Assessing environmental risk factors of noncommunicable diseases: Ambient and household air pollution

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Abstract

Over the past decade, the mortality rates of noncommunicable diseases have continued to rise, especially in lower developed countries. Furthermore, the purpose of this paper is to estimate the average marginal effects of ambient and household air pollution, measured by $PM_{2.5}$ concentration levels and the proportion of efficient cooking technologies, respectively, on the ratio of premature[1] deaths from noncommunicable diseases (NCDs) to all death from NCDs. Using linear regression, I find a statistically significant relationship for both indicators of air pollution. Additionally, I validate the presence of a Health "Kuznets" curve, an inverse "U" shape relationship between the Human Development Index (HDI) and health inequalities.

Keywords: disease; air pollution; environment; public health

JEL: I14; I15; I18

Introduction

Bennett et al. [2018] stated in their report, *NCD Countdown 2030: worldwide trends in non-communicable disease mortality and progress towards Sustainable Development Goal target 3.4*, that in 2016, an estimated 16.9 million people had died prematurely worldwide from (NCDs). Similarly, commenting on the human losses due to NCDs, but focusing on the global environmental impacts, the World Health Organization (WHO), a partner with the United Nations (UN) on the 2030 Sustainable Development Agenda, concluded in their 2016 report that an estimated 65% of the 12.6 million global deaths caused by the environment occurred from NCDs ("Preventing," 2017). The global 2016 NCD deaths attributed to the environment account

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[1] "Premature" deaths are denoted as deaths that have occurred under the age of 70 (Bennett et al., 2018).

for stroke (2.5 million), ischemic heart disease (2.3 million), cancers (1.7 million) and chronic respiratory diseases (1.4 million) among others. More specifically, in 2016, 25% of stroke related deaths were caused by ambient air pollution and 26% of stoke-related deaths were attributable to household air pollution. Unfortunately, over the past decade, the mortality rates of NCDs have continued to rise.

It is critical to obtain accurate marginal estimates of environmental causes of death, like the impacts of ambient and indoor pollution on NCDs, so that leaders can make better informed policy decisions such as implementing more restrictive environmental policies. In total, the aforementioned 12.6 million global deaths attributed to the environment accounted for 23% of total global deaths in 2016. Put another way, an estimated 23% of all deaths worldwide could have been prevented by healthier environments.

Likewise, due to health inequalities[2], it is important to implement effective strategies to both prevent and combat NCDs as it is likely that diagnosis and treatment costs will become less affordable in the future, leaving developing countries most vulnerable to NCDs; more than 85% of premature deaths are concentrated in developing countries (Soheylizard et al., 2018; "U.S." 2019). In turn, global communities, country leaders and private citizens worldwide should attempt to reduce risk factors of NCDs globally, regardless of their country's population health and economic standing, as it has been shown that the presence of NCDs in one country can negatively impact the world economy through disrupting international supply chains, depleting

[2] Health inequalities is a broad term that encompasses a variety of inequalities including those in the quality and access to care and treatments or the health statuses between socio-economic factors, genders, or geographies (Williams et al., 2020).

labor and capital supply, and decreasing the productivity of businesses (Abegunde and Stanciole, 2006). However, despite recent efforts to study the effects of the environment on NCDs, research is limited, and current estimates may be underestimated because of overcoming challenges such as determining lag times of exposure to pollutants, accuracy of primary records, and assessing the exposure to multiple toxins (Bennett et al., 2018).

This research paper aims to estimate the marginal effects of air pollution on NCDs because health determinants may impact conclusions for policy and health care. Specifically, I measure the effects of ambient and household air pollution on the ratio of premature NCD deaths to all NCD deaths. Additionally, I will examine the validity of a Health "Kuznets" curve, the association between health inequalities and economic development.

Literature Review

$PM_{2.5}$ are fine particulate matter with a diameter less than 2.5 micrometers like combustion particles that can penetrate deep into the lungs and cause severe health problems (Meng, 2019). $PM_{2.5}$ particles have an average lifetime of 1 to 2 weeks; therefore, reducing $PM_{2.5}$ emissions could result in an immediate decline in air pollution problems. Zheutlin et al. [2014] find a statistically significant relationship ($p\text{-value} < .0001$) between $PM_{2.5}$ and diabetes prevalence. For every additional 10 microgram/m^3 of $PM_{2.5}$, it is estimated that diabetes prevalence increases by 0.90%, though this may be a conservative result as the sample consisted of adults who are less susceptible to the exposure of pollutants than children as mentioned by Cosbey et al. [2005].

While the WHO estimates that 3.7 million people die yearly from ambient air pollution-related causes, 4.3 million people die yearly due to household air pollution-related causes (Apte and Salvi, 2017). In general, household air pollution is more profound in developing countries due to ill-ventilated housing structures and cooking with inefficient fuels and stoves. More efficient fuels produce less pollution, but are more expensive, leaving lower income and less developed countries more vulnerable to adverse health outcomes like chronic obstructive pulmonary disease. Coincidentally, developing countries, as mentioned in Soheylizard et al. [2018], typically have less access to medical facilities and have poorer quality diagnostic tools, leading to lower reported prevalence in diseases, but higher mortality rates.

Exploring deeper the relationship between country development and health outcomes, Molini et al. [2010] explains that the HDI can explain an inverted "U" shape of health inequalities based on the traditional Kuznets curve[3]. Molini et al. [2010] use Body Mass Index (BMI) rates as a proxy for health inequalities and adopt the following explanation for the inverse "U" relationship between health inequalities and economic development: at lower HDI levels, accessibility of medical products and services and high quality foods may be scarcer, increasing prices which, in turn, increases health inequalities. However, health inequalities may decrease when medical supplies become more affordable and accessible as country development increases.

Moreover, assessing the relationship between health inequalities and economic development measured by the HDI is appropriate when studying the effects of air pollution and

[3] The traditional Kuznets curve is a hypothesis that is graphically expressed as an inverted "U" and explains that initial increases in a country's economic development (measured by GDP per capita) are associated with increases in a country's economic inequalities (Molini et al., 2010). Then, after some turning point, GDP per capita is associated with decreases in economic inequalities.

health outcomes. Chronic stress, due to higher probability of crime rates and violence from health inequalities, may increase the risk for poorer health outcomes, like ischemic heart disease, an NCD that accounted for more than 9 million global deaths in 2016 (Woodward and Kawachi, 2000; Nurias et al., 2016; Nowbar et al., 2019). However, concerning the link, specifically, between environment related NCD deaths and chronic stress, stress has been shown to lower the immune system's ability to fight against air pollution, as described by Apte and Salvi [2017].

One way that countries are globally contributing to the fight against NCDs is through the United Nation's Sustainable Development Goals (SDGs). Specifically, SDG target 3.4 calls for a "one-third reduction, relative to 2015 levels, of the probability of dying between 30 years and 70 years of age" from NCDs by 2030 (Bennett et al., 2018, p. 1072). However, as of 2018, three years after the adoption of the SDGs, less than 50% of countries were on track to reach the target.

When analyzing the study of Bennett et al. [2018], the authors only briefly cover ambient air pollution, but do not discuss the implications on NCDs, such as greenhouse gases or $PM_{2.5}$, beyond behavioral factors[4]. Furthermore, I contribute to the literature by using the ratio of premature deaths due to NCDs out of all NCD deaths to estimate the marginal effects of environmental determinants on health outcomes and to validate the Health "Kuznets" curve.

Model

I use a linear regression to estimate the marginal effects of ambient and household air pollution on health outcomes across countries worldwide. Because SDG target 3.4 is focused on tracking the NCD-related deaths (Bennett et al., 2018), the response variable in my model is the ratio of premature NCD deaths to all NCD deaths (NCD_P). The explanatory variables of interest

[4] Behavioral factors include activities such as tobacco smoke (Bennett et al., 2018).

are $PM_{2.5}$ concentration levels ($PM_{2.5}$) and the proportion of population with primary reliance on clean fuels and technologies as the primary source of domestic energy for cooking (*eTech)*. Higher concentrations of $PM_{2.5}$ levels have been associated with poorer health while the usage of more efficient cooking technologies has been associated with less adverse health outcomes (Meng, 2019; Apte and Salvi, 2017). To hold constant countries' domestic financial power of combating NCDs, as Bokhari et al. [2007] suggests that increasing domestic medical research may increase population health, I control for the domestic general government health expenditures per capita (*DomHE)*. Likewise, access to high-quality treatments and diagnostics may be dependent on the level of a country's development (Soheylizard et al., 2018). To account for this, I control for the Human Development Index (*HDI*).

My model is represented by the equation

$$\log(NCD_P) = \beta_0 + \beta_1\log(PM_{2.5}) + \beta_2\log(eTech) + \beta_3\log(DomHE) + \beta_4 HDI + \beta_5 HDI^2 + u$$

where u is the error term with the usual assumptions that the error conditionally follows a normal distribution with 0 mean and constant variance. Concerning the functional form of the variables, NCD_P, $PM_{2.5}$, *eTech*, and *DomHE* are given a logarithmic transformation so that their coefficients can be interpreted as elasticities. Conversely, *HDI* is not given a logarithmic transformation to replicate the methodology of Molini et al. [2010].

While the primary goal of this model is to obtain the average marginal effects of air pollution, measured by $PM_{2.5}$ and *eTech*, a secondary goal is to evaluate how health inequalities are dependent on a country's level of human development. To that end, I incorporate a quadratic term for the variable *HDI* to assess the validity of a Health "Kuznets" curve between health inequalities (measured by NCD_P) and economic development (measured by *HDI*). Then, if the Health "Kuznets" curve theory holds as theorized by Molini et al. [2010], I can further investigate at what value of a country's economic development health inequalities begin to decrease.

Moreover, NCD_P is a better proxy for health inequalities than the BMI indicator used by Molini et al. [2010] because "beyond a certain threshold" of the BMI measure, being overweight or underweight is considered unhealthy, whereas a "poverty and inequality analysis requires that a welfare indicator provides a monotonic ranking of individuals or households" (p. 1013). Conversely, every increase in NCD_P can be reasonably associated with poorer health outcomes for a population because of the economic losses related with premature death (Abegunde and Stanciole, 2006).

Data

Table 1 shows the five-number summaries and standard deviations of all variables used. Notably, *eTech* has a negative skew with a mean and median of 64.04 and 85.00, respectively. The variables will each be discussed in greater detail below.

Premature deaths due to NCDs as a proportion of all NCD deaths (%)

The *NCD Countdown 2030* study uses 2016 data of the mean probability of dying between 30 and 70 years of age for the SDG target 3.4. Because no data was found that would indicate the numeric value of premature deaths for easier interpretation, I use 2016 mean estimates of the premature NCD ratio to account for all premature deaths (*Premature*, 2016) from the WHO data bank. The indicator is measured as a percentage.

My study includes data for 170 countries and territories; 13 countries were excluded from the original dataset due to lack of data from the explanatory variables. Standardized definitions and methods were used to ensure comparability among countries (*Premature*, 2016). Figure 1 is a histogram of NCD_P, which shows that there is no obvious skew and that NCD_P looks reasonably symmetric.

Measurement and monitoring gaps exist among high, middle, and low-income countries. As a result, the WHO adjusts the estimates by assessing the "completeness of the death registration, the quality of the cause-of-death information, and the timeliness of publication" (Bennett et al., 2018, p. 1082). However, incomplete coverage could still impact results. For my analysis, only 49 of 170 (28.8%) countries and territories contain "high-quality" data while 68 (40.0%) countries and territories were characterized as "very low."

$PM_{2.5}$ concentration levels

I use the 2016 estimates of the $PM_{2.5}$ mean annual concentration exposure levels, measured by micrograms/m^3, from the World Bank Group (WBG) to gauge ambient air pollution (*$PM_{2.5}$ air*, 2016). The Global Burden of Disease study calculated the estimates by using combined data from atmospheric models, satellite observations, and ground-level monitoring. Exposure levels are derived from both urban and rural areas and then aggregated.

Proportion of population with primary reliance on clean fuels and technologies

I used 2016 annual estimates of the proportion of population with primary reliance on clean fuels and technologies as the primary source of domestic energy for cooking from the WHO to measure the ability of each respective country to combat household air pollution (*Percentage*, 2016). The indicator is measured as a percentage; the number of people who use efficient cooking technologies is divided by the total country population. Several census and surveys on national and regional levels are used and thus, inconsistent definitions among countries of "clean fuels and technologies" may be used, distorting full comparability.

Domestic general government health expenditures per capita

I also control for the 2016 domestic general government health expenditures per capita (*Domestic*, 2016) from the World Bank Group. The data is measured in international dollars at purchasing power parity (PPP) to increase compatibility for cross-country analysis.

Human Development Index

I control for the 2016 HDI levels calculated by the United Nations Development Programme (UNDP) (*United*, 2016). The HDI is measured on a scale with values ranging from 0 to 1 where higher values represent a higher levels of country development and consists of the following indicators: Life expectancy at birth, expected years of schooling, mean years of schooling and GNI per capita (PPP) ("Human", n.d.). However, the HDI does not account for measures such as the quality of products or income inequality.

Results

Summary Statistics

Table 2 shows the summary statistics of the estimated linear regression model. Robust standard errors were used for inference due to evidence of heteroscedasticity. All statistical significance is based at the .05 level. Robust standard errors were used for inference due to evidence of heteroskedasticity[5]. Based on my slope coefficient estimates, shown in column 1, all the covariates show a positive relationship with NCD_P except for *eTech*. The positive and

[5] Figure 2 shows a residuals vs. fitted values plot for the estimated model. From this plot, there is some visual evidence indicating heteroskedasticity, which is further verified when conducting a Breusch-Pagan test (p-value = 0.0005818).

negative coefficients on *HDI* and HDI^2, respectively, indicate an inverted "U" re relationship[6] with health inequalities.

While the normal Q-Q plot shown in Figure 4 provides some evidence that the residuals diverge from normality, particularly in the tails, the sample size is large enough to justify valid statistical inference. The variables $PM_{2.5}$ (p-value = .003479) and *eTech* (p-value = .005751) were found to be statistically significant, while *DomHE* (p-value = .1634) was not. Despite high multicollinearity which increases the difficulty of achieving statistical significance, the variables $PM_{2.5}$ and *eTech* obtained low p-values of .003479 and .005751, respectively, indicating statistically significant effects. See Table 3 for the variance inflation factors (VIF) for the model. It is expected that *HDI* and HDI^2 have large VIF values of 144.53 and 128.52, respectively, since one is a function of the other. Log (*DomHE*) also has a relatively large VIF value of 11.86, which may explain its lack of statistical significance and is likely due to its close relationship with *HDI* and HDI^2 (Soheylizard et al., 2018). I also conduct an overall F test to show that the covariates are collectively statistically significant (p-value $< 2.2 * 10^{-16}$).

Altogether, my results largely corroborate the existing literature and my initial hypotheses. Consistent with Meng [2019] and Zheutlin et al. [2014] who find in their studies that an increase in the concentration of $PM_{2.5}$ is correlated with adverse health outcomes, I find that a 1% increase in $PM_{2.5}$ is estimated to be associated with a .1362% increase in NCD_P, ceteris paribus.

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[6] To validate the Health “Kuznets” theory, I perform an F test for exclusion restrictions and conclude that the variables *HDI* and HDI^2 are jointly statistically significant (p-value = $1.394 * 10^{-13}$).

In addition, I find that a 1% increase in *eTech* is estimated to be associated with a .0781% decrease in NCD_P, ceteris paribus. This is consistent with Apte and Salvi [2017] who suggest that households with efficient cooking stoves and use clean fuels for cooking are less susceptible to deaths attributed to household air pollution.

Inconsistent with Bokhari et al. [2007] who finds that an increase in domestic health expenditures is correlated with positive health outcomes, I find that a 1% increase in *DomHE* is estimated to be associated with a .0428% increase in NCD_P, ceteris paribus, which may be attributed to corrupt healthcare systems (Kiross et al., 2020). The sign is not as expected but since the effect is fairly small and not significant (p-value = .1634), it should not be over-interpreted as *DomHE* was not the focus of my research.

Health "Kuznets" Curve

The inverse "U" relationship is shown by Figure 3. I find that *HDI* has an increasing marginal effect on health inequalities (as measured by NCD_P) until *HDI* reaches .495.[7] When a country reaches an HDI level of .495, health inequalities are expected to stop increasing and will begin to decrease. Even though my model shows that a Health "Kuznets" curve exists when using NCD_P and HDI as indicators, only 17 out of 170 countries in my dataset are characterized by a 2016 HDI score lower than .495. However, based on past research, these impacts may still be globally significant (Abegunde and Stanciole, 2006).

Discussion

The results of this analysis have some important implications. Even though the marginal

[7] The vertex turning point of my Health "Kuznets" curve is obtained as follows:

$\hat{\beta}_4$ / [2* $\hat{\beta}_5$] = | 4.4156 / | [2 * -4.4588] | ≈ 0.495.

effects of $PM_{2.5}$ and *eTech* on NCD_P may seem small and practically insignificant, my results indicate that $PM_{2.5}$ and *eTech* are both individually statistically significant at the .05 level. This provides evidence that the current rising trend of NCDs deaths may be hampered if effective measures are taken to combat air pollution and increase the distribution of efficient cooking fuels and technologies ("Preventing", 2017). As was highlighted earlier, an estimated 23% of global deaths in 2016 could have been prevented by living in healthier environments.

Conclusion

NCDs are "among the leading causes of preventable illness and related disability" and accounted for 16.9 million premature deaths in 2016 ("U.S.", 2019, para. 3). My study adds value to Bennett et al. [2018] and the *NCD Countdown 2030* campaign as I have shown that ambient air pollution is associated with increases, and efficient cooking technologies are associated with decreases in the premature NCD ratio. Additionally, I find that *HDI* may be correlated with increasing marginal effects of health inequalities at low HDI levels but that the marginal effects in health inequalities peak and then begin to decrease at higher HDI levels; the Health "Kuznets" theory supports the statistic that over the past decade the number of NCD deaths have continued to increase as more than 85% of premature deaths are concentrated in developing countries ("Preventing", 2017; "U.S.", 2019).

Future research should test which sectors of our industrialized society like transportation or energy production have the largest impacts on $PM_{2.5}$. Greenhouse gasses like nitrogen and sulfate oxides, by-products of using gas powered vehicles, are $PM_{2.5}$ precursors[8] and contribute

[8] A $PM_{2.5}$ precursor is "any chemical that contributes to the formation of $PM_{2.5}$ particles but is not emitted directly from its source as $PM_{2.5}$" (Hodan and Barnard, 2005, p. ii).

to 4 to 37% and 7 to 47%, respectively, to $PM_{2.5}$ formation (Hodan and Barnard, 2005). As a result, manufacturers could deflect the costs of pollutants more accurately.

Additionally, given my results, specifically the positive and statistically significant marginal effect of $PM_{2.5}$ on NCD_P, the collection and publication of data should be done more carefully and expeditiously because tracking trends in marginal estimates of the air pollution effects on population health is of great concern. For example, NCD_P data is released by the WHO every two to three years and the Environmental Protection Agency synthesizes research to assess air quality regulations only every five years. (*Premature*, n.d.; "Air", n.d.).

The results of this study, specifically the effects of ambient and household air pollution, should be beneficial for organizations like the UN to better understand the global implications of environmental health determinants. Hopefully these results as well as further research in epidemiology analytics contribute to the *NCD Countdown 2030* campaign and help the campaign to reach its goal to "reduce by one third premature mortality from non-communicable diseases" by 2030 (Bennett et al., 2018, p. 1072).

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Tables and Figures

TABLE 1

Data Summary

	NCD_P	PM_2.5	eTech	DomHE	HDI
Minimum	16.00	5.894	5.00	4.226	0.3650
1st Quartile	32.00	13.865	28.25	69.046	0.5920
Median	47.00	21.429	85.00	358.991	0.7330
Mean	45.28	26.931	64.04	974.904	0.7111
3rd Quartile	57.75	33.338	95.00	1228.226	0.8335
Maximum	76.00	98.055	95.00	8077.926	0.9510
Std. Deviation	15.27	18.747	35.82	1372.518	0.1518

Table 1[9] shows the five-number summaries and standard deviation of all variables used.

TABLE 2

[9] Source: WHO, World Bank Group, and United Nations Development Programme.

Summary Statistics (with robust-standard errors)

	Estimate	Std. Error	Pr(>|t|)	95% CI [LB,UB]
(Intercept)	2.5952	0.3397	$1.727e^{-12}$*	1.9246, 3.2658
log(PM_25)	0.1362	0.0459	0.003479*	0.0455, 0.2269
log(eTech)	-0.0781	0.0279	0.005751*	-0.1333, -0.0230
log(DomHE)	0.0428	0.0305	0.1634	-0.0175, 0.1030
HDI	4.4156	0.7897	9.232^{e-08}*	2.8567, 5.9745
HDI^2	-4.4588	0.5763	9.795^{e-13}*	-5.5963, -3.3212
Note:	*p<0.05			

Table 2[10] shows the summary statistics of the linear regression model when using robust standard errors to correct for heteroskedasticity.

TABLE 3

Variance Inflation Factor (VIF)

log(PM_2.5)	log(eTech)	log(DomHE)	HDI	HDI^2
1.665224	5.850765	11.859549	144.527084	128.516761

Table 3[11] shows the VIF values for the model's explanatory variables.

[10] Source: Own calculations using data from WHO, WBG and UNDP.

[11] Source: Own calculations using data from WHO, WBG and UNDP.

FIGURE 1

Histogram of the Premature NCD Mortality Ratio

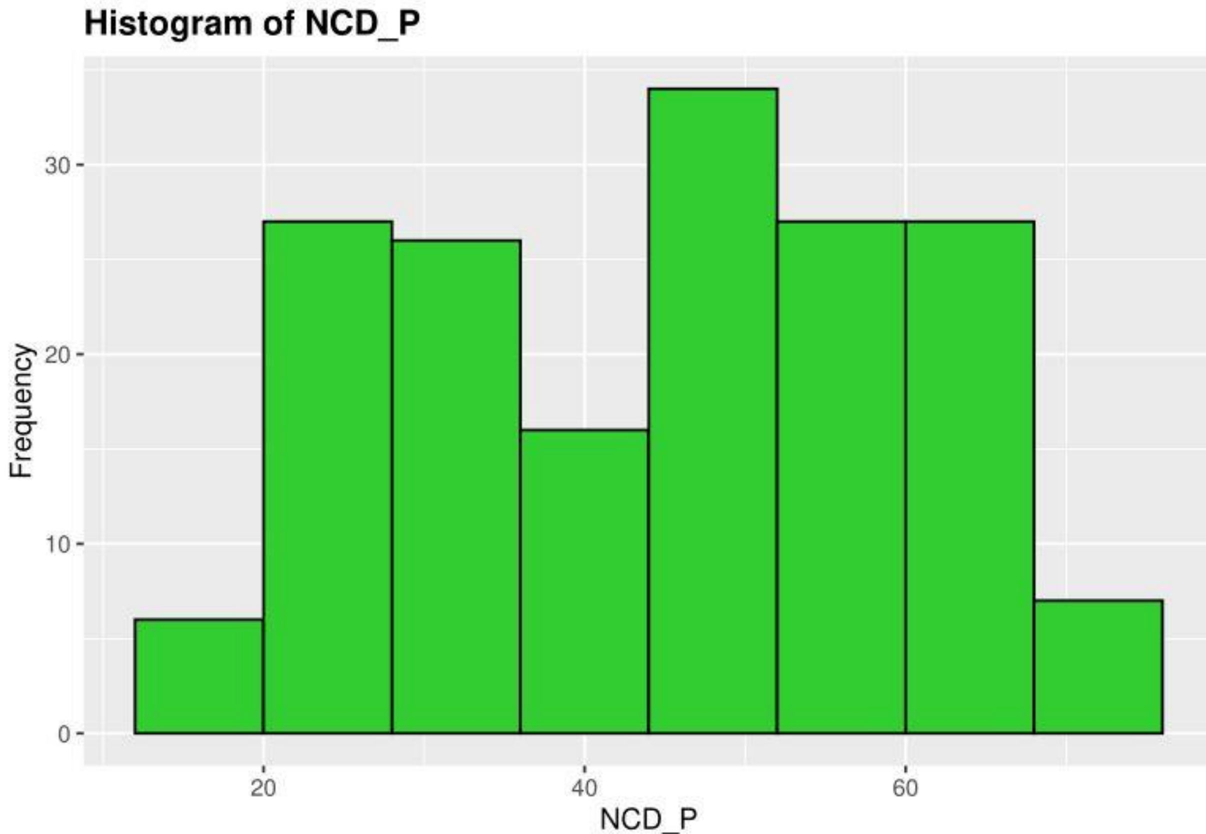

Figure 1[12] shows the histogram of the 2016 premature NCD mortality ratio across the 170 counties used in my study.

[12] Source: WHO

FIGURE 2

Residuals vs. Fitted value plot

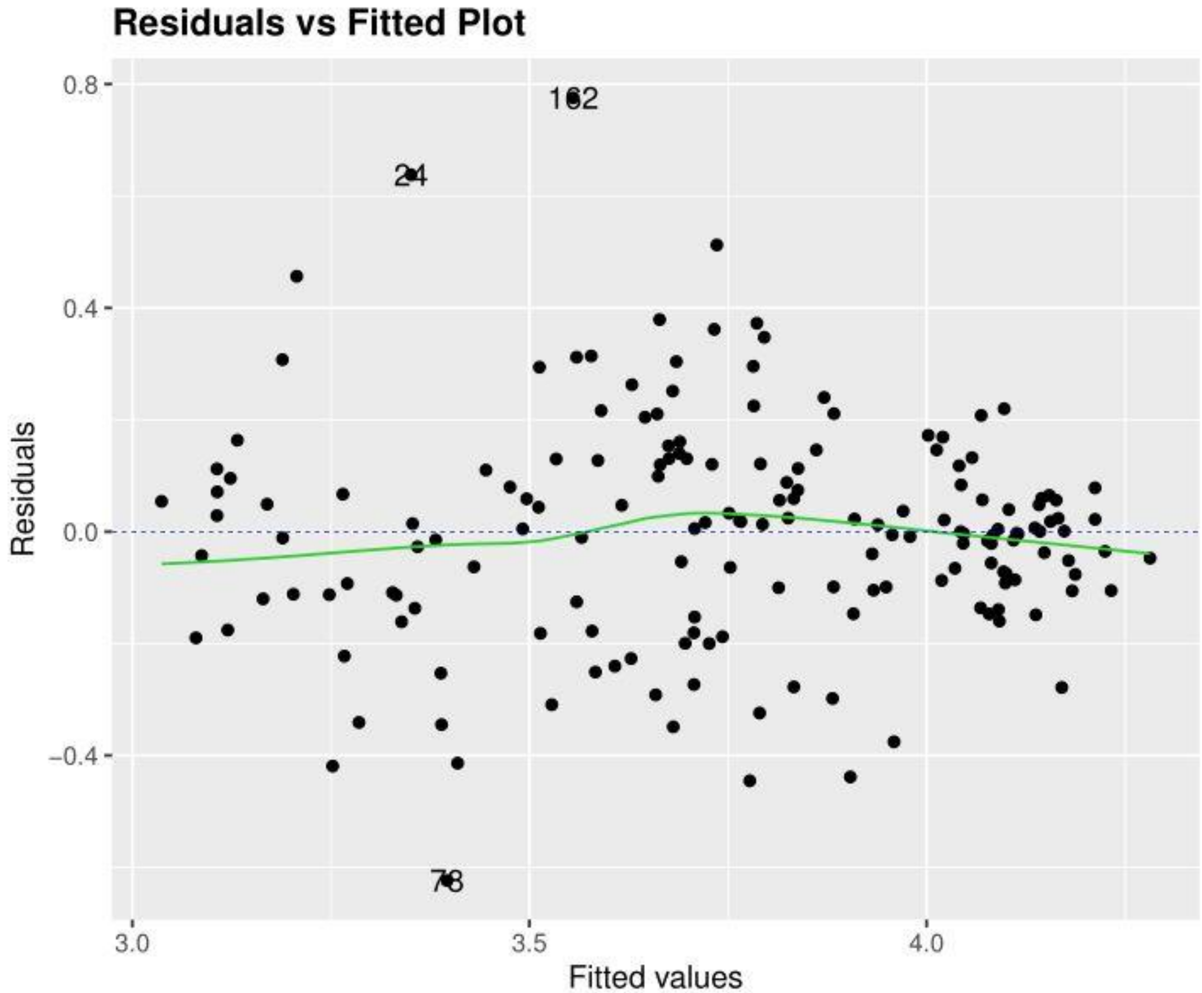

Figure 2[13] shows a Residuals vs. Fitted plot to verify Homoskedasticity.

[13] Source: Own calculations using data from WHO, WBG and UNDP.

FIGURE 3

Health "Kuznets" Curve

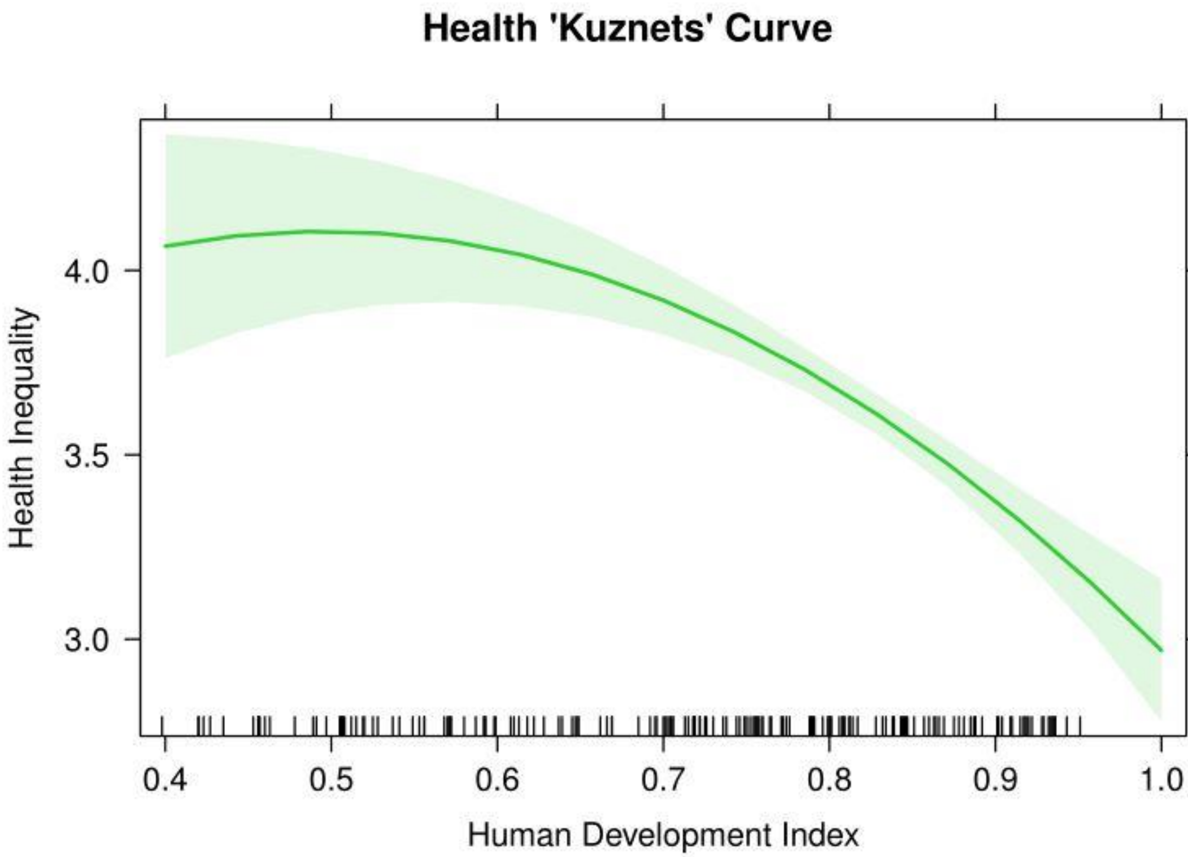

Figure 3[14] shows the Health 'Kuznets' Curve with a vertex of 0.495. Each tick mark on the x-axis represents the HDI level of each respective country in my study.

[14] Source: Own calculations using data from WHO, WBG, and UNDP.

FIGURE 4

Q-Q Plot

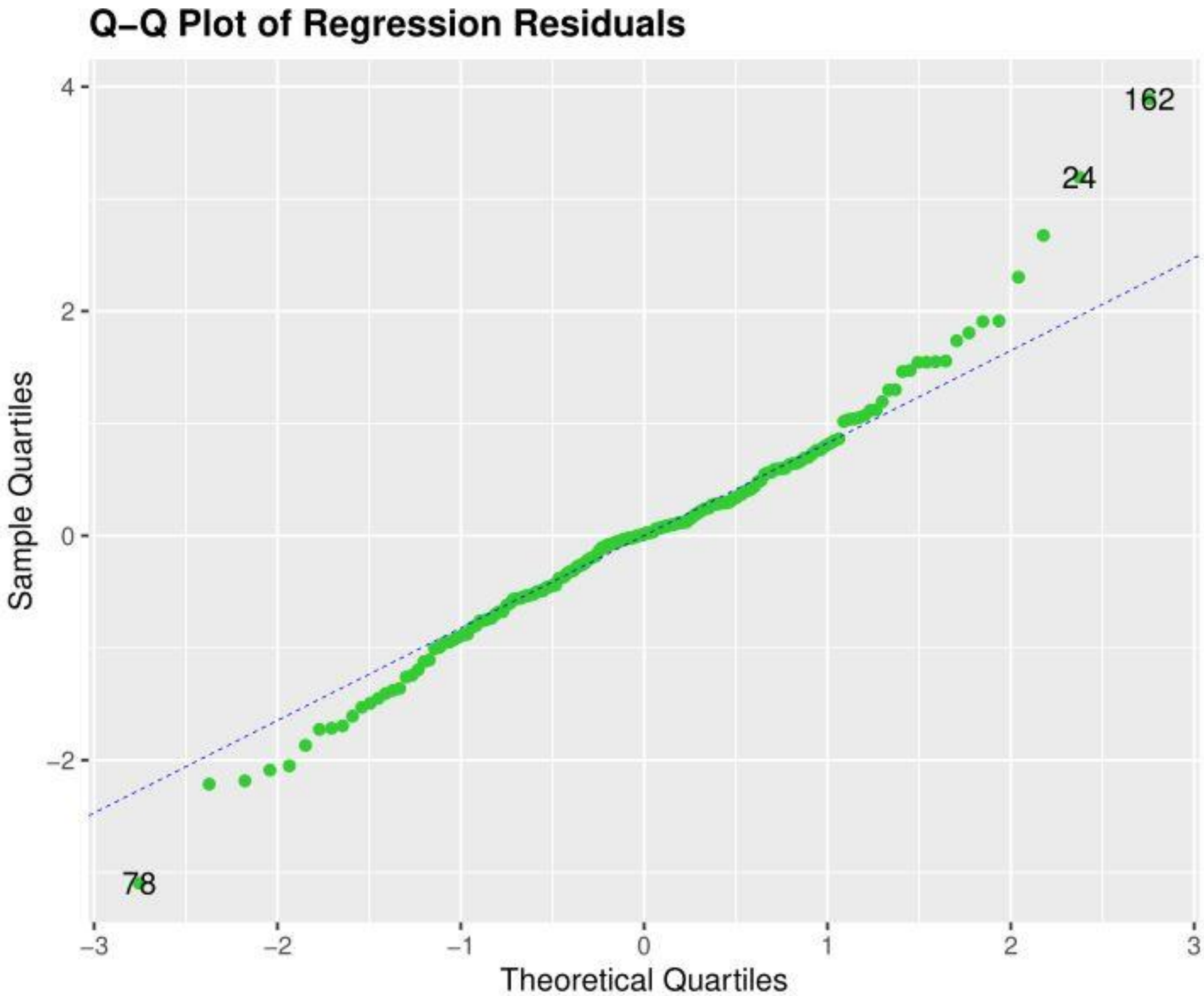

Figure 4[15] shows a Q-Q plot to verify the normality of the error term.

[15] Source: Own calculations using data from WHO, WBG, and UNDP.