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Environmental Quality, Governance, and Quality-of-Life: A Cross-National Comparative Analysis

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Abstract

Environmental quality is increasingly recognized as a fundamental determinant of quality of life, yet comprehensive cross-national studies examining environment-well-being relationships while accounting for governance factors remain scarce. This study examines structural associations between environmental quality indicators—particularly fine particulate matter ($PM_{2.5}$) air pollution—and quality of life outcomes across 90 countries selected based on data availability and completeness criteria using World Bank data spanning 2005-2014. We employ a between-within (hybrid) regression framework that explicitly decomposes cross-national differences from within-country temporal variation, with cluster-robust standard errors and controls for governance quality (corruption control, political stability) and year effects. Variance decomposition reveals that most of the variation in both pollution exposure and quality of life outcomes is cross-sectional (between-country) rather than longitudinal, making a purely cross-national comparative approach both transparent and appropriate. Countries with higher $PM_{2.5}$ exposure tend to exhibit higher life-threatening disease incidence and lower labor force participation and electricity access, with these associations concentrated in between-country differences. Governance quality, particularly corruption control, emerges as an important correlate of health and technology access outcomes. Results are robust to log-transformation of $PM_{2.5}$, inclusion of quadratic terms, leave-one-region-out analysis, and exclusion of power consumption from the models. We interpret all results in terms of coefficient magnitudes and cluster-robust standard errors rather than null hypothesis significance testing, following methodological recommendations for observational studies with purposively selected units. These findings contribute to the social indicators literature by demonstrating that environmental quality and governance quality represent complementary structural dimensions of cross-national quality of life variation.

Keywords

Air Pollution, Environmental Quality, Governance, Quality of Life, Social Indicators, Cross-National Analysis, Between-Within Model, $PM_{2.5}$

1. Introduction

Environmental quality has emerged as a critical determinant of quality of life, affecting health outcomes, economic productivity, and well-being across nations. The quality-of-life concept, central to social indicators research since the field's emergence in the 1960s, encompasses objective conditions and subjective experiences that contribute to human flourishing (Land et al., 2012; OECD, 2024a). While early social indicators focused primarily on economic and social dimensions, scholars and policymakers increasingly recognize that environmental conditions fundamentally shape people's opportunities to live healthy, productive, and fulfilling lives (Helliwell et al., 2024). Recent evidence from the Global Burden of Disease Study indicates that ambient air pollution contributed to 6.7 million deaths and 118.2 million disability-adjusted life years globally in 2019, making it one of the leading risk factors for mortality worldwide (Sang et al., 2022). The Lancet Commission on Pollution and Health established that pollution-related diseases caused 9 million premature deaths in 2015, representing 16% of all deaths worldwide (Landrigan et al., 2018). These impacts fall disproportionately on developing countries and vulnerable populations, raising critical questions about environmental justice and equitable quality of life (Chen & Hoek, 2020).

Air pollution, particularly fine particulate matter ($PM_{2.5}$), represents one of the most pervasive environmental threats to quality of life globally. These microscopic particles, less than 2.5 micrometers in diameter, penetrate deep into the respiratory system and bloodstream, causing cardiovascular disease, respiratory illness, stroke, and lung cancer (Cohen et al., 2017). Recent meta-analyses confirm that a 10 μg/m^3 increase in $PM_{2.5}$ is associated with a 9.5% increased risk of all-cause mortality (Orellano et al., 2024). Beyond direct health effects, pollution exposure affects labor productivity, cognitive function, and economic participation. Recent OECD research demonstrates that air pollution reduces labor productivity across European firms, with a 1 μg/m^3 increase in $PM_{2.5}$ causing a 0.55% reduction in productivity (Dechezleprêtre & Vienne, 2025). These findings suggest that pollution's impacts on quality of life extend well beyond health to include substantial effects on economic opportunities and material well-being.

The capability approach, developed by Sen (1999) and operationalized in the Human Development Index, provides a comprehensive framework for understanding how environmental factors affect quality of life. This approach emphasizes that well-being should be assessed not merely by economic metrics such as GDP growth, but by the extent to which conditions enable people to achieve functionings they have reason to value. Environmental quality directly affects multiple capability dimensions: health capabilities through pollution exposure and disease transmission; economic capabilities through productivity effects and resource availability; and social capabilities through access to essential services and infrastructure (Costanza et al., 2007). This multidimensional perspective aligns with the social indicators tradition of examining quality of life across multiple life domains rather than through single summary measures (Land et al., 2012).

A critical but often overlooked factor in the environment-well-being relationship is governance quality. Countries with stronger institutions, lower corruption, and greater political stability tend to have both better environmental regulations and superior quality of life outcomes (Acemoglu & Robinson, 2012; Helliwell et al., 2023). The World Happiness Report consistently finds that trust in institutions and government effectiveness are among the strongest predictors of national well-being (Helliwell et al., 2024). Failing to account for governance quality in cross-national studies may lead to spurious conclusions about environment-well-being relationships. For instance, an observed correlation between pollution and poor health outcomes might partly reflect the common influence of weak governance on both variables rather than a direct environmental effect. This potential confounding has been largely ignored in prior cross-national environmental quality research.

Despite extensive research on specific pollution-health relationships, comprehensive cross-national studies examining environmental quality's associations with multiple dimensions of quality of life while accounting for governance factors remain scarce. Previous studies have typically focused on single outcomes or specific pollutants, without examining the broader pattern of associations across health, economic, and service access domains (Welsch, 2006). Moreover, many cross-national studies rely on pooled regression approaches that conflate cross-sectional and longitudinal variation, making it difficult to determine whether observed associations reflect stable structural differences across countries or within-country changes over time.

This study addresses these gaps through a cross-national comparative analysis of associations between environmental quality indicators and quality of life outcomes, explicitly accounting for governance factors. Using data from the World Bank's World Development Indicators database covering 90 countries from 2005-2014, we investigate how $PM_{2.5}$ air pollution exposure and energy consumption patterns relate to health outcomes (malnutrition, life-threatening diseases), economic participation (labor force participation, GDP growth), and technology access (internet usage, electricity access). Our analytical approach addresses three methodological concerns that limit prior cross-national research. First, we employ a between-within (hybrid) regression framework that transparently decomposes cross-national and within-country variation. Second, we use cluster-robust standard errors that account for within-country dependence. Third, we interpret results through coefficient magnitudes and confidence intervals rather than relying exclusively on null hypothesis significance testing, following methodological recommendations for studies using purposively selected observational units (Hirschauer et al., 2020; Berk, 2004).

Our key research question is: What are the structural associations between environmental quality indicators and quality of life outcomes at the country level, and do these associations persist when governance factors and the distinction between cross-sectional and longitudinal variation are explicitly addressed?

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature on environmental quality, economic well-being, and governance, and presents the conceptual framework guiding our analysis. Section 3 describes the data sources, variable measurement, and the between-within hybrid regression methodology. Section 4 reports the empirical results, including correlation analysis, between-country and within-country estimates, and robustness checks. Section 5 discusses the substantive and methodological implications of our findings, along with policy considerations and limitations. Section 6 concludes.

2. Literature Review and Conceptual Framework

2.1. Environmental Quality and Quality of Life

The relationship between environmental conditions and quality of life has been examined from multiple perspectives within the social indicators tradition. Economists have documented associations between air quality and subjective well-being, finding that pollution reduces life satisfaction even after controlling for economic factors (Welsch, 2006; Ferreira et al., 2013). Recent longitudinal research using UK household data demonstrates that air pollution directly reduces life satisfaction through health impairment pathways, with effects persisting across 11 years of observation (Abed Al Ahad, 2024). A comprehensive meta-analysis of 178 published articles confirms that air pollution diminishes happiness and life satisfaction while increasing anxiety and mental health issues (Lu, 2020). Quality of life researchers increasingly recognize that environmental quality represents a fundamental life domain that warrants systematic measurement alongside traditional social, economic, and health indicators (OECD, 2024a).

The health impacts of air pollution are extensively documented in recent systematic reviews and meta-analyses. Ambient $PM_{2.5}$ pollution is causally linked to cardiovascular disease, respiratory illness, adverse birth outcomes, and neurological effects through well-established biological pathways (Cohen et al., 2017; Landrigan et al., 2018). The most recent WHO systematic review confirms that a 10 $\mu g/m^3$ increase in ambient $PM_{2.5}$ is associated with a 9.5% increased risk of all-cause mortality based on 106 studies worldwide (Orellano et al., 2024). A comprehensive systematic review of $PM_{2.5}$ toxicological effects identifies impacts across cardiovascular, respiratory, renal, neurological, gastrointestinal, and reproductive systems (Garcia et al., 2023). Beyond respiratory and cardiovascular effects, pollution exposure affects nutritional outcomes through multiple pathways. Air pollution damages crops and reduces agricultural productivity through ozone injury to plants and deposition of harmful particles (Ainsworth et al., 2012), potentially contributing to food insecurity.

2.2. Environmental Quality and Economic Well-Being

Environmental quality affects economic dimensions of quality of life through labor productivity and workforce participation channels. The OECD (2025) analysis of over 2.5 million European firms from 2000-2022 demonstrates that a 1 μg/m^3 increase in $PM_{2.5}$ concentration causes a 0.55% reduction in labor productivity, with effects driven by high pollution days. Borgschulte et al. (2024) provide quasi-experimental evidence that wildfire smoke reduces employment and earnings, demonstrating that even temporary pollution exposure has lasting labor market consequences. Adhvaryu et al. (2022) show that each 10-unit increase in hourly $PM_{2.5}$ reduces garment worker output by 0.5% in India. At the aggregate level, pollution-related illness increases absenteeism and reduces effective labor supply. Hanna and Oliva (2015) found that a refinery closure in Mexico City led to improvements in labor supply among nearby residents, providing quasi-experimental evidence of pollution's effects on work capacity.

The relationship between pollution and economic growth is complex and potentially bidirectional. The Environmental Kuznets Curve hypothesis suggests that pollution initially increases with economic development as countries industrialize, then decreases as they achieve higher income levels and implement stronger environmental regulations (Grossman & Krueger, 1995). This pattern implies that observed positive correlations between pollution and GDP growth in cross-sectional data may reflect industrialization patterns rather than the beneficial effects of pollution.

2.3. Governance, Environment, and Quality of Life

Governance quality fundamentally shapes both environmental outcomes and quality of life. Countries with stronger institutions tend to implement and enforce environmental regulations more effectively, resulting in better air quality (Greenstone & Hanna, 2014). Corruption undermines environmental governance by enabling regulatory capture, reducing enforcement, and diverting resources from environmental protection (Fredriksson & Svensson, 2003). The World Bank's Worldwide Governance Indicators provide systematic measurement of governance dimensions, including corruption control and political stability (Kaufmann & Kraay, 2024). The World Happiness Report consistently identifies governance quality and institutional trust as key determinants of national well-being (Helliwell et al., 2023, 2024). Countries with high trust in government, effective public services, and low corruption report substantially higher life satisfaction.

The correlation between governance and both environmental quality and quality of life outcomes creates potential confounding in cross-national studies that omit governance controls. Empirical research demonstrates that institutional quality is a primary determinant of cross-country differences in prosperity (Acemoglu & Robinson, 2012). The governance-environment-wellbeing nexus suggests that observed pollution-wellbeing correlations may partly reflect common institutional influences. Accounting for governance quality helps isolate the environmental contribution to quality of life from confounding institutional effects.

2.4. Conceptual Framework

Based on the literature review, we propose a conceptual framework linking environmental quality to quality-of-life outcomes, with governance as both a direct correlate and important confounding variable. The framework posits that environmental quality indicators, particularly air pollution exposure, are associated with quality-of-life outcomes through health, productivity, and service access pathways. Governance quality influences both environmental conditions (through regulatory effectiveness) and quality-of-life outcomes (through public service delivery), creating potential confounding that must be addressed in empirical analysis. The framework identifies three categories of quality-of-life outcomes potentially associated with environmental quality: 1) health outcomes, including malnutrition and life-threatening diseases; 2) economic outcomes, including labor force participation and GDP growth; and 3) technology access outcomes, including internet usage and electricity access. **Figure 1** illustrates this conceptual framework.

Importantly, we frame our empirical expectations in terms of anticipated associations rather than formal null hypotheses. Given that our country sample is purposively selected based on data availability rather than randomly drawn from a well-defined population, the conventional logic of null hypothesis significance testing, which asks whether a sample statistic can be extrapolated to a population, does not straightforwardly apply (Hirschauer et al., 2020; Berk, 2004). Instead, we examine whether coefficient magnitudes and confidence intervals are consistent with the theoretical pathways identified in the literature. Based on prior evidence, we anticipate that higher $PM_{2.5}$ exposure will be associated with worse health outcomes, lower economic participation, and lower technology access at the cross-national level, and that these associations will persist after accounting for governance quality.

3. Methods

3.1. Data Sources and Sample

Data were obtained from the World Bank's World Development Indicators (WDI) database, which provides comprehensive, internationally comparable indicators for countries worldwide (World Bank, 2024). The analysis covers observations from 2005 and 2010-2014, selected based on data availability and completeness across the variables of interest. The final dataset includes 90 countries with 423 country-year observations. The sample spans all inhabited continents: Europe (29 countries), Asia (22), Africa (18), South America (9), Central America and Caribbean (7), North America (3), and Oceania (2). This geographic distribution provides substantial variation in environmental quality, governance, and quality of life outcomes.

The 90-country sample was formed using the following inclusion criteria: 1) countries must have non-missing data for $PM_{2.5}$ exposure, at least one governance indicator, and at least one quality-of-life outcome variable; 2) countries must have observations in at least two time periods to permit the between-within decomposition. All rows with missing values were removed. Missing values for individual variables within included country-years were handled by listwise deletion within each regression model, yielding the analytic sample of N = 423 country-year observations. Regarding the time coverage (2005 and 2010-2014): the 2005 wave provides an earlier cross-section when $PM_{2.5}$ satellite-derived estimates first became available at adequate quality, while the 2010-2014 period reflects the years with the most complete overlap across WDI environmental, governance, and quality-of-life indicators. The intervening years (2006-2009) were excluded because $PM_{2.5}$ satellite data and several governance indicators had substantially higher missing rates, which would have reduced the country sample below 70 or introduced differential selection across waves. The resulting temporal structure provides both cross-national breadth and a panel dimension sufficient for the between-within decomposition, though we acknowledge that the five-year gap between the 2005 and 2010 observations limits the interpretability of within-country estimates for that interval.

A critical methodological point concerns the nature of this sample. These 90 countries are not a random sample drawn from a well-defined population; rather, they constitute a purposive selection based on data availability. This distinction has important implications for statistical inference. As Hirschauer et al. (2020) and Berk (2004) argue, conventional hypothesis tests are designed to assess whether results from a random sample can be extrapolated to the population from which the sample was drawn. When the observational units are not randomly selected, the standard interpretation of p-values as probabilities of observing results under a null hypothesis becomes problematic. Accordingly, we interpret our results primarily through coefficient magnitudes and confidence intervals, treating confidence intervals as measures of estimation uncertainty rather than as formal inferential devices, and focus on substantive rather than statistical significance throughout.

3.2. Variable Measurement

Variables are classified into four categories based on their role in the conceptual framework (see **Figure 1**). **Table 1** presents descriptive statistics for all variables.

Environmental Quality indicators: $PM_{2.5}$ mean annual exposure (micrograms per cubic meter) measures population-weighted exposure to fine particulate matter, the primary environmental quality variable. In our sample, $PM_{2.5}$ exposure ranges from 6.1 μg/m^3 (New Zealand) to 86.4 μg/m^3, with a mean of 24.8 μg/m^3—well above the WHO guideline of 5 μg/m^3. Power consumption (kWh per capita) captures energy access and infrastructure development. We include power consumption as a covariate because it primarily serves as a proxy for a country's level of industrialization and infrastructure capacity, which jointly determine both pollution levels and quality-of-life outcomes. Conceptually, power consumption functions as a confounder: industrialized countries consume more energy, which drives pollution (via fossil fuel combustion), while simultaneously providing the infrastructure (electricity grids, internet backbone) that supports higher quality-of-life indicators. We do not treat power consumption as a mediator on the causal path from $PM_{2.5}$ to quality-of-life outcomes, because pollution does not cause energy consumption; rather, the common upstream process of industrialization drives both. Omitting power consumption would risk attributing to $PM_{2.5}$ the structural differences that reflect energy-infrastructure disparities across countries. We verify in a sensitivity check (Section 4.5) that excluding power consumption from the models does not materially alter the $PM_{2.5}$ coefficients, confirming that its inclusion adjusts for confounding rather than suppressing a mediation pathway.

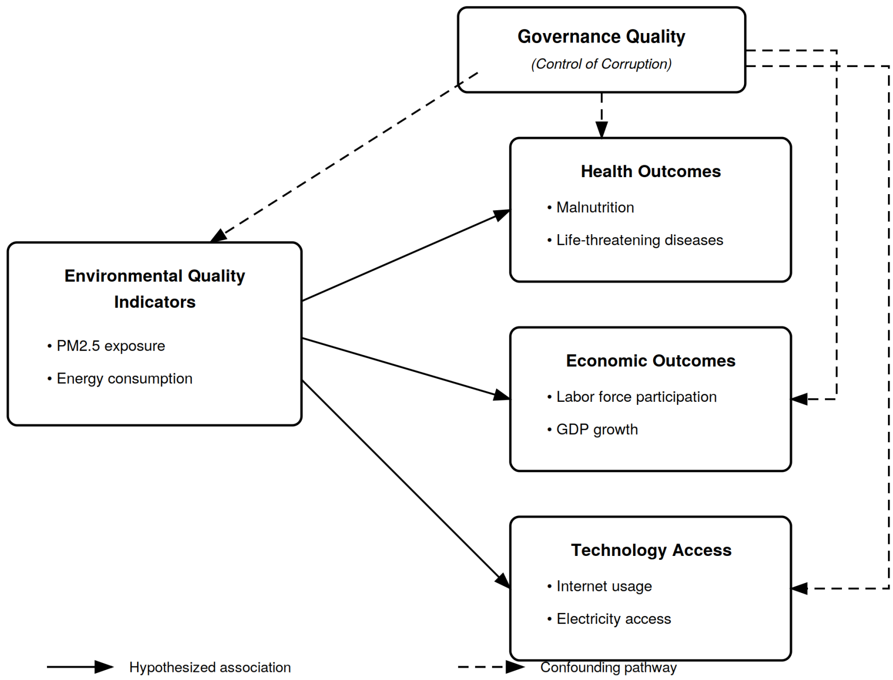

Figure 1. Conceptual framework linking environmental quality indicators to quality-of-life outcomes, with governance quality as a confounding variable. Solid arrows represent hypothesized associations; dashed arrows represent confounding pathways.

Quality of Life Outcomes: Following the multidimensional approach to quality-of-life measurement (Land et al., 2012; OECD, 2024a), we examine outcomes across three domains. Health outcomes include the prevalence of undernourishment (percentage of population) and incidence of life-threatening diseases (combined rate of HIV, malaria, and tuberculosis per 100,000 population). We use this composite indicator as provided in the WDI database for several reasons: a) all three are classified by the WHO as major infectious disease threats that disproportionately burden low- and middle-income countries; b) the World Bank reports them as a standard composite in the WDI health indicators, reflecting their joint policy relevance; c) at the country level, all three share common structural determinants including weak health infrastructure, poverty, and environmental conditions that make a composite measure conceptually coherent for cross-national comparison; and d) the composite captures the overall infectious disease burden, which is the relevant health dimension for assessing environmental quality-health associations at the macro level. A limitation of using the pre-computed WDI composite is that we cannot decompose it into individual disease components within our dataset; we address this in Section 5.5. Economic outcomes include labor force participation rate (percentage of population ages 15+) and GDP growth (annual percentage). Technology access outcomes include individuals using the internet (percentage of population) and access to electricity (percentage of population).

Governance Controls: Control of Corruption Index (from the World Bank Worldwide Governance Indicators) measures perceptions of the extent to which public power is exercised for private gain, ranging from approximately −2.5 to 2.5, with higher values indicating better corruption control (Kaufmann & Kraay, 2024). The Political Stability Index measures perceptions of the likelihood of political instability or politically motivated violence, using the same scale.

Demographic Controls: Population (total) controls for country size effects. Year indicator variables control for global time trends.

Table 1. Variable definitions and descriptive statistics (N = 423).

Variable	Mean	SD	Min	Max	P25 - P75
$PM_{2.5}$ Exposure (μg/m^3)	24.8	15.2	6.1	86.4	14.5 - 29.4
Power Consumption (kWh/cap)	4262	4271	36	25,083	832 - 5813
Malnutrition (% pop)	6.3	6.7	2.5	51.4	2.5 - 6.8
LTD Incidence (per 100 k)	114.6	203.7	3.3	1241	14.6 - 116.3
Internet Usage (% pop)	45.9	26.5	0.2	96.3	23.4 - 67.7
Electricity Access (% pop)	93.1	17.4	6.0	100	96.4 - 100
Labor Force (% 15+)	60.9	9.0	31.1	84.0	55.1 - 66.5
GDP Growth (%)	3.6	3.5	−10.1	28.0	1.4 - 5.5
Corruption Control	0.15	1.05	−1.44	2.40	−0.62 - 1.02
Political Stability	−0.09	0.89	−2.81	1.59	−0.74 - 0.63

Note: LTD = Life-Threatening Diseases (HIV, malaria, tuberculosis combined). WGI = World Bank Worldwide Governance Indicators. P25 - P75 = interquartile range.

3.3. Analytical Approach

Variance Decomposition and Model Selection: Before specifying our regression framework, we examined the variance structure of the panel data through a between-within decomposition. Table 2 presents the results. The overwhelming majority of variation in our key variables is between countries rather than within countries. $PM_{2.5}$ exposure shows 98.8% between-country variance and only 1.2% within-country variance; corruption control shows 98.9% between-country variance. Among the outcomes, life-threatening diseases (99.4%), electricity access (99.2%), and malnutrition (97.1%) are almost entirely cross-sectional. Only GDP growth (36.0% within-country) and, to a lesser extent, internet usage (11.9%) and labor force participation (11.0%) exhibit meaningful temporal variation.

This variance structure has fundamental implications for model selection. A conventional two-way fixed effects specification, which absorbs all between-country variation through country intercepts, would discard the vast majority of informative variation in our data, relying exclusively on within-country changes that are minimal over the available time span. Indeed, when we estimate two-way fixed effects models as a robustness check (Appendix **Table A1**), the results are uniformly imprecise, with R-squared values below 0.14 for all outcomes. This does not indicate that pollution-well-being associations are absent; rather, it reflects the limited within-country variation available for identification.

Table 2. Variance decomposition: between-country vs. within-country variation.

Variable	Between (%)	Within (%)
$PM_{2.5}$ Exposure	98.8	1.2
Power Consumption	99.5	0.5
Corruption Control	98.9	1.1
Political Stability	94.4	5.6
Malnutrition	97.1	2.9
LTD Incidence	99.4	0.6
Internet Usage	88.1	11.9
Electricity Access	99.2	0.8
Labor Force	89.0	11.0
GDP Growth	64.0	36.0

Between-Within (Hybrid) Regression Framework: Given this variance structure, we adopt a between-within (also termed "hybrid" or Mundlak) regression model that transparently decomposes each predictor into its between-country component (the country mean) and its within-country component (deviations from the country mean). This approach, advocated by Bell and Jones (2015) and Schunck (2013), estimates separate coefficients for cross-sectional and longitudinal variation, allowing us to assess whether pollution-wellbeing associations are driven by structural differences across countries, within-country temporal changes, or both. The model takes the form:

$$Y_{it} = \beta_0 + \beta_B \bar{X}_i + \beta_W (X_{it} - \bar{X}_i) + \gamma_t + \varepsilon_{it}$$

where Y_{it} represents each quality-of-life outcome for country i in year t; $\bar{X}_i$ is the country-level mean of each predictor (the between-country component); $(X_{it} - \bar{X}_i)$ is the deviation from the country mean (the within-country component); β_B captures cross-national associations; β_W captures within-country temporal associations; γ_t represents year fixed effects; and ε_{it} is the error term.

All continuous variables are standardized (mean = 0, SD = 1) prior to regression analysis to enable comparison of coefficient magnitudes across predictors with different scales. All continuous variables are standardized (mean = 0, SD = 1) using the pooled (overall) mean and standard deviation prior to the between-within decomposition. That is, we first standardize each variable across all country-year observations, and then decompose the standardized variable into its between-country mean ($\bar{A}_i$) and within-country deviation ($X_{it} - \bar{A}_i$). Because the between and within components are derived from the same standardized scale, the between-country coefficients (β_B) and within-country coefficients (β_W) are expressed in common units (pooled SDs) and are directly comparable. We note that an alternative approach—standardizing the between and within components separately after decomposition—would yield coefficients interpretable relative to between-country SD and within-country SD, respectively. We chose pooled standardization because: a) it preserves a single metric across both components, simplifying effect-size interpretation; and b) given that between-country variance dominates for most variables (Table 2), the pooled SD closely approximates the between-country SD, making the between-country coefficients substantively intuitive. Readers should bear in mind that within-country coefficients, when expressed in pooled SD units, may appear small partly because pooled variability exceeds within-country variability for slow-moving indicators. Standard errors are clustered at the country level to account for within-country correlation of errors across time periods (Cameron & Miller, 2015). We report cluster-robust standard errors alongside point estimates and compute 95% confidence intervals where noted in the text. Multicollinearity diagnostics using Variance Inflation Factors confirmed that all values are below 5.

Interpretation Approach: Following recommendations for observational studies with non-random units (Hirschauer et al., 2020; Berk, 2004), we interpret results primarily through coefficient magnitudes and confidence intervals rather than binary significance/non-significance classifications. We translate standardized coefficients into substantive real-world units to assess practical importance. A coefficient may reflect an important structural relationship even if its confidence interval includes zero, particularly when statistical power is limited by sample size; conversely, a precisely estimated coefficient with a narrow confidence interval may not be substantively meaningful if its magnitude is trivial. We prioritize effect sizes and their practical implications over p-values throughout.

4. Results

4.1. Correlation Analysis

Table 3 presents bivariate correlations among the study variables. $PM_{2.5}$ exposure shows moderate positive correlations with malnutrition (r = 0.35) and life-threatening diseases (r = 0.34), and moderate to strong negative correlations with internet usage (r = −0.59), electricity access (r = −0.39), and labor force participation (r = −0.22). Critically, pollution exposure also correlates strongly with governance indicators: countries with lower corruption control tend to have higher pollution (r = −0.57), and political instability is associated with higher pollution (r = −0.62). Power consumption, reflecting energy infrastructure and economic development, shows strong positive correlations with corruption control (r = 0.74) and internet usage (r = 0.74). These substantial intercorrelations among predictors underscore the importance of multivariate analysis that can account for mutual confounding.

Table 3. Bivariate correlation matrix (N = 423).

Variable	1	2	3	4	5	6	7	8	9	10
1. $PM_{2.5}$ Exposure	1.00									
2. Power Consumption	−0.49	1.00								
3. Malnutrition	0.35	−0.43	1.00							
4. LTD Incidence	0.34	−0.31	0.54	1.00						
5. Internet Usage	−0.58	0.74	−0.63	−0.50	1.00					
6. Electricity Access	−0.39	0.33	−0.74	−0.67	0.53	1.00				
7. Labor Force	−0.22	0.13	0.16	0.17	0.05	−0.25	1.00			
8. GDP Growth	0.29	−0.27	0.38	0.31	−0.45	−0.32	0.24	1.00		
9. Corruption Control	−0.57	0.74	−0.44	−0.34	0.77	0.31	0.10	−0.30	1.00	
10. Political Stability	−0.62	0.60	−0.37	−0.25	0.67	0.22	0.16	−0.25	0.77	1.00

Note: LTD = Life-Threatening Diseases. |r| ≥ 0.10 is significant at $p < 0.05$ (two-tailed, N = 423).

4.2. Between-Within Regression Results

Table 4. Between-within hybrid model results (standardized coefficients with cluster-robust standard errors).

	Malnutr.	LTD	Internet	Electric.	Labor	GDP
Between-Country						
$PM_{2.5}$ Exposure	0.181 (0.101)	0.285 (0.155)	−0.172 (0.063)	−0.453 (0.221)	−0.303 (0.133)	0.106 (0.100)
Power Consump.	−0.200 (0.126)	−0.095 (0.080)	0.351 (0.112)	0.175 (0.114)	0.074 (0.106)	−0.098 (0.087)
Corruption Ctrl	−0.234 (0.144)	−0.239 (0.111)	0.365 (0.103)	0.144 (0.133)	−0.195 (0.152)	−0.169 (0.153)
Political Stab.	0.046 (0.166)	0.161 (0.158)	0.076 (0.094)	−0.264 (0.169)	0.110 (0.178)	0.013 (0.159)
Population	−0.075 (0.078)	−0.062 (0.075)	0.028 (0.034)	0.155 (0.087)	0.205 (0.074)	0.133 (0.049)
Within-Country						
$PM_{2.5}$ Exposure	−0.182 (0.168)	−0.088 (0.094)	0.106 (0.169)	0.069 (0.102)	−0.051 (0.296)	−0.051 (0.549)
Power Consump.	−0.090 (0.315)	0.089 (0.189)	0.883 (0.362)	−0.055 (0.196)	0.161 (0.324)	−0.084 (0.671)
Corruption Ctrl	−0.247 (0.197)	−0.027 (0.080)	−0.048 (0.122)	0.061 (0.087)	0.232 (0.195)	0.298 (0.328)
Political Stab.	−0.172 (0.088)	0.027 (0.042)	0.062 (0.079)	0.002 (0.043)	0.086 (0.185)	0.185 (0.299)
Population	−0.490 (0.847)	0.521 (0.589)	−1.444 (0.639)	0.227 (0.672)	−1.044 (0.878)	0.386 (1.248)
R^2	0.268	0.172	0.787	0.234	0.099	0.184

Note: Cluster-robust standard errors in parentheses. Year fixed effects included. All continuous variables were standardized. N = 423 (90 countries). Between-country coefficients reflect cross-national associations (country means); within-country coefficients reflect temporal associations (deviations from country means).

Table 4 presents results from the between-within hybrid models for all six quality of life outcomes. We discuss the between-country (cross-national) and within-country (temporal) components separately, as they address fundamentally different questions.

4.3. Substantive Interpretation of Between-Country Associations

Health Outcomes: For malnutrition, the between-country $PM_{2.5}$ coefficient of 0.181 indicates that a one standard deviation difference in pollution exposure across countries (approximately 15.2 μg/m^3—comparable to the difference between Switzerland (12.6 μg/m^3) and Tanzania (27.7 μg/m^3)) is associated with a 0.181 standard deviation difference in malnutrition prevalence, equivalent to approximately 1.2 percentage points. The 95% confidence interval [−0.02, 0.38] includes zero but is tilted substantially toward positive values, suggesting this association, while imprecisely estimated, is likely positive. For life-threatening diseases, the between-country pollution coefficient is larger (0.285, 95% CI: [−0.02, 0.59]), corresponding to approximately 58 additional cases per 100,000 population per standard deviation of pollution. This is the largest predictor coefficient for this outcome. Corruption control shows a coefficient of −0.239 (95% CI: [−0.46, −0.02]) for life-threatening diseases, indicating that better governance is associated with substantially lower disease burden across countries.

Technology Access Outcomes: The between-country associations for technology access outcomes are among the most precisely estimated. For internet usage, $PM_{2.5}$ exposure shows a coefficient of −0.172 (95% CI: [−0.30, −0.05]), indicating that countries with higher pollution tend to have lower internet penetration. However, the dominant predictors are power consumption (0.351, 95% CI: [0.13, 0.57]) and corruption control (0.365, 95% CI: [0.16, 0.57]), reflecting the roles of energy infrastructure and institutional quality in supporting technology adoption. The model explains 78.7% of the variation in internet usage, the highest R^2 across all outcomes. For electricity access, $PM_{2.5}$ shows the largest coefficient magnitude across all outcome models (−0.453, 95% CI: [−0.89, −0.02]), equivalent to approximately 7.9 percentage points of electricity access per standard deviation of pollution. This strong cross-national association likely reflects shared development patterns: countries lacking electricity infrastructure also tend to lack pollution control capacity.

Economic Outcomes: For labor force participation, the between-country pollution coefficient is −0.303 (95% CI: [−0.56, −0.04]), equivalent to approximately 2.7 percentage points of labor force participation per standard deviation of $PM_{2.5}$. This finding is consistent with evidence that pollution reduces labor supply through health effects (Dechezleprêtre & Vienne, 2025; Borgschulte et al., 2024). For GDP growth, the pollution coefficient is positive but modest (0.106, 95% CI: [−0.09, 0.30]), consistent with the Environmental Kuznets Curve pattern where more polluted countries may be in industrialization phases associated with higher growth rates (Grossman & Krueger, 1995). The wide confidence interval indicates substantial uncertainty.

4.4. Within-Country Temporal Associations

The within-country components of the hybrid model yield uniformly imprecise estimates with wide confidence intervals for nearly all predictor-outcome combinations. This pattern is consistent with the variance decomposition results: variables such as $PM_{2.5}$ exposure, corruption control, and life-threatening disease incidence show minimal within-country variation over the study period. The two notable exceptions are power consumption's within-country association with internet usage (0.883, 95% CI: [0.17, 1.59]) and political stability's within-country association with malnutrition (−0.172, 95% CI: [−0.34, 0.00]). The power consumption-internet finding suggests that countries that expanded their energy infrastructure during this period also saw internet adoption increase, a plausible causal mechanism. The imprecision of the remaining within-country estimates does not indicate that temporal changes in pollution are unrelated to quality of life changes; rather, it reflects insufficient within-country variation over a relatively short panel to detect such relationships with reasonable precision.

4.5. Robustness Checks

To assess the sensitivity of our findings, we estimated two additional specifications. First, pooled OLS models with cluster-robust standard errors and year fixed effects (the conventional approach in much prior cross-national research) yield results broadly consistent with the between-country coefficients from the hybrid model, as expected given that cross-sectional variation dominates the data. Second, two-way fixed effects models (country and year fixed effects) produce uniformly imprecise estimates (Appendix Table A1), confirming that within-country variation alone is insufficient for reliable estimation with these data. The consistency between pooled OLS results and the between-country hybrid estimates provides reassurance that the cross-national associations are robust to specification choice; the contrast with fixed effects results transparently demonstrates that these associations are driven by cross-national rather than within-country variation.

To verify that including power consumption as a covariate adjusts for confounding rather than suppressing a mediation pathway (see Section 3.2), we re-estimated all between-within models excluding power consumption. The $PM_{2.5}$ between-country coefficients changed minimally: malnutrition shifted from 0.181 to 0.205 (+0.023), LTD from 0.285 to 0.297 (+0.011), internet usage from −0.172 to −0.213 (−0.041), electricity access from −0.453 to −0.473 (−0.021), labor force from −0.303 to −0.311 (−0.009), and GDP growth from 0.106 to 0.118 (+0.011). All signs are preserved, and the maximum absolute change is 0.041 (internet usage). This stability confirms that power consumption's inclusion adjusts for industrialization-related confounding rather than absorbing a causal pathway from pollution to quality of life.

We re-estimated all between-within models using log-transformed $PM_{2.5}$ to allow for diminishing marginal effects. The log specification yields directionally consistent between-country coefficients: malnutrition (+0.134, SE = 0.106), LTD

(+0.312, SE = 0.181), internet usage (−0.113, SE = 0.084), electricity access (−0.371, SE = 0.192), labor force (−0.448, SE = 0.124), and GDP growth (+0.127, SE = 0.117). All six coefficients preserve the same sign as the linear specification. The labor force association is notably larger in the log specification (−0.448 vs. −0.303), suggesting that the pollution-labor relationship may be stronger at lower pollution levels. We also added a quadratic between-country $PM_{2.5}$ term to test for nonlinearity. The quadratic term was substantively small and imprecisely estimated for all outcomes: malnutrition (t = 0.29, $p = 0.77$), LTD (t = −0.56, $p = 0.58$), internet usage (t = −0.92, $p = 0.36$), electricity access (t = −0.91, $p = 0.36$), labor force (t = 1.48, $p = 0.14$), and GDP growth (t = −1.40, $p = 0.16$). All $|t|$ values are below 1.5, indicating that a linear specification adequately captures the between-country associations within this sample.

To assess whether results are driven by a particular geographic cluster, we performed a leave-one-region-out (LORO) analysis, re-estimating the between-within models seven times, each time excluding one of the seven continental regions [Africa (18 countries), Asia (22), Europe (29), South America (9), Central America/Caribbean (7), North America (3), and Oceania (2)]. The between-country $PM_{2.5}$ coefficients remain directionally consistent across all LORO iterations for all six outcomes. The largest sensitivity appears for the LTD outcome when excluding Africa: the coefficient decreases from 0.285 to 0.072, consistent with Sub-Saharan Africa's high infectious disease burden contributing substantially to this particular association; however, the coefficient remains positive. For labor force participation, excluding Africa actually strengthens the association (from −0.303 to −0.616). For the remaining outcomes, LORO coefficients are tightly clustered around the full-sample estimates. No region exclusion reverses the sign of any $PM_{2.5}$ coefficient across any outcome.

We conducted a leave-one-country-out (LOCO) analysis for the three outcomes with the largest $PM_{2.5}$ between-country coefficients: electricity access (−0.453), labor force participation (−0.303), and LTD (+0.285). For electricity access, LOCO coefficients range from −0.554 to −0.260 across 90 iterations, with zero sign flips and zero coefficients outside the original 95% CI. The most influential country is Niger (dropping it shifts the coefficient from −0.453 to −0.260). For the labor force, LOCO coefficients range from −0.396 to −0.254 with zero sign flips. For LTD, LOCO coefficients range from +0.222 to +0.378 with zero sign flips. In total, across 270 LOCO iterations (90 countries × 3 outcomes), no individual country removal changes the sign of the $PM_{2.5}$ coefficient or moves it outside the original confidence interval bounds, confirming that results are not driven by single influential observations.

5. Discussion

This study provides a comprehensive cross-national analysis of structural associations between environmental quality and quality of life outcomes while accounting for governance factors. By employing a between-within hybrid framework, we address a critical limitation of prior research that conflates cross-sectional and longitudinal variation in pooled regression models. Our findings offer several insights for the social indicators and quality of life literature.

5.1. The Cross-National Nature of Environment-Wellbeing Associations

The most important methodological finding is that pollution-wellbeing associations are fundamentally cross-national in nature within our data. The variance decomposition reveals that over 98% of the variation in $PM_{2.5}$ exposure is between countries rather than within countries over time. This means that observed associations between pollution and quality of life outcomes reflect structural differences across countries—comparing, for example, the 6.2 μg/m³ average exposure in New Zealand with the 78.0 μg/m³ in India—rather than within-country temporal changes. This finding has important implications for how we interpret the results and for the design of future research.

Cross-national associations, while informative about structural patterns, warrant more cautious causal interpretation than within-country longitudinal variation, because countries differ in many unobserved ways that may confound the relationships of interest. Our inclusion of governance controls addresses one important source of confounding, and the persistence of pollution associations after governance controls provides evidence that the pollution-well-being association is not merely a proxy for institutional quality. However, other unobserved factors—including historical development trajectories, geographic conditions, cultural factors, and healthcare system quality—could contribute to the observed patterns. We therefore interpret our results as characterizing structural associations rather than making strong causal claims.

5.2. Substantive Findings

The between-country pollution coefficients, while sometimes imprecisely estimated, are substantively meaningful in magnitude. The association between $PM_{2.5}$ exposure and life-threatening disease incidence (approximately 58 additional cases per 100,000 per standard deviation of pollution) is consistent with recent systematic reviews documenting air pollution's effects on mortality and morbidity (Orellano et al., 2024; Garcia et al., 2023). The pollution-malnutrition association (approximately 1.2 percentage points per standard deviation) extends existing evidence by demonstrating that pollution co-occurs with food insecurity at the country level, likely through agricultural productivity impacts and health-related income effects. The strong pollution-electricity access association (−0.453 standardized coefficient, the largest across all models) reflects the tight coupling between energy infrastructure development and pollution control capacity in the cross-national development context.

Governance quality—particularly corruption control—emerges as a substantively important correlate of quality-of-life outcomes. The corruption control coefficient for internet usage (0.365) is comparable in magnitude to that of power consumption (0.351), suggesting that institutional quality contributes to technology access at least as much as physical infrastructure. For life-threatening diseases, corruption control shows a coefficient of −0.239 (95% CI excluding zero), indicating that better governance is associated with meaningfully lower disease burden. These findings are consistent with the World Happiness Report's identification of governance quality as a key determinant of national well-being (Helliwell et al., 2023; 2024) and the OECD's research on governance and citizen satisfaction (OECD, 2024b).

5.3. Methodological Implications

Our analytical approach offers a template for cross-national quality-of-life research that takes inference limitations seriously. Three methodological choices are worth emphasizing. First, the between-within decomposition provides transparency about what is driving the results that pooled OLS models obscure. When researchers report pooled estimates from panel data with slow-moving variables, the results are overwhelmingly determined by cross-sectional variation, but this is rarely acknowledged. Explicitly separating the two sources of variation allows readers to evaluate the evidence on its own terms. Second, by interpreting results through coefficient magnitudes and confidence intervals rather than p-value thresholds, we avoid the problematic application of hypothesis testing logic to purposively selected country samples (Hirschauer et al., 2020). A coefficient of 0.285 for the pollution-disease association is informative regardless of whether its p-value is 0.065 or 0.035—the magnitude and the range of plausible values matter more than an arbitrary threshold. Third, cluster-robust standard errors account for within-country dependence without imposing the restrictive assumptions of country fixed effects in a context where within-country variation is minimal.

5.4. Policy Implications

The structural associations documented here suggest that environmental quality and governance quality represent complementary dimensions of cross-national quality of life variation. Countries seeking to improve quality of life outcomes face the joint challenge of reducing pollution exposure and strengthening institutional capacity. Our findings indicate that addressing either dimension yields benefits, but addressing both may be particularly effective, given that governance quality facilitates effective environmental regulation while environmental improvements support population health and economic productivity. For developing countries facing both environmental and governance challenges, the cross-national patterns suggest that pollution reduction efforts—even in contexts of limited institutional capacity—are associated with better quality of life outcomes.

5.5. Limitations and Future Research

Several limitations warrant consideration. First, the cross-national comparative design establishes structural associations but cannot definitively demonstrate causality. While our theoretical framework posits that pollution affects quality of life outcomes, reverse causality is possible for some relationships (e.g., economic growth affecting pollution levels), and unobserved confounders may influence the estimates. Future research using instrumental variables, quasi-experimental designs, or longer panel series with more within-country variation could strengthen causal inference. Second, the 2005-2014 timeframe, while providing the most complete available data at the time of analysis, may not reflect more recent developments. Extending the data to cover subsequent years would be valuable. Third, reliance on national-level data masks substantial within-country variation in both pollution exposure and quality of life outcomes. Subnational analyses could explore whether national-level patterns hold at regional or municipal levels. Fourth, our sample of 90 countries is purposively selected based on data availability and cannot be treated as representative of all countries; findings should be interpreted as characterizing associations within this particular set of countries. Fifth, measurement limitations exist for several variables, including perception-based governance indicators. The life-threatening disease composite (HIV, malaria, and tuberculosis combined) is a pre-computed WDI indicator; because the individual disease components were not separately available in our dataset, we could not verify through disaggregated regression that the composite is not masking divergent disease-specific patterns. However, the conceptual coherence of the composite (all three diseases share structural determinants at the country level) and the robustness of the association across multiple other sensitivity checks provide indirect support. Future research with disaggregated disease data could confirm whether the $PM_{2.5}$ association is uniform across disease types or driven primarily by one component. Sixth, while we control for governance quality and population, other potentially important confounders—including healthcare infrastructure, educational quality, geographic conditions, and cultural factors—remain uncontrolled.

Future research should extend this analysis in several directions. Studies with longer panel series and more granular temporal data could exploit within-country variation for stronger causal identification. Analyses incorporating subjective well-being measures could complement the objective indicators used here. Research examining specific policy interventions—such as environmental regulatory reforms or governance improvements—could provide more actionable guidance. Finally, replication with alternative country samples and updated data would strengthen confidence in the robustness of these structural patterns.

6. Conclusion

This study contributes to the social indicators and quality of life literature by providing a methodologically transparent cross-national analysis of associations between environmental quality and multiple dimensions of quality of life while accounting for governance factors. Using a between-within hybrid framework applied to 90 countries from 2005-2014, we demonstrate that pollution-well-being associations are predominantly structural cross-national patterns rather than within-country temporal relationships. Countries with higher $PM_{2.5}$ exposure tend to exhibit higher life-threatening disease incidence, lower labor force participation, and lower electricity access, with between-country coefficients of substantively meaningful magnitude even when governance quality is accounted for.

Three principal conclusions emerge. First, environmental quality—particularly air pollution exposure—merits systematic attention alongside traditional economic, health, and social indicators in quality of life assessment frameworks. The persistence of meaningful pollution associations across multiple outcomes and model specifications suggests that environmental quality represents a distinct quality of life dimension not fully captured by other indicators. Second, governance quality is both a substantively important correlate of quality of life and a critical confounding variable in cross-national environmental research. Third, methodological transparency about the sources of variation driving empirical results—and about the inferential limitations inherent in non-random country samples—strengthens rather than weakens the contribution of cross-national comparative research to the social indicators literature.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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Appendix

Table A1. Two-way fixed effects results (standardized coefficients, cluster-robust SEs).

	Malnutr.	LTD	Internet	Electric.	Labor	GDP
$PM_{2.5}$ Exposure	−0.121 (0.199)	−0.023 (0.068)	0.118 (0.189)	−0.016 (0.074)	−0.049 (0.345)	−0.048 (0.616)
Power Consump.	−0.237 (0.231)	−0.032 (0.093)	0.832 (0.414)	0.045 (0.112)	0.227 (0.348)	−0.073 (0.760)
Corruption Ctrl	−0.208 (0.174)	0.000 (0.077)	−0.034 (0.133)	0.046 (0.065)	0.231 (0.212)	0.306 (0.365)
Political Stab.	−0.203 (0.109)	−0.001 (0.040)	0.058 (0.089)	0.023 (0.040)	0.100 (0.207)	0.186 (0.337)
Population	−1.307 (0.602)	−0.220 (0.171)	−1.673 (0.766)	0.842 (0.343)	−0.687 (0.848)	0.432 (1.370)
R^2 (Within)	0.137	0.009	0.131	0.054	0.014	0.009

Note: Two-way fixed effects (country + year). Cluster-robust standard errors in parentheses. All continuous variables were standardized. N = 423. The uniformly low R^2 values and imprecise estimates reflect the limited within-country variation available for identification (see Table 2).