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Environmental Sustainability and Human Capital Development

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ABSTRACT: This study utilizes a multiple log regression model to examine how markers of environmental wellbeing are able to explain disparities in human capital globally. This paper utilizes data from The World Bank to examine relationships between emissions, air pollution, land and water conservation, renewable energy reliance, development status, and human capital levels. The results find that carbon emissions and particulate matter air pollution are the largest environmental predictors of human capital index scores, and that the positive relationship between carbon emissions and human capital level all but disappears amongst developed nations. This study fills a gap in the literature, providing a non-geographically isolated examination of particularly relevant explanatory variables, as opposed to solely utilizing index scores.

Keywords: development, human capital, emissions, growth

AUTHOR'S NOTE: Our planet and way of life are in dire straits. In the past several decades we have seen an explosion in awareness regarding the dangers posed by unchecked industrial development. This study at hand hopes to add to the body of dialogue regarding proactive approaches to dealing with our changing climate. My hope is to draw attention to the sort of strategies that can be successful in promoting the sort of economic development that much of our world still needs while also protecting and restoring our planet's ecosystems. Hopefully, future policy will take into consideration studies such as this. Development and environmental stewardship do not need to exist separately.

Introduction

Economic development has historically come at the expense of environmental wellbeing. More recently, however, governments have increasingly focused on ecologically responsible growth and the protection and restoration of natural resources. This shift has occurred alongside momentous increases in standard of living for people across the planet. Nations and international organizations are placing a renewed importance on advancing global quality of life while also ensuring environmental viability.

Researchers are finding that environmental consciousness and improvements in quality of life are not mutually exclusive. Dr. P.V. Baiju, an Indian researcher in social development, wrote that sustainable development occurs at the intersection of ecological conservation, economic growth, and improvement of social wellbeing (Baiju, 2007, p. 184). The second two dimensions, economic growth and improvements in social well being, are tied together in the concept of human capital. Human capital here refers to the contribution of the individual worker to the output of an economy. Human capital is the sum of the educational, health, and societal outcomes an individual experiences and brings into the workplace.

Despite an increased focus on sustainability in recent years, past decades of economic growth have come at the costs of environmental degradation and excessive natural resource exploitation. This does not need to be the norm. The study at hand seeks to examine the relationships between environmentally sustainable practice and positive life outcomes for the individual, representative of overall quality of life. Its ramifications can help advise sustainable policy, in both the developing world and more slowly growing economies.

Literature Review

There is an abundance of literature linking environmental health to the social well-being of a nation's denizens. However, much of the literature relies on index scores to represent various factors of sustainability, rather than examining the underlying indicators that inform

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these index scores. This approach is problematic in that it unnecessarily limits the scope of factors examined. The Ecological Footprint (EF) index, based upon the number of references in publication, is the most widely used ecological and environmental index (Strezov, Evans & Evans, 2017, p. 247). This index is also the only major index that solely examines environmental factors. Despite its benefits, the index fails to account for factors such as air pollution concentrations that humans are in constant interaction with ("Data and Methodology", 2019). Another commonly used index in economic literature is the Sustainable Society Index, which assesses a nation's sustainability. Using this measure to represent environmental sustainability is problematic in that the SSI contains indicators of sustainability outside of environmental well-being. This index seeks to encapsulate the whole of sustainability, at its environmental, social, and economic levels (Strezov, Evans & Evans, 2017, p. 245). While this approach has merit, SSI index scores consistently fail to mirror environmental markers. Scores are excessively influenced by the other factors considered. As such, this index is not an adequate measure of the interaction between human capital development and environmental factors. There is no single index score that can account for the intersectionality between environmental, economic, and social factors that make up sustainability (Rodriguez-Rosa, Gallego-Alvarez, Vincente-Galindo & Galindo-Villardon, 2017, p. 547).

Some literature has linked environmental quality to human development and economic health. The most famous example of this is in the "Kuznet Curve" which hypothesizes that environmental degradation is essential to the early stages of a nation's economic growth. This theory posits that the concentration of carbon emissions will increase in these early stages of development, only reducing once the nation finds stable economic footing (Jain and Nagpal, 2017, p. 126-127). The same paper by Jain and Nagpal (2017) found that across South Asia, environmental protection is positively related to Human Development Index scores (p. 130). Economic losses that are a result of environmental degradation are inextricably linked to human capital depreciation (Zhao, Yu, Wang & Fan, 2016, p. 11716). The same study from Zhao et al. (2016) hypothesized that between 1.2% and 2.0% of newly generated wealth globally is lost each year due to health deterioration from air pollution (p. 11718). This is demonstrative of the massive economic cost imposed by the market failure of negative environmental externalities (the unintended environmental cost inherent in industrial activity). The failure of an economy to develop in an environmentally sustainable manner imposes not only ecological and social costs, but also significant monetary loss.

Air pollution has possibly the largest environmental influence on human capital depreciation (Schmidt, 2019, p. 1). Particulate matter air pollution (PM) has been linked to a loss of productivity due to reduced mental functioning (Schmidt, 2019, p. 4). This reduced productivity, when coupled with the increased mortality associated with other forms of air pollution is a leading contributor to the decline in human capital as the effects of industrialization take hold. Zhao et al. (2016) found that 12.5% of annual global deaths are attributable to air pollution (p. 11717). They concluded that as concentrations of air pollution increase, mortality also increases (p. 11723).

Existing literature indicates a link between environmental and human well-being. Environmental factors that are of primary interest are water usage, forest coverage, clean air, and renewable energy usage (Baiju, 2007, p. 190-191). A similar list includes renewable water resources, air quality, renewable energy, and greenhouse gas emissions (Rodriguez-Rosa et al., 2017, p. 548). Rodriguez-Rosa et al. (2017) also made clear the relationship between national income level and commitment to sustainable development (p. 561). Because the relevance of these factors is well established, they will be examined in the study at hand.

The current body of literature is lacking in that it either fails to solely examine the environmental dimension of sustainability or the study in question is geographically isolated. This study seeks to remedy this by focusing solely on the environmental factors impacting human development, while looking at a broad swath of nations across the globe. As such, this paper will fill an important place in the current body of literature: providing a global perspective on the role environmental well being plays in human capital development.

Data Description

All data utilized in this study is drawn from the World Bank DataBank's World Development Indicators from the most recent year for which data is available. 2017 Human Capital Index scores are used to represent each nation's quality of life. This index score accounts for a child's probability of survival to age 5, survival rate from age 15-60, expected years of schooling, and the percentage of children under age 5 whose growth has not been stunted. According to the World Bank (2018), this index is meant to showcase the amount of human capital that a child can expect to attain by age 18. They state that this index was "designed to highlight how improvements in current

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health and education outcomes shape the productivity of the next generation of workers" (World Bank, 2018). While this index score and the underlying factors that determine its value are not necessarily representative of the myriad definitions of what could constitute human capital, they do provide a useful base-level instrument for an even-keeled evaluation.

Predictor variables were selected to represent different indicators of a nation's commitment to environmental sustainability. These variables, along with a brief description of each are listed in Table 1.

These variables were chosen because they represent a broad swath of the objectives of environmental sustainability. Together these factors can reveal a nation's performance on several metrics of eco-progress. It does bear stating that these are not the sole environmental factors that can be considered as part of the broader field of environmental sustainability. However, amongst those factors quantified and made accessible by The World Bank these are the predictors that have the strongest relationship to environmental wellbeing. The human capital index score indicates a value between 0 and 1, with higher values being associated with higher levels of human capital. The dummy variable takes a value of 0 as default. A value of 0 represents a nation that is not yet considered to be developed. A value of 1 represents a nation that is considered fully developed.

157 nations were initially examined. This selection of countries had the most recent HCI score available. Together, they represented a broad swath of the globe, with every populated continent represented. 46 African countries, 40 Asian countries, 40 European countries, 13 North American countries (including Central America and Caribbean Islands), 9 countries from Australia and Oceania, and 9 South American countries were represented. However, some nations had incomplete data. Those without complete data on all metrics considered were excluded from further analysis. Following this elimination, outliers in observations were controlled for. Any nation which held an outlier in any of its associated metrics was deleted from consideration. For the purposes of this study, any indicator variable outside of three standard deviations from its mean was considered an outlier.

This control was implemented to prevent any outlier observations from exerting undue leverage on the regression. In all, 56 nations were removed from consideration, the vast majority of which were removed due to incomplete data. Upon implementing this control, 101 nations were left for analysis.

Table 1: Table of Variables

Predictor Variables	Description
Protected area	2017 data. This indicator measures the percentage of a nation's territory, both terrestial and marine, that is designated as protected from development
Level of water stress	2015 data. This is the ratio between total freshwater withdrawn by industry and the total amount of renewable freshwater sources
pm25 air pollution	2017 data. Measured in mean annual exposure in micrograms per cubic meter.
co2 emissions	2014 data. This is measured in metric tons per capita.
Agricultural land	2016 data. This is the percentage of a nation's total land area that is dedicated to agricultural production.
Forest land	2016 data. This is the percentage of a nation's total land area that sits under planted or natural trees and is not used in agricultural production.
Combustible renewables and waste	2014 data. This is the percentage of nation's total energy that is drawn from solid biomass, liquid biomass, biogas, industrial waste, and municipal waste.
Other greenhouse gas emissions	2012 data. This a measurement of greenhouse gas emissions other than co2, such as hydrofluorocarbons, perfluorocarbons, and sulfur hexafluoride. It is measured in thousands of metric tons of co2 equivalent.
Developed Nation	Values are drawn from a 2014 United Nations report. This is a dummy variable with a value of either 0 or 1. Nations that are listed in the report as being developed recieve a value of 1, while nations that are listed as developing or in transition recieve a value of 0.

Response Variable	Description
Human Capital Index	2017 data. This is scaled from zero to one. This is a measurement of the future productivty as a worker of a child born today, relative to a benchmark of full health and complete education.

Methodology

The primary objective of this study is to test the theory that regardless of a nation's development status, a nation's focus on environmental wellbeing is positively related to a higher quality of life for its citizens. Before taking an in-depth look at the statistical modeling underpinning this article, several basic ideas regarding regression analysis should be stated. The models at hand were fit using an ordinary least squares method (OLS). This technique essentially plots all known data points onto a theoretical multi-dimensional space and seeks to fit a functional form as closely to those data points as possible. The objective is to mirror reality as closely as possible, minimizing the distance between known observations and the model's predictions. These disparities are termed "errors" and the OLS regression fits a model that minimizes the squares of these error terms. The model is algebraically represented in a functional form. The response variable "Y" in this case is a Human Capital Index score. The β coefficients represent the degree to which a change in the "X" variable they are attached to will bring a resultant change in the response variable "Y". The first β coefficient (the one without a variable attached) is a constant, and functions as the y-intercept in basic algebra. The γ coefficient has a similar meaning but is attached to a yes or no dummy variable "Z". α is used similarly for coefficients of the interaction between factors. For regression analysis, most of the calculations are computed using statistical software that will output values for these coefficients as well as diagnostic markers. The ε at the end of the function represents the error term. It is not used in making predictions, as its value differs with each observation.

While explaining the function of the relevant diagnostic summary statistics is beyond the scope of this paper, a familiarity with a few would be valuable. R^2 is a measurement between 0 and 1 of the degree of variability

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in "Y" explained by changes in the predictor "X" and "Z" variables. It is often considered a measure of "goodness of fit". Each variable considered has an accompanying "p-value".

This value indicates the degree to which the variable is statistically different from zero. This validates the relation between that particular predictor and the response variable. Lower values mean an increased certainty that the predictor and response are related. Typically, we are looking for a 90-99% certainty that the factors are related to maintain their presence for consideration.

Other summary statistics will be explained as they are encountered in the remainder of this paper's methodology section. To begin, the following model was selected and fit to the available data:

Model 1: Regression model with all predictors considered

$$Y = \beta_0 + \beta_1 X_{Protected\ Area} + \beta_2 X_{Water\ Stress} + \beta_3 X_{pm25} + \beta_4 X_{co2} + \beta_5 X_{Ag\ Land} + \beta_6 X_{Forest\ Land} + \beta_7 X_{Combustibles} + \beta_8 X_{Other\ Greenhouse\ Gas} + \gamma Z_{Developed} + \varepsilon$$

Upon fitting the model to the data at hand using an OLS regression, the following results shown in Table 2 were obtained.

An R^2 value of 0.83 was obtained. This demonstrates a good degree of variability in human capital being explained by the environmental factors considered. Also of note is the fact that not all of these predictors are statistically significant. Of particular note: level of water stress, percentage of land dedicated to agriculture, percentage of forested land, and greenhouse gas emissions (excluding pm25 and co2) were found to be statistically insignificant in the model. The percentage of total area that is protected was found to only be significant at the 90% level.

It was then important to determine if there was significant interaction between the dummy variable representing a nation's development status and the other predictor variables. The below model was utilized to test for interaction.

Model 2: Regression Model with all predictors and interaction

$$Y = \beta_0 + \beta_1 X_{Protected\ Area} + \beta_2 X_{Water\ Stress} + \beta_3 X_{pm25} + \beta_4 X_{co2} + \beta_5 X_{Ag\ Land} + \beta_6 X_{Forest\ Land} + \beta_7 X_{Combustibles} + \beta_8 X_{Other\ Greenhouse\ Gas} + \gamma Z_{Developed} + \alpha_1 (Z \times X_{Protected\ Area}) + \alpha_2 (Z \times X_{Water\ Stress}) + \alpha_3 (Z \times X_{pm25}) + \alpha_4 (Z \times X_{co2}) + \alpha_5 (Z \times X_{AgLand}) + \alpha_6 (Z \times X_{Forest\ Land}) + \alpha_7 (Z \times X_{Combustibles}) + \alpha_8 (Z \times X_{Other\ Greenhouse}) + \epsilon$$

When fitted through OLS regression, this model provided the output shown in Table 3.

To determine whether there is a statistically significant interaction in the data, an F test was conducted to compare the Reduced Model 1 with the Full Model 2. The initial Model 1 did not consider that the yes or no (represented in binary fashion) value of a nation's development status may interact with any of the other factors considered to negate or confound their impact on human capital. A F test in this case is essentially used to compare which model is superior, the model without any interaction or the model with every factor interacting. The idea that there is no interaction is taken as a default or "null hypothesis" and the full model's supremacy is taken as the alternative hypothesis. A F value of 1.77517 was returned. This value, in the case of this comparison (based upon number of observations and number of predictor variables between the models), does not lead to the rejection of the null hypothesis. Model 1 without any interaction is a better predictor than Model 2 with all predictor variables interacting with the dummy variable. However, all but one of the interaction terms were, based on their p-values, statistically insignificant. This value (interaction 4), was highly significant.

Following this result, a new model was generated, removing all predictors that were statistically insignificant on the basis of p-values in Model 1. This model, Model 3, which does not include interaction between variables was compared to the new Model 4. Model 4 contains solely the predictors that were deemed statistically significant, along with the interaction that was deemed significant on the basis of its p-value in Model 2's analysis. This is the interaction between the dummy variable of a nation's development status and its co2 emissions. These new models are:

Model 3: Simplified regression model

$$Y = \beta_0 + \beta_1 X_{Protected\ Area} + \beta_2 X_{pm25} + \beta_3 X_{co2} + \beta_4 X_{Combustibles} + \gamma Z_{Developed} + \varepsilon$$

Running an OLS regression on this model yields Table 4 and Model 4.

Model 4: Model with statistically significant interaction

$$Y = \beta_0 + \beta_1 X_{Protected\ Area} + \beta_2 X_{pm25} + \beta_3 X_{co2} + \beta_4 X_{Combustibles} + \gamma Z_{Developed} + \alpha (Z \times X_{co2}) + \varepsilon$$

Running an OLS regression on Model 4 yields the output in Table 5:

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Table 2: Output from regression Model 1 fitting

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5	(6) Model 6	(7) Model 7	(8) Model 8	(9) Model
protectedarea	0.002 (0.001)	0.002* (0.001)	0.001 (0.001)	0.000 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	-0.001* (0.001)
waterstress		0.000 (0.000)	0.002*** (0.000)	0.001** (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
pm25			-0.007*** (0.001)	-0.005*** (0.001)	-0.004*** (0.001)	-0.004*** (0.001)	-0.004*** (0.001)	-0.004*** (0.001)	-0.002*** (0.001)
co2				0.016*** (0.002)	0.013*** (0.002)	0.012*** (0.002)	0.012*** (0.002)	0.012*** (0.002)	0.009*** (0.002)
combustables					-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.001)	-0.002*** (0.000)
agland						-0.001** (0.000)	-0.001 (0.000)	-0.001 (0.000)	-0.000 (0.000)
forestland							0.000 (0.001)	0.000 (0.001)	0.001 (0.000)
greenhousegas								0.000 (0.000)	0.000 (0.000)
development									0.119*** (0.018)
Constant	0.579*** (0.024)	0.570*** (0.028)	0.712*** (0.025)	0.628*** (0.023)	0.655*** (0.022)	0.696*** (0.029)	0.680*** (0.040)	0.680*** (0.040)	0.628*** (0.034)
Observations	101	101	101	101	101	101	101	101	101
R-squared	0.03	0.03	0.50	0.69	0.74	0.75	0.75	0.75	0.83

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Regression output from fitting Model 2

VARIABLES	(1) Regression 1	(2) Regression 2	(3) Regression 3	(4) Regression 4	(5) Regression 5	(6) Regression 6	(7) Regression 7	(8) Regression 8	(9) Regression 9
protectedarea	0.002 (0.001)	0.002* (0.001)	0.001 (0.001)	0.000 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	-0.001* (0.001)
waterstress		0.000 (0.000)	0.002*** (0.000)	0.001** (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
pm25			-0.007*** (0.001)	-0.005*** (0.001)	-0.004*** (0.001)	-0.004*** (0.001)	-0.004*** (0.001)	-0.004*** (0.001)	-0.002*** (0.001)
co2				0.016*** (0.002)	0.013*** (0.002)	0.012*** (0.002)	0.012*** (0.002)	0.012*** (0.002)	0.009*** (0.002)
combustables					-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.001)	-0.002*** (0.000)
agland						-0.001** (0.000)	-0.001 (0.000)	-0.001 (0.000)	-0.000 (0.000)
forestland							0.000 (0.001)	0.000 (0.001)	0.001 (0.000)
greenhousegas								0.000 (0.000)	0.000 (0.000)
development									0.119*** (0.018)
interactionprotectedarea									
interactionwaterstress									
interactionpm25									
interactionco2									
interactioncombustibles									
interactionagland									
interactionforestedland									
interactionothergreenhousegasses									
Constant	0.579*** (0.024)	0.570*** (0.028)	0.712*** (0.025)	0.628*** (0.023)	0.655*** (0.022)	0.696*** (0.029)	0.680*** (0.040)	0.680*** (0.040)	0.628*** (0.034)
Observations	101	101	101	101	101	101	101	101	101
R-squared	0.03	0.03	0.50	0.69	0.74	0.75	0.75	0.75	0.83

VARIABLES	(10) Regression 10	(11) Regression 11	(12) Regression 12	(13) Regression 13	(14) Regression 14	(15) Regression 15	(16) Regression 16	(17) Regression 17	(18) Regression 18
protectedarea	-0.002 (0.001)	-0.002 (0.001)	-0.002 (0.001)	-0.002 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
waterstress	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
pm25	-0.002*** (0.001)	-0.002*** (0.001)	-0.002*** (0.001)	-0.002*** (0.001)	-0.002*** (0.001)	-0.002*** (0.001)	-0.002*** (0.001)	-0.002*** (0.001)	-0.002*** (0.001)
co2	0.009*** (0.002)	0.009*** (0.002)	0.009*** (0.002)	0.009*** (0.002)	0.013*** (0.002)	0.013*** (0.002)	0.013*** (0.002)	0.013*** (0.002)	0.013*** (0.002)
combustables	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)
agland	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.001 (0.000)	-0.001 (0.000)	-0.001 (0.000)	-0.001 (0.000)	-0.001 (0.000)
forestland	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.000 (0.001)	-0.000 (0.001)
greenhousegas	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
development	0.103*** (0.032)	0.103*** (0.032)	0.100** (0.042)	0.100** (0.042)	0.204*** (0.051)	0.174*** (0.057)	0.172** (0.066)	0.142* (0.083)	0.149* (0.084)
interactionprotectedarea	0.000 (0.002)	0.000 (0.002)	0.000 (0.002)	0.000 (0.002)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)
interactionwaterstress	0.001 (0.001)	0.001 (0.001)	0.000 (0.001)	0.000 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001* (0.001)
interactionpm25			0.000 (0.003)	0.000 (0.003)	-0.004 (0.003)	-0.004 (0.003)	-0.004 (0.003)	-0.003 (0.003)	-0.003 (0.003)
interactionco2					-0.013*** (0.004)	-0.011*** (0.004)	-0.011** (0.004)	-0.011** (0.004)	-0.012*** (0.004)
interactioncombustibles						0.002 (0.002)	0.002 (0.002)	0.002 (0.002)	0.002 (0.002)
interactionagland							0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
interactionforestedland								0.001 (0.001)	0.000 (0.001)
interactionothergreenhousegasses									0.000 (0.000)
Constant	0.638*** (0.039)	0.638*** (0.039)	0.638*** (0.040)	0.638*** (0.040)	0.637*** (0.038)	0.642*** (0.038)	0.643*** (0.039)	0.650*** (0.042)	0.650*** (0.042)
Observations	101	101	101	101	101	101	101	101	101
R-squared	0.83	0.83	0.83	0.83	0.85	0.85	0.85	0.85	0.85

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Taking the reduced (sans interaction) Model 3's adequacy as the null hypothesis, and the new full Model 4's superiority as the alternative hypothesis, an F statistic of 11.541 was obtained. This value is enough to reject the null hypothesis at the 99% significance level, and to state that Model 3 is inadequate when compared to Model 4. Model 4 is the best fit for representing the relationship. There is significant interaction between co2 emissions and a nation's development status. From this point forth, all discussion and analysis will be based upon Model 4 and its output in Table 5.

To verify the results obtained, several tests needed to be conducted. The theoretical explanations behind these tests are beyond this paper's scope. They are included in the body of this paper so as to validate the model and give credence to the quantitative and qualitative conclusions

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Table 4: Output from simplified Model 3

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
protectedarea	0.002	0.001	0.000	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
pm25		-0.005***	-0.004***	-0.003***
		(0.001)	(0.001)	(0.000)
co2			0.018***	0.014***
			(0.002)	(0.002)
development				0.131***
				(0.020)
Constant	0.579***	0.723***	0.620***	0.592***
	(0.024)	(0.028)	(0.023)	(0.020)
Observations	101	101	101	101
R-squared	0.03	0.36	0.68	0.78

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Regression output after fitting model 4

VARIABLES	(1) Regression 1	(2) Regression 2	(3) Regression 3	(4) Regression 4	(5) Regression 5
Protected Area	0.002	0.001	0.000	-0.002***	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
pm25		-0.005***	-0.004***	-0.003***	-0.003***
		(0.001)	(0.001)	(0.000)	(0.000)
co2			0.018***	0.014***	0.018***
			(0.002)	(0.002)	(0.002)
Development				0.131***	0.213***
				(0.020)	(0.028)
Interaction with co2					-0.014***
					(0.004)
Constant	0.579***	0.723***	0.620***	0.592***	0.576***
	(0.024)	(0.028)	(0.023)	(0.020)	(0.019)
Observations	101	101	101	101	101
R-squared	0.03	0.36	0.68	0.78	0.81

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

derived from it. These tests ensure that the model posits the most realistic relationships possible.They are in essence the statistically derived "evidence" of this paper's primary arguments.

The simplest visual test to conduct is that of the verification of the linear relationships that exist between the response variable and the predictors in question. To do this, a scatter plot matrix was generated (Figure 1). This matrix did not account for the dummy variable for development status or the interaction term. The matrix solely looked at the four examined quantitative predictors.

While it is not necessary to examine these correlations in detail, it is worth noting that, at first glance, there appears to be more or less linear relations between the HCI and three of the four predictors. The correlation between the HCI and the percentage of protected area is questionable. This finding does go in line with the insignificant p-value that the regression output yielded. Further, there is no cause for concern regarding the potential issue of collinearity (that predictor factors are themselves related to one another) as there does not appear to be significant correlation between predictor variables. These results, derived visually, were confirmed by checking Variable Inflation Factor values between individual predictor values and the model as a whole. No VIF values were close to the threshold levels that would indicate multicollinearity, the highest VIF value between variables was below 1.5. Subsequently, autocorrelation needed to be tested. First, an index plot of standardized residuals was generated (Figure 2).

A visual inspection of this diagnostic plot does not give cause for concern regarding autocorrelation. The standardized residuals are more or less evenly distributed around the zero line, as would be expected of observations with independent errors. To confirm this result, a Durbin-Watson test for autocorrelation was conducted using a statistical software package. This returned a Durbin-Watson statistic of 1.9107. This is above the upper limit in question of 1.693. As such the hypothesis of autocorrelation is rejected at the 99% significance level, and by proxy at the 95% significance level. There is no autocorrelation present amongst the data.

Following these promising results, testing for heteroskedasticity was conducted. To do this, a plot of residuals versus fitted values was generated (Figure 3).

It is unclear whether there is a pattern present in Figure 3. A data set with homoscedastic variance amongst error terms would exhibit a straight line pattern amongst the residuals. The errors above potentially illustrate what is called "fanning", where the variance amongst error values grows larger as the fitted value grows larger. This is suggestive of heteroskedasticity. To confirm the results of this visual inspection, a Breusch-Pagan/ Cook-Weisberg test for heteroskedasticity was administered using a statistical software package. This test takes homoscedasticity as the null hypothesis and heteroskedasticity as the alternative hypothesis. This test returned a chi squared value of 0.03 and a p value of 0.8684. This is not a high enough value to reject the null hypothesis. This data set does not exhibit heteroskedasticity.

After confirming the validity and significance of the proposed model, to ease in the explanation of relevant trends, a log linear transformation was performed on the datal. This form is simply a transformation of the previously validated form, allowing for clearer interpretations of the data's mathematical relationships. In this form, the percent change in the response variable as a result of a 1% change in the predictor variable can be deduced.. The coefficients of the linear log model tell us what the values of these percentage changes are. This model, once transformed, takes the form of Model 5.

Model 5: Log Transformation of Model 4

$$lnY = \beta_0 + \beta_1 lnX_{Protected\ Area} + \beta_2 lnX_{pm25} + \beta_3 lnX_{co2} + \beta_4 lnX_{Combustibles} + \gamma Z_{Developed} + \alpha\ (Z \times lnX_{co2}) + \varepsilon$$

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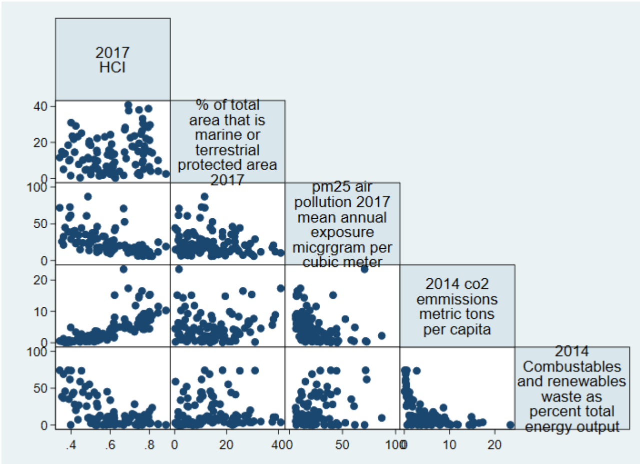

Figure 1: Scatter plot matrix of response and quantitative predictors

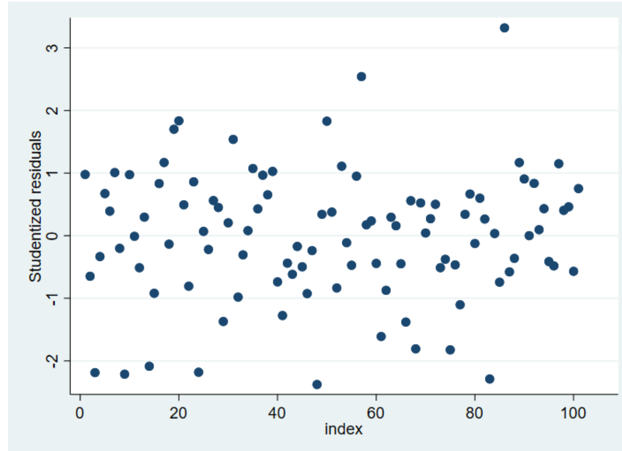

Figure 2: An index plot of standardized residuals

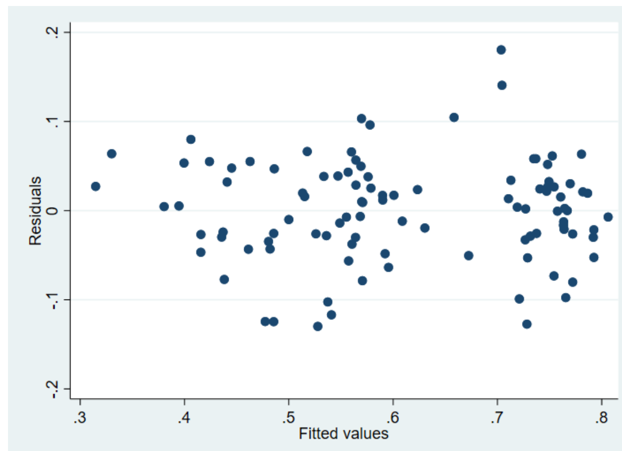

Figure 3: Residuals versus fitted values

This model, when fitted using an OLS regression provided the output shown in Table 6. This output is in the easiest form for examination of trends. As such, it will be utilized in the remainder of this paper.

Discussion

The most striking trend evidenced by these results can be inferred logically: that developed nations have, on average, 28.2% higher human capital index scores. This is hardly surprising considering the increased quality of healthcare and education available in the developed world. This illustrates the disadvantage those born in developing countries immediately face from birth.

Following the tests of significance, the predictors left are emissions, particulate matter air pollution, and combustible reliance. These are the sole factors of environmental sustainability that have a statistically significant impact on quality of life as represented by human capital index scores. What is perhaps least surprising amongst the established relationships is the inverse relationship between particulate matter air pollutants and human capital. For every 1% increase in particulate matter air pollution, a corresponding decrease of 0.12% in human capital was observed. This relationship is significant when considering the high levels of particulate matter in nations such as Brazil and China during early stages of their economic development (Zhao et al., 2016). The correlation between air pollution and increasing mortality is well established. This poses a significant threat to sustainable human development across the heavily polluted industrialized urban cores of the developing world. In addition to the lost productivity per worker due to the mentally degenerative effects of particulate matter air pollution (see Schmidt 2019), there is a systemic burden imposed by this contamination. Individuals experience stunted mental development and suffer premature deaths due to respiratory complications. Workers are therefore never able to reach full productive potential, and an excessive burden is placed onto healthcare resources. This has the knock-on effect of removing individuals from the workforce and slowing economic growth. There is a need in the current body of research for studies that directly quantify the magnitude of economic losses attributable to particulate matter air pollution. These economic losses may be demonstrably excessive when compared to the temporary advantage an economy gains from this type of environmentally irresponsible growth. This is to say nothing of the unquantifiable human cost.

Among developing nations, there is a strong positive relationship between CO2 emissions and human capital. Increases in carbon emissions are associated with increasing human capital. In these developing nations,

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Table 6: Regression output for log transformed Model 5

VARIABLES	(1) Regression 1	(2) Regression 2	(3) Regression 3	(4) Regression 4	(5) Regression 5	(6) Regression 6
logtotalareaprotected	0.017	-0.010	0.001	0.008	-0.008	-0.006
	(0.024)	(0.018)	(0.011)	(0.012)	(0.012)	(0.012)
logpm25airpollution		-0.268***	-0.144***	-0.157***	-0.118***	-0.122***
		(0.030)	(0.021)	(0.023)	(0.024)	(0.024)
logco2emissions			0.131***	0.118***	0.100***	0.106***
			(0.011)	(0.014)	(0.014)	(0.014)
logcombustibles				-0.010	-0.012**	-0.012**
				(0.006)	(0.006)	(0.006)
dummyvariable					0.128***	0.282***
					(0.034)	(0.085)
loginteractionco2anddummy						-0.0875**
						(0.0446)
Constant	-0.560***	0.299***	-0.230***	-0.174**	-0.276***	-0.270***
	(0.059)	(0.105)	(0.080)	(0.086)	(0.085)	(0.084)
Observations	101	101	101	101	101	101
R-squared	0.00	0.46	0.78	0.79	0.82	0.82

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

every 1% increase in carbon emissions translates into a nearly 0.11% increase in human capital. The increasing quality of life associated with higher carbon emissions is most likely a product of the industrialization these emissions are associated with. As a low-income nation's industrial sector expands, both GDP growth and quality of life should rapidly improve.

Carbon emissions can be viewed as a proxy for industrial growth. For developed nations, however, the carbon emissions that result from increasing industrial output bear a diminished rate of return. For these economies, increases in carbon emissions have a nearly negligible effect on human capital. Each 1% rise in carbon emissions is accompanied by a less than 0.02% increase in quality of life. This hardly incentivizes the sort of environmentally destructive growth that is exhibited early in a nation's development, as hypothesized by the Kuznet curve (Qain & Nagpal, 2017). The effect of carbon emissions on human capital development may have been better represented functionally by a parabolic form (visually taking the shape of the "Kuznet Curve"). This potentially could have better captured the diminishing rate of return that was evidenced and approximated by the interaction of the dummy variable development status with emissions. All in all, carbon emissions likely do not directly affect human health or capital. As such, future research would do well to capture this peculiarity by devoting study to the topic. Strategies such as instrumental variable regression, where the effect of carbon emissions on human capital development by proxy can be examined and quantified, may be better suited for that endeavor.

Lastly, reliance on combustible renewals for energy has a nearly negligible, yet statistically significant, inverse relationship with quality of life. Each percentage increase in combustible reliance is associated with a 0.01% reduction is human capital. Combustibles, including biofuel, are the world's most utilized renewable energy sources ("Combustible renewables and waste", 2014). Although many posit the economic benefits of biofuel production in developing nations, increasing biofuel crop cultivation in these countries has presented issues of food insecurity. The cultivation of crops for biofuel production processes in nations with growing biofuel industries has caused significant swells in food and feedstock prices (Kojima & Klytchnikova, 2008, p. 14). This adverse effect on food security is the most likely explanation for the small but significant inverse relationship between human capital and combustible renewable reliance. As with carbon emissions, this does provide another potentially fruitful avenue for future research. An investigation into the quantification of the interplay between reliance on renewable combustible energies, human capital levels, and quality of life as gauged by food security levels seems ripe for a similar instrumental variable approach.

Also of interest are the relationships found to be statistically insignificant. From the initial pool of nine explanatory variables, only four had a statistically significant relationship with human capital levels. This tells us that the level of water stress, amount of national territory set aside for preservation, amount of land left forested, and the amount of land reserved for agriculture have no effect on the quality of life of an individual, as approximated by their human capital index score. While these factors are undoubtedly important, they do not have a significant effect on a worker's wellbeing in terms of productivity, health, and educational attainment. The average citizen's life outcomes are not impacted by their county's commitment to forestry, land and water resource preservation, or domestic agricultural production.

This lack of a relationship holds true across both developed and developing nations. The worker is largely unaffected by these outside factors. These factors are, however, intrinsically linked to the health of the nation and the environment in other ways. As such, despite having no effect on a worker's lifetime productivity, they are of value for reasons beyond the scope of this paper.

The fact that these factors were not found to be significantly linked to human capital levels does not divorce them from individual wellbeing. Human capital, the metric by which this study approximated quality of life, is far from the only measure of individual well-being. Human capital levels are based solely upon individual productivity and the factors that underpin and contribute to that productivity. While the factors that contributed to the human capital index scores (life expectancy, expected educational attainment, etc...) are all positive things associated with quality of life, they are not the only such factors. Other

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indexes may well be better equipped to approximate mean quality of life, such as the United Nations' National Happiness Scores. This study, however, solely sought to examine individual well being within the context of economic development. As such, for this purpose, the Human Capital Index is certainly appropriate. Once again, this points towards other potential avenues for future research utilizing varying definitions and metrics for quality of life.

Likewise, greenhouse gas emissions other than CO_2 had no significant relationship to human capital levels. This could be due to these more varied emissions not being as apparent of a byproduct of industrial processes. As such, their presence does not serve as an approximation of a nation's industrial output. As there is little adverse health impact attributed to greenhouse gas emissions, there is little reason to suspect a relationship between human capital levels and greenhouse gas emissions other than co_2.

Policymakers would do well to heed some of the evidence posited above. Air pollution's danger is clear and present. Efforts aimed at reducing particulate matter air pollution would likely pay for themselves rapidly in terms of increased production output. A nation that reduces its particulate matter air pollution by 10% can expect to see a 1.2% increase in human capital levels, and corresponding increases in GDP levels, the magnitude of said rise determined by a particular economy's structure. It is likely that economies more heavily reliant on human capital would experience the greatest GDP gains. This is all in addition to the human benefits — health and mortality — that would be reaped.

Without further research in the directions described above, it is difficult to make policy recommendations regarding carbon emissions and renewable combustible forms of energy. However, the observed diminishing rate of returns to carbon emissions suggests that developing economies may do well to get ahead of the curve earlier. Developed economies demonstrate that sustained growth does not rely on continuing increases in carbon emissions. As such, there is reason to believe that slower paced, less carbon intensive growth, cannot achieve the same levels of economic output that would otherwise have been achieved with the rapid growth of carbon emissions. This may eventually prove beneficial for policy makers, as there is significant cost inherent in the eventual carbon clean up that seems inevitable for today's growing economies. Conscious development may allow for economies to achieve the same eventual level of output while avoiding the excessive costs of rectifying the externalities imposed by emissions.

Conclusion

This paper has examined the relationships present between quality of life, as approximated by human capital index scores, and markers of environmental sustainability. According to the study, a moderate relationship is present. Three indicators of environmental sustainability were found to have no statistically significant relationship with human capital levels. The primary environmental factors that do have an influence on quality of life are emissions and particulate matter air pollution. While particulate matter air pollution has already been demonstrated in other literature to have a negative relationship to human capital, the study at hand is unique in that its findings are not limited in geographic scope.

Furthermore, this study was able to substantiate the argument that the positive relationship between carbon emissions and quality of life in developing nations all but disappears once a nation has reached a threshold in its economic development. Future research would do well to introduce further layers of a country's development status so as to quantify the actual diminishing relationship between carbon emissions, development level, and human capital. Such research would be invaluable in identifying a nation's optimum point of carbon intensive industrialization for human capital growth at a given level of development status.

The paper's findings point policymakers towards the essential reduction in particulate matter air pollution. Clean air may not itself be a major driver of human development. However, its absence is certainly a quantifiable factor in suppressing potential economic output. A nation's removal of heavy pollutants from its air will bring about significant increases in human capital, decreasing mortality and health care costs and increasing productivity. The effects of such a policy can be readily quantified, and found to be worthwhile. As such, policymakers and stakeholders need to push for industrial regulation aimed at observable reductions in air pollutants. It is ultimately in the best interests of the individual and the economy as a whole. Otherwise, it may be advisable that those living in areas of excessive air pollution regularly utilize respirators of some variety to mitigate the human effects of this pollution.

If the development of human capital is a priority, it is worth examining economic development strategies that have the growth of biofuel industries as a central component. The economic gains these industries bring about, however, need to be carefully weighed against the human capital losses brought about by the industry's destabilization of agricultural markets.

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Relationships clearly exist between the wellbeing of a nation's citizens and the environmental health of that nation. Policy makers would do well to tread slowly while progressing towards green industries as more research is done on the most effective directions to proceed while maintaining growth in human capital. For now, perhaps it is best to focus on cleaning up harmful externalities, such as air pollution, that are associated with current industrialization before proceeding towards new paths that have the potential to destabilize current food security, doing more harm than good. While environmental sustainability in development is certainly a necessary objective, growth must occur conscientiously to ensure that human social development does not fall to the wayside.

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