articles/906519). OECD is Organization for Economic Cooperation and Development.

A. Correlation between λ^* growth and per capita GDP growth (r = 0.6553)



B. Correlation between λ^{**} growth and per capita GDP growth (r = 0.6749)

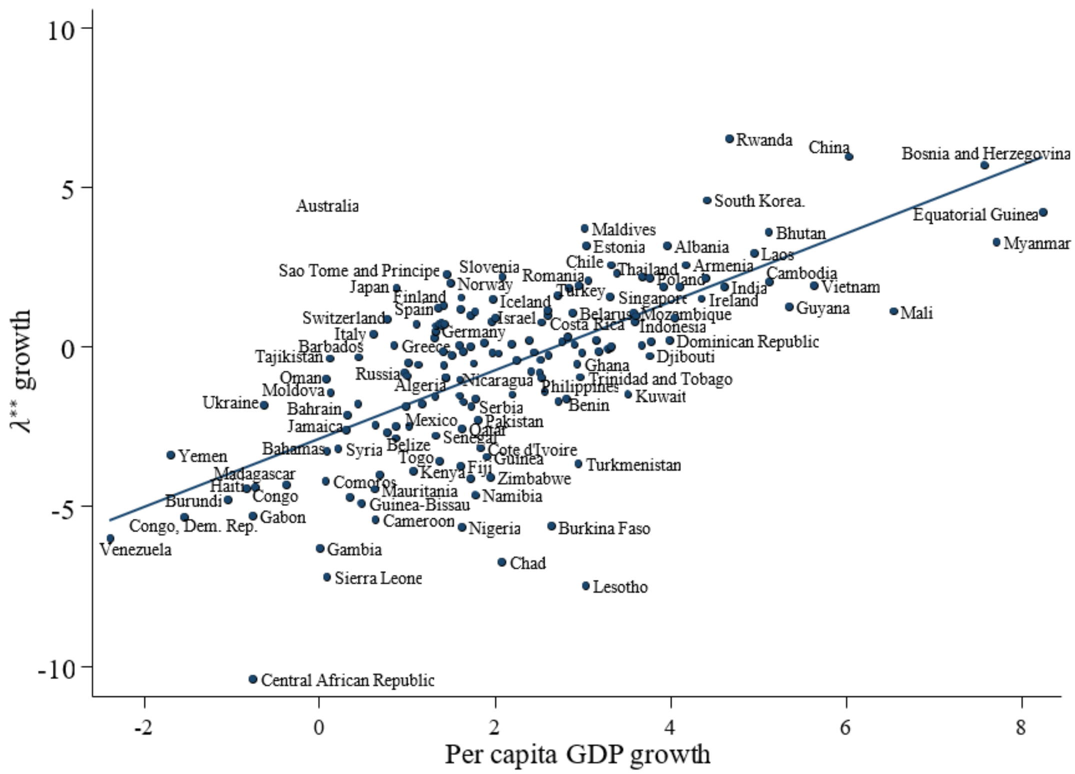


Figure C.1: Welfare and Income Growth (annual average percentage change, 1990-2019)

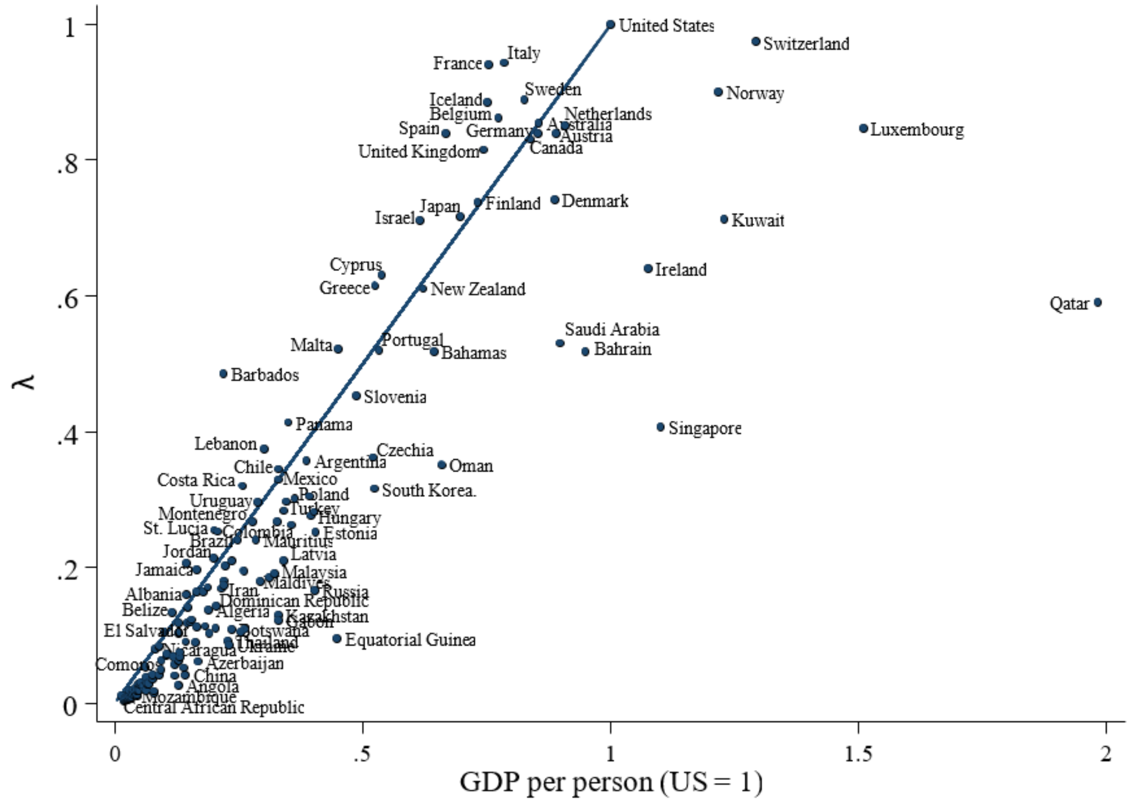


Figure C.2: Welfare and GDP per capita (1990-2019 average).

Note: Correlation between welfare measure λ and income (r = 0.8763)

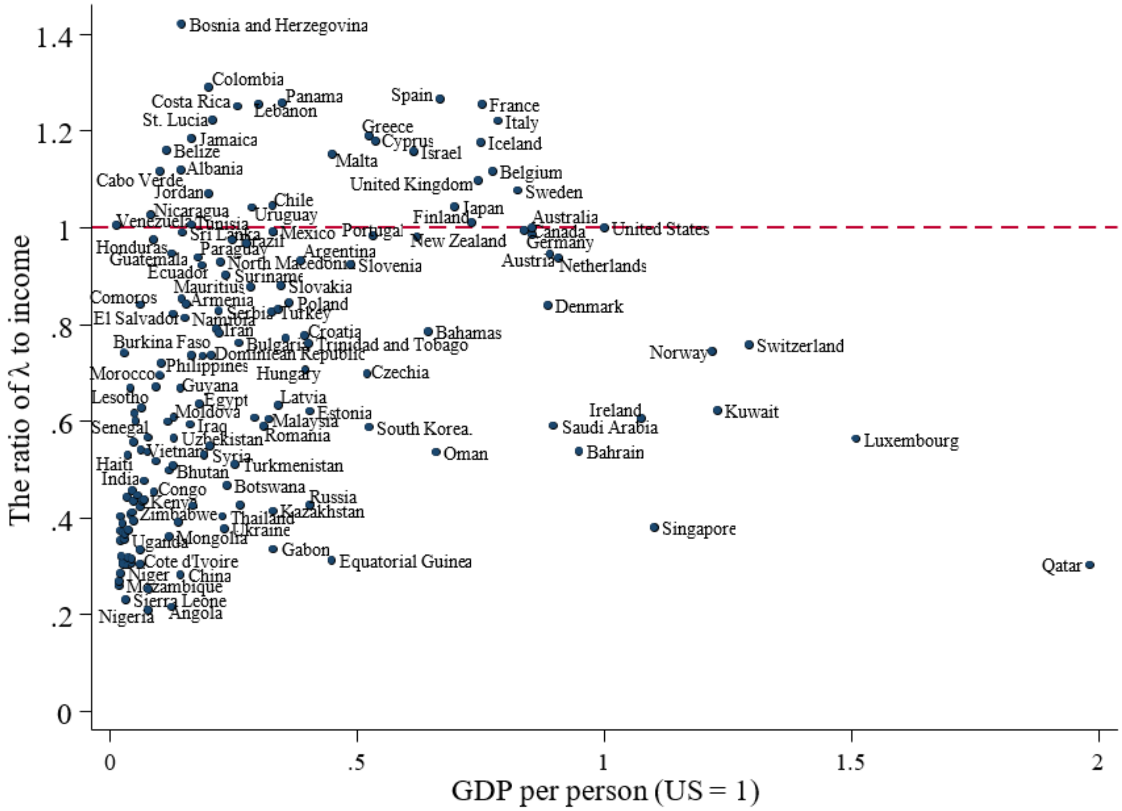


Figure C.3: Welfare-Income Ratio and GDP per capita (1990-2019 average).

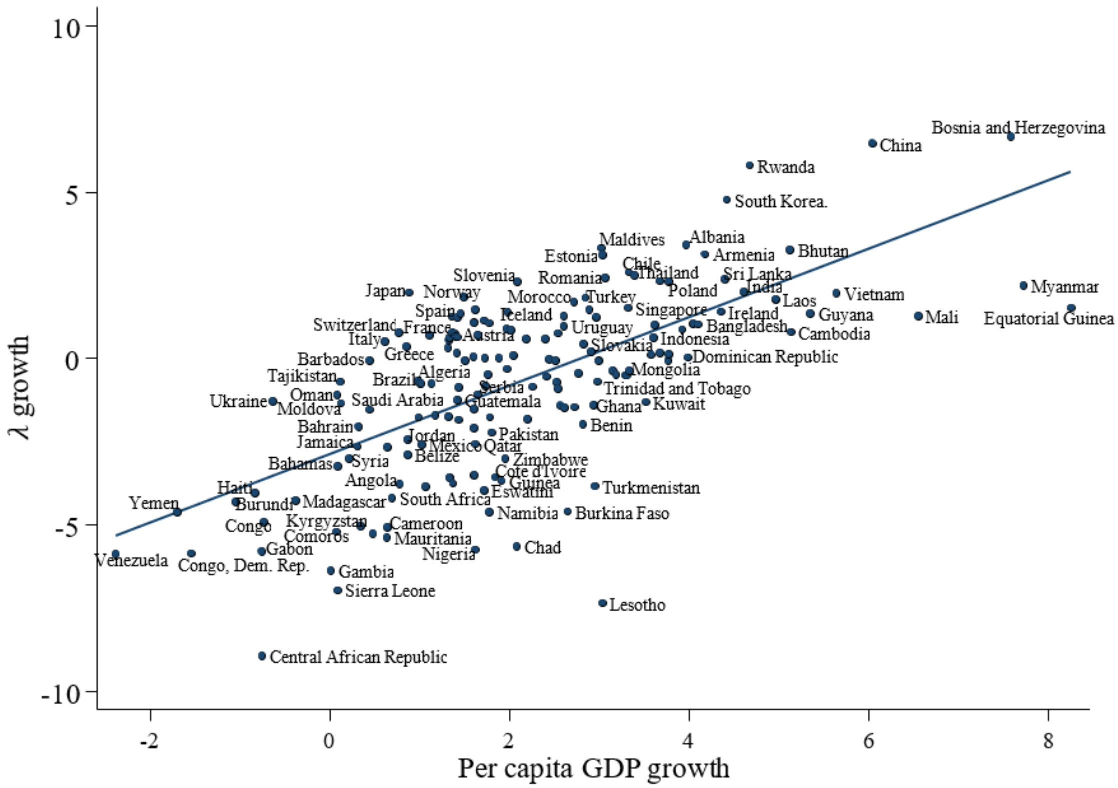


Figure C.4: Welfare and Income Growth (annual average percentage change, 1990-2019).

Note: Correlation between λ growth and per capita GDP growth (r = 0.6574)