Economic Development and Under-5 Mortality: Analyzing Differential Returns Across Income Groups

Chen Ke Yuan Kowin (A0329512H)
Chaisathid Patanan (A0327119E)
Shi Boyuan (A0333653E)
Shreya Sriram (A0327236E)
Vivian Witjaksono (A0326440M)

October 27, 2025

1 Background

Child mortality is a key measure of development and health system effectiveness, as targeted by SDG 3.2 [United Nations, 2015]. While wealthier countries generally have lower child mortality rates [Swift, 2018], we want to understand whether the strength of this relationship varies by development level. In low-income countries, additional income can fund basic high-impact interventions such as vaccines, clean water, and nutrition programs. In contrast, high-income countries have already addressed these preventable causes of death, so further economic growth yields smaller health gains. By testing this hypothesis in 80 countries, we seek to provide evidence on the factors that could contribute the best to achieving the SDG 3.2 targets in different development contexts.

2 Sustainable Development Goals addressed

- SDG 3 (Good Health and Well-being)
- SDG 8 (Decent Work and Economic Growth)
- SDG 10 (Reduced Inequalities)

3 Objective & Hypothesis

3.1 Objective

To investigate whether income level moderates the relationship between economic development and under-5 mortality rates.

3.2 Hypothesis Testing

H_0: The relationship between GDP per capita and under-5 mortality is uniform across all development levels.

H_a: Low-income countries experience significantly larger reductions in under-5 mortality per unit increase in GDP per capita compared to high-income countries ($\beta_{interaction} \neq 0$), reflecting differential returns to economic development across income levels.

4 Method

4.1 Data & Exploratory Data Analysis

Attribute	Source
Under-5 mortality	https://ourworldindata.org/grapher/child-mortality
GDP per capita	https://data.worldbank.org/indicator/NY.GDP.PCAP.PP.KD
Income Classification	https://ourworldindata.org/grapher/world-bank-income-groups
Health expenditure	https://data.worldbank.org/indicator/SH.XPD.CHEX.GD.ZS
DPT3 immunization	https://data.worldbank.org/indicator/SH.IMM.IDPT
Population density	https://data.worldbank.org/indicator/EN.POP.DNST
Access to safely managed drinking water	https://data.worldbank.org/indicator/SH.H2O.SMDW.ZS

Under-5 mortality (SDG Indicator 3.2.1), DPT3 immunization (SDG Indicator 3.b.1), Access to safely managed drinking water (SDG Indicator 6.1.1) are classified as Tier 1 as per the Tier Classification for Global SDG Indicators, the other attributes are supporting statistics used in analysis. While GDP per capita and income classification [World Bank, 2024] relate to the broader themes of SDG 8 (Economic Growth) and SDG 10 (Reduced Inequalities), they serve as contextual variables rather than official SDG indicators in our analysis.

We merged and cleaned data from 2000-2021 across all countries, excluding countries with over 40% missing attributes to balance data retention with imputation reliability, resulting in 1760 observations across 80 countries. We imputed missing values using time series methods (linear interpolation) & central tendency measures (median/mode) and transformed inputs & target to approximate normality & satisfy OLS assumptions: log transformation for right-skewed variables (GDP per capita, population density, child mortality), with Box-Cox applied to the target variable [Statistics How To, 2025]. We then standardized all numerical variables and one-hot encoded income classification (see Appendix A for details).

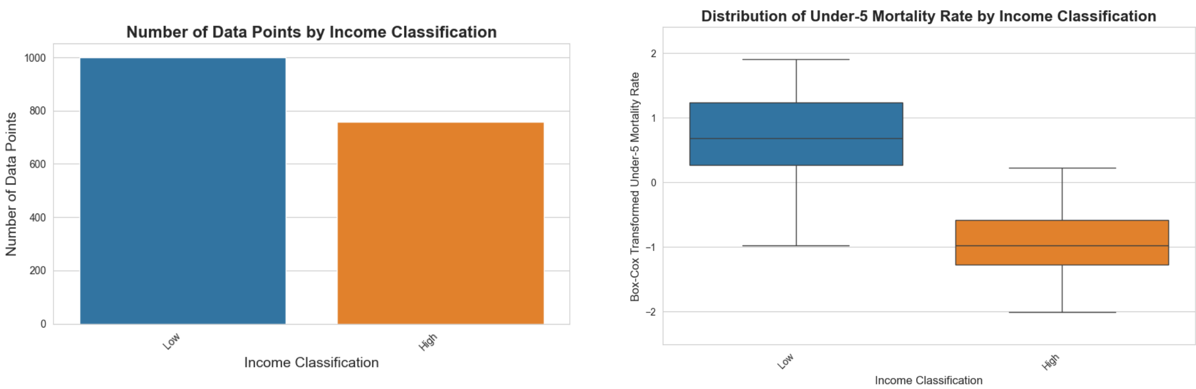

Figure 1: Distribution of datapoints and mortality across income groups

Figure 1 denotes the distribution of data between the two income groups and the distribution of under-5 mortality across the income groups - the former shows we have sufficient data across the two groups, with more data for low income and the latter indicates higher mortality in the low income group compared to the high income group.

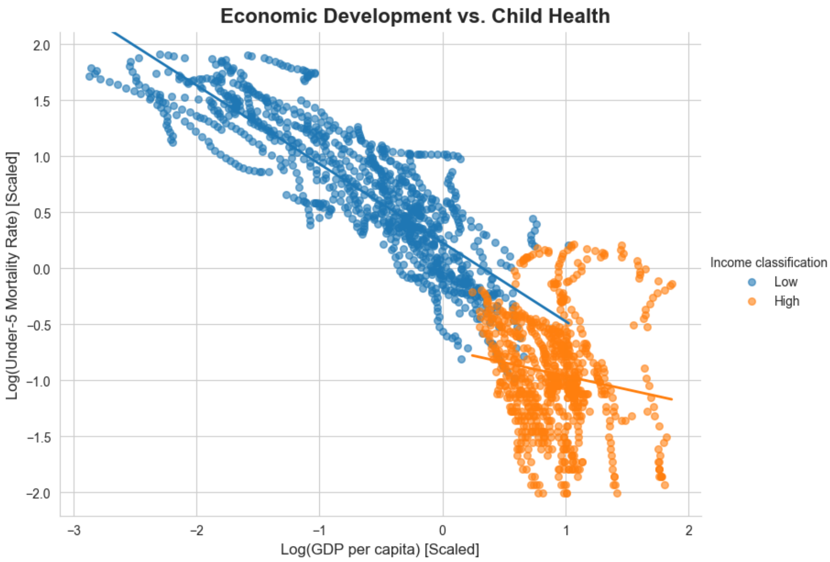

Figure 2: Distribution of transformed mortality rate vs transformed GDP across income groups

Figure 2 reveals a steeper negative relationship between GDP and mortality in low-income countries, suggesting that economic development yields stronger mortality reductions in low-income settings compared to high-income countries where the relationship appears flatter. This visual pattern supports our hypothesis that income level moderates the GDP-mortality relationship, which we formally test using three regression approaches.

4.2 Model specification

We tested three modeling approaches: pooled Ordinary Least Squares, simple random effects, and Mundlak random effects (see Appendix B for pooled OLS and simple Random Effects details).
Pooled OLS produced suggestive patterns but failed to account for country-specific heterogeneity, yielding non-significant interaction terms ($p = 0.123$).
Simple random effects improved significance ($p = 0.0009$) by including country random intercepts [Fitzmaurice et al., 2012; Gelman and Hill, 2007] but mixed within-country and between-country effects.
Since our hypothesis specifically concerns between-country differences—whether low-income countries as a group experience stronger mortality reductions from GDP growth, we adopt the Random Effects with Mundlak approach [Wooldridge, 2021] as our primary model. This approach decomposes each time-varying predictor into its country-specific mean (capturing between-country effects) and deviations from that mean (capturing within-country effects), allowing us to isolate the between-country relationship central to our hypothesis.

As a part of Random effects with Mundlak approach [Wooldridge, 2021], we define country level means for log_gdp_per_capita, sqrt_health_expenditure, log_reflected_dpt3 _immunization, log_reflected_secondary_education, log_population_density, logit_water_services and textIncome_High.

$$\begin{aligned}
\text{boxcox_mortality} \sim 1 &+ \text{log_gdp_per_capita} + \text{log_gdp_per_capita} \times \text{Income_High} + \\
&\text{sqrt_health_expenditure} + \text{log_reflected_dpt3_immunization} + \\
&\text{log_reflected_secondary_education} + \text{logit_water_services} + \\
&\text{log_population_density} + \text{log_gdp_per_capita_mean} + \\
&\text{log_gdp_per_capita_mean} \times \text{Income_High_mean} + \\
&\text{sqrt_health_expenditure_mean} + \text{log_reflected_dpt3_immunization_mean} + \\
&\text{log_reflected_secondary_education_mean} + \text{logit_water_services_mean} + \\
&\text{log_population_density_mean} + \text{TimeEffects}
\end{aligned} \tag{1}$$

Model diagnostic checks including residual normality assessments are provided in Appendix C.

5 Results

The Random Effects model using Mundlak's approach strongly supports the hypothesis that income level moderates the GDP-mortality relationship. The between-country interaction term ($\beta = 0.9595, p = 0.0016$) demonstrates that high-income countries experience significantly weaker mortality reductions from GDP growth compared to low-income countries.

The regression results of Random Effects using Mundlak's approach are described in Figure 3. The key coefficients from the results are described below:

- **Between-country effect (Primary evidence for H_a)**:
  The coefficient of log_gdp_per_capita_mean:Income_High_mean is 0.9595 with the p value being 0.0016 i.e., the result is statistically significant at the 0.05 level.
  This coefficient shows that countries persistently classified as high-income experience a significantly weaker relationship between GDP per capita and under-5 mortality compared to low-income countries. The positive coefficient indicates that each unit increase in average GDP per capita is associated with smaller mortality reductions in high-income countries. This directly supports our hypothesis that low-income countries experience stronger health returns from economic growth compared to high-income countries.

- **Within-country effect (evidence for policy changes)**:
  The coefficient of log_gdp_per_capita:Income_High is -0.5486 with the p value being 0.0121 i.e., the result is statistically significant at the 0.05 level.
  Within countries over time, high-income countries show a statistically different (slightly stronger) absolute response to GDP growth compared to low-income countries. This reflects that low-income countries operate in a different context—they start with higher baseline mortality, so the same absolute reduction represents a larger proportional improvement in child health outcomes.

```
                          RandomEffects Estimation Summary
================================================================================
Dep. Variable:       boxcox_mortality   R-squared:                        0.6643
Estimator:              RandomEffects   R-squared (Between):              0.9091
No. Observations:                1760   R-squared (Within):               0.6258
Date:                Thu, Oct 16 2025   R-squared (Overall):              0.8908
Time:                        12:54:37   Log-likelihood                    744.99
Cov. Estimator:             Clustered
                                        F-statistic:                      215.54
Entities:                          80   P-value                           0.0000
Avg Obs:                       22.000   Distribution:                 F(16,1743)
Min Obs:                       22.000
Max Obs:                       22.000   F-statistic (robust):             67.012
                                        P-value                           0.0000
Time periods:                      22   Distribution:                 F(16,1743)
Avg Obs:                       80.000
Min Obs:                       80.000
Max Obs:                       80.000

                                         Parameter Estimates
=============================================================================================================
                                         Parameter  Std. Err.     T-stat    P-value    Lower CI    Upper CI
-------------------------------------------------------------------------------------------------------------
Intercept                                   0.2776     0.0709     3.9159     0.0001      0.1386      0.4167
log_gdp_per_capita                         -0.7552     0.1013    -7.4573     0.0000     -0.9538     -0.5565
Income_High                                 0.0760     0.1217     0.6247     0.5322     -0.1626      0.3146
sqrt_health_expenditure                    -0.1530     0.0350    -4.3701     0.0000     -0.2217     -0.0843
log_reflected_dpt3_immunization            -0.0145     0.0161    -0.9029     0.3667     -0.0461      0.0170
log_reflected_secondary_education          -0.0890     0.0376    -2.3637     0.0182     -0.1628     -0.0151
log_gdp_per_capita_mean                     0.2012     0.1159     1.7369     0.0826     -0.0260      0.4285
Income_High_mean                           -1.0712     0.2695    -3.9751     0.0001     -1.5998     -0.5427
sqrt_health_expenditure_mean               -0.0670     0.0562    -1.1929     0.2331     -0.1772      0.0432
log_reflected_dpt3_immunization_mean        0.1293     0.0515     2.5110     0.0121      0.0283      0.2302
log_reflected_secondary_education_mean      0.0710     0.0611     1.1614     0.2457     -0.0489      0.1908
logit_water_services                       -0.0851     0.0645    -1.3185     0.1875     -0.2116      0.0415
logit_water_services_mean                   0.1312     0.1141     1.1502     0.2502     -0.0926      0.3550
log_population_density                     -0.3555     0.1352    -2.6294     0.0086     -0.6207     -0.0903
log_population_density_mean                 0.3752     0.1425     2.6337     0.0085      0.0958      0.6546
log_gdp_per_capita:Income_High             -0.5486     0.2183    -2.5133     0.0121     -0.9766     -0.1205
log_gdp_per_capita_mean:Income_High_mean    0.9595     0.3038     3.1579     0.0016      0.3636      1.5554
=============================================================================================================
```

Figure 3: Regression results of Random Effects with Mundlak approach

Since we scaled and normalized attributes in the preprocessing step, we scale them back so as to interpret the results in the original scale.

6 Discussion and Conclusion

For the purpose of interpretation, we simulate a 10% increase in GDP across income groups, while keeping all other model inputs constant at their empirically observed or derived values from the dataset :

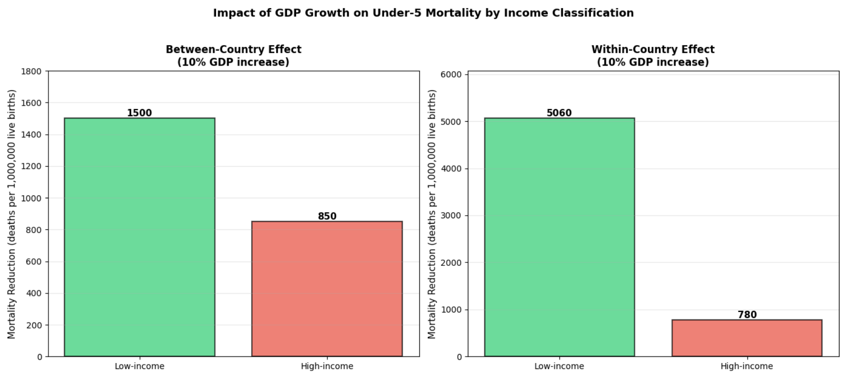

Figure 4: Results of simulating 10% GDP on between-country and within-country effects

Figure 4 suggests that between countries, a 10% GDP increase is associated with 1.76x greater mortality reduction in persistently low-income countries compared to high-income countries. Within countries, the absolute mortality reduction is larger for low-income countries (5,060 deaths averted per 1MM births) than high-income countries (780 deaths averted per 1MM births), reflecting both steeper GDP-mortality gradients and higher baseline mortality in low-income settings.

This confirms our hypothesis: low-income countries experience substantially stronger health returns from economic growth than high-income countries, supporting targeted resource allocation toward lower-income contexts to achieve SDG 3.2 targets. See Appendix D for detailed interpretation of coefficient differences.

6.1 Future Work

- **Lagged effects of predictors**: Our analysis assumes immediate effects of economic and health variables on mortality. However, improvements in GDP, health expenditure, or education may take several years to translate into mortality reductions. Future research could incorporate time lags to capture delayed impacts and identify optimal policy horizons.

- **Income group transitions**: 14 of the 80 countries transitioned between income classifications during 2000-2021, these have been denoted as 'Low and High' in Figure 5. While we retained them in our analysis, examining these transitioning countries separately could reveal whether the GDP-mortality relationship shifts gradually as countries develop or exhibits threshold effects at classification boundaries.

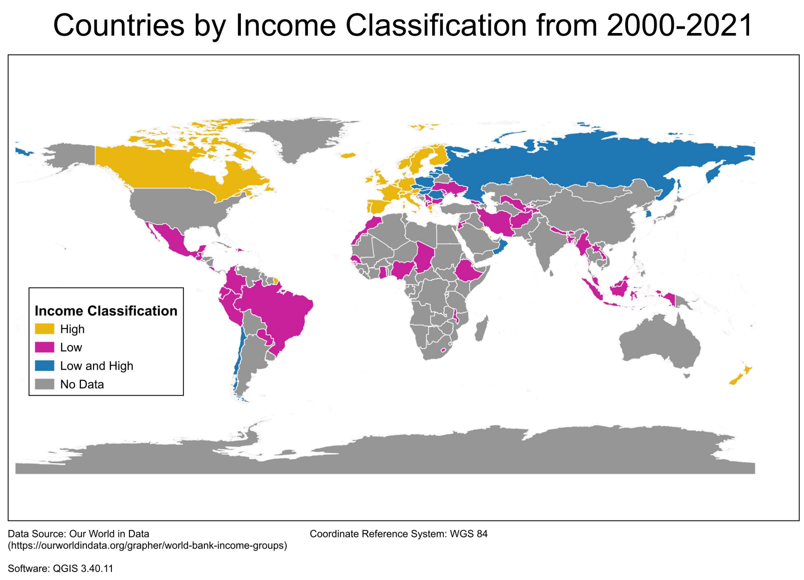

Figure 5: Income classification of countries from 2000 to 2021

- **Additional mediating factors**: Incorporating variables such as governance quality, disease burden, healthcare infrastructure, and income inequality could help identify the mechanisms through which GDP affects mortality and reveal which interventions yield the highest returns in different development contexts.

7 References

Fitzmaurice, G. M., Laird, N. M., & Ware, J. H. (2012). *Applied longitudinal analysis* (2nd ed.). Wiley.

Gelman, A., & Hill, J. (2007). *Data analysis using regression and multilevel/hierarchical models*. Cambridge University Press.

Statistics How To. (2025). *Box Cox transformation: Definition, examples*. https://www.statisticshowto.com/probability-and-statistics/normal-distributions/box-cox-transformation/

Swift, R. (2018). The relationship between health and GDP in OECD countries in the very long run [PubMed Central, National Library of Medicine]. https://pmc.ncbi.nlm.nih.gov/articles/PMC6001628/

United Nations. (2015). Transforming our world: The 2030 agenda for sustainable development. https://sdgs.un.org/2030agenda

Wooldridge, J. M. (2021). *Two-way fixed effects, the two-way mundlak regression, and difference-in-differences estimators* (tech. rep.) (Manuscript). Michigan State University. https://economics.princeton.edu/wp-content/uploads/2021/08/two_way_mundlak-Wooldridge.pdf

World Bank. (2024). *World Bank country and lending groups* (tech. rep.). World Bank. https://datahelpdesk.worldbank.org/knowledgebase/articles/906519

8 Appendix

A Preprocessing of Data: Cleaning, Imputation, and Scaling

A.1 Data Cleaning

We merged the data from the different sources after ensuring a consistent format and including data from 2000 to 2021 (both years inclusive). We standardized the country names across datasets and dropped data of countries that had more than 40% of attributes missing. The 40% threshold ensures that the majority of each country's data comes from observed rather than imputed values, maintaining data integrity while maximizing sample size. This resulted in a dataset with 1760 rows across 80 countries.

A.2 Imputation

While processing our data, we observed missing data:

Table 1: Iteration 1: Missing Data statistics across attributes

Attribute	**Missing %**
Secondary education, pupils female	22.3864
People using safely managed drinking water services	0.6250
Population density (people per sq. km of land area)	0.3409
Income classification	0.3409
Current health expenditure	0.1136

Note: Attributes not noted above do not have any missing data.

As the missing percentages are reasonable, we proceeded to impute the data using the following techniques:

- As educational enrollment changes gradually and predictably over time within countries, so does population density. Hence, we impute the missing values for *Secondary education, pupils female* and *Population density (people per sq. km of land area)* using **linear interpolation** with the country.
- As health expenditure and water access percentages fluctuate without predictable directional change year-to-year, we impute the missing values for *Current health expenditure* and *People using safely managed drinking water services* the country's **median** a more stable estimate than assuming linear progression between sparse observations.
- As income classifications are categorical and change infrequently—the World Bank reclassifies countries only when they cross thresholds, we impute the *Income classification* using the mode within the country.

After this exercise, when we rechecked the missing data statistics, we see the following:

Table 2: Iteration 2: Missing Data statistics across attributes

Attribute	**Missing %**
Secondary education, pupils female	0.7386
Population density (people per sq. km of land area)	0.3409

Note: Attributes not noted above do not have any missing data.

- After linear interpolation, there are remaining gaps are at series endpoints for *secondary education, pupils female*, where interpolation did not work. We choose to **carry forward/backward the nearest observed value** within a country for imputation since we do not anticipate dramatic jumps between consecutive years within a country.
- As population density changes predictably within countries, we use the **mean** for imputation, as it provides a reasonable country-specific estimate when no temporal neighbors exist for interpolation, capturing the country's typical density level across the observed period.

With this second iteration, all missing data was successfully imputed.

A.3 Normalization, Scaling and One Hot Encoding

We checked the distribution of each of the attributes, the representation is in Figure 6.

Figure 6: Distribution of the inputs and the target

As indicated in the plots above, the following attributes are extremely right-skewed:

- GDP per capita
- Population density
- Child mortality rate

Using log transformation for these aforementioned attributes using *np.log*1*p* because many density values are close to zero, $log(0)$ is undefined. *Current health expenditure percentage* has a mild positive right-skew, square root transformation is often ideal for mild positive skew as it is gentler than the log and can stabilize variance. *People using safely managed drinking water services percentage* is bimodal, a logit transformation would be appropriate to use. *Secondary education, pupils female percentage* is heavily left-skewed, but it has a bell shaped curve, so we leverage the reflect-and-transform technique: recentering it and doing a log transformation. Similarly, as *DPT3 immunization percentage* is also left-skewed, we use reflect-and-transform technique.

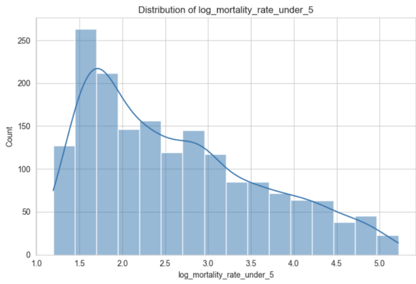

Figure 7: Distribution of log transformed target

Since child mortality rate was still right-skewed after this exercise, as indicated in Figure 7, we used Box-Cox transformation on the transformed target to make its distribution normal.

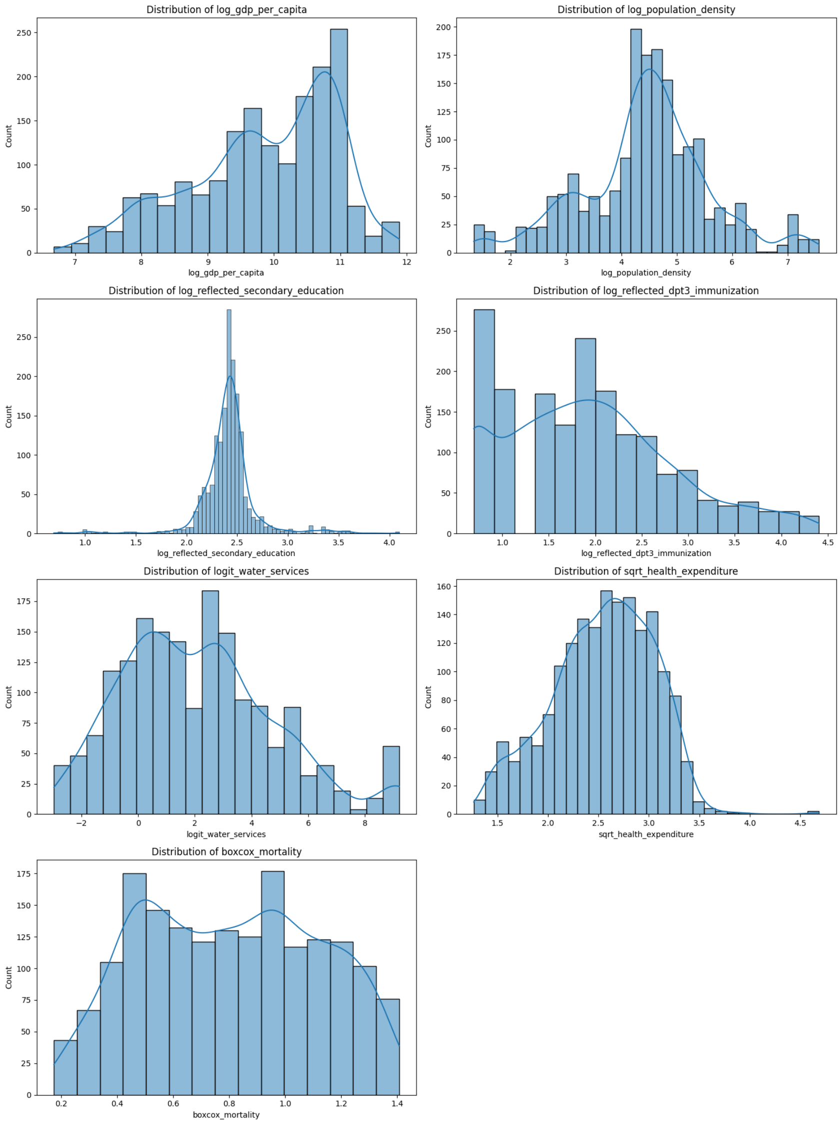

Figure 8: Distribution of all transformed inputs and target

Post the Box-Cox transformation, all attributes are nearly normal as indicative of Figure 8. Normalizing both inputs and target variables stabilizes variance, reduces outlier influence, and helps satisfy OLS assumptions, particularly normality of residuals. This which is essential for valid hypothesis testing and reliable inference about the moderating effect of income level on the GDP-mortality relationship.

We then scale all the numerical columns using standard scaling—centering by the mean and scaling by the standard deviation. We perform one-hot encoding for the categorical variable, income classification, so the data is ready to be used for modeling.

B Model Specification

B.1 Pooled Ordinary Least Squares

To test the interactions between our target and the attributes in our panel data, we start off with a simple model, Pooled Ordinary Least Squares (Pooled OLS) with standard errors clustered at the country level to account for within-country correlation over time. Representation of the model is as below :

$$
\begin{aligned}
\text{boxcox\_mortality} \sim & \text{log\_gdp\_per\_capita} \times \text{Income\_High}+ \\
& \text{sqrt\_health\_expenditure}+ \\
& \text{log\_reflected\_dpt3\_immunization}+ \\
& \text{log\_reflected\_secondary\_education}+ \\
& \text{logit\_water\_services}+ \\
& \text{log\_population\_density}+
\end{aligned} \tag{2}
$$

```
                            OLS Regression Results
==============================================================================
Dep. Variable:       boxcox_mortality   R-squared:                       0.876
Model:                            OLS   Adj. R-squared:                  0.875
Method:                 Least Squares   F-statistic:                     112.0
Date:                Sun, 26 Oct 2025   Prob (F-statistic):           7.22e-40
Time:                        18:33:13   Log-Likelihood:                -663.48
No. Observations:                1760   AIC:                             1345.
Df Residuals:                    1751   BIC:                             1394.
Df Model:                           8
Covariance Type:              cluster
============================================================================================================
                                              coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------------------------------------
Intercept                                   0.1870      0.051      3.641      0.000       0.086       0.288
Income_High[T.True]                        -0.7118      0.178     -4.002      0.000      -1.060      -0.363
log_gdp_per_capita                         -0.6070      0.070     -8.731      0.000      -0.743      -0.471
log_gdp_per_capita:Income_High[T.True]      0.3089      0.200      1.543      0.123      -0.084       0.701
sqrt_health_expenditure                    -0.2168      0.048     -4.516      0.000      -0.311      -0.123
log_reflected_dpt3_immunization             0.0722      0.031      2.344      0.019       0.012       0.133
log_reflected_secondary_education          -0.0285      0.035     -0.815      0.415      -0.097       0.040
logit_water_services                       -0.0138      0.075     -0.184      0.854      -0.161       0.133
log_population_density                      0.0171      0.045      0.378      0.706      -0.071       0.105
==============================================================================
Omnibus:                       25.591   Durbin-Watson:                   0.175
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               25.256
Skew:                          -0.268   Prob(JB):                     3.28e-06
Kurtosis:                       2.762   Cond. No.                         11.8
==============================================================================

Notes:
[1] Standard Errors are robust to cluster correlation (cluster)
```

Figure 9: Regression results for Pooled OLS

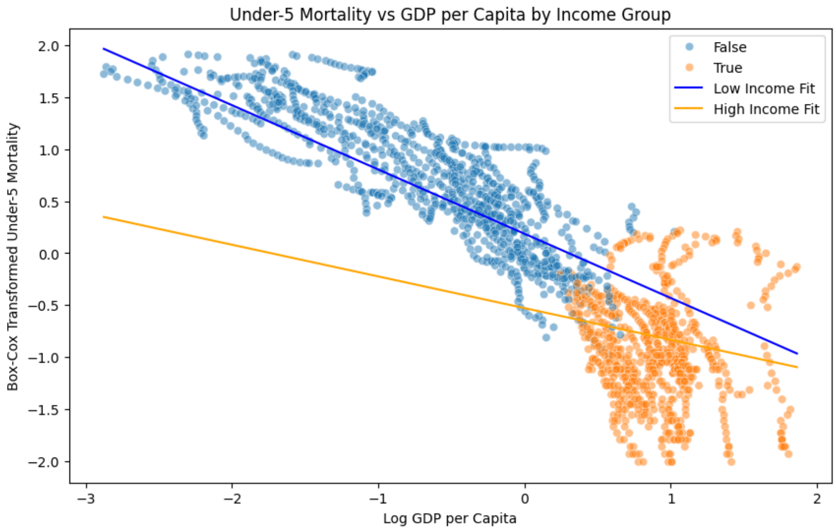

Figure 10: Fit for Pooled OLS

Figure 10 indicates steeper negative slopes for the low-income group as compared to high-income group, as also noted in Figure 2.

Pooled OLS produces suggestive results: Low-income countries show a steeper GDP-mortality gradient (0.62 units) compared to high-income countries (0.31 units); the model fit has a high R^2 of 0.875 yet the difference between the GDP-mortality gradients for the income groups is not statistically significant at the 0.05 level (p-value = 0.123) as indicated in Figure 9.

A fundamental limitation of pooled OLS is that it assumes that countries are homogeneous except for measured predictors. In practice, countries differ substantially in unmeasured dimensions—institutional quality, geographic characteristics, and healthcare system maturity—that independently affect child mortality. When these country-specific factors are omitted, they remain in the error term, introducing bias and inflating standard errors that mask genuine patterns.

To address this, we employ a random effects model, which allows each country to have a country-specific baseline while maintaining a common relationship between GDP and mortality.

B.2 Random effects model

Random Effects Model assumes that individual country effects are uncorrelated with the explanatory variables [Fitzmaurice et al., 2012; Gelman and Hill, 2007]. This allows for the inclusion of time-invariant variables, which is not possible in fixed effects models. The country-specific random intercept captures unmeasured time-invariant characteristics (such as geography or cultural factors) that affect baseline mortality levels.

$$
\begin{aligned}
\text{boxcox\_mortality} \sim\, & 1 + \text{log\_gdp\_per\_capita} + \\
& \text{log\_gdp\_per\_capita} \times \text{Income\_High} + \\
& \text{sqrt\_health\_expenditure} + \\
& \text{log\_reflected\_dpt3\_immunization} + \\
& \text{log\_reflected\_secondary\_education} + \\
& \text{logit\_water\_services} + \\
& \text{log\_population\_density} + \\
& \text{TimeEffects}
\end{aligned}
\tag{3}
$$

RandomEffects Estimation Summary

Dep. Variable:	boxcox_mortality	R-squared:	0.6403
Estimator:	RandomEffects	R-squared (Between):	0.7994
No. Observations:	1760	R-squared (Within):	0.6187
Date:	Thu, Oct 16 2025	R-squared (Overall):	0.7878
Time:	11:19:30	Log-likelihood	700.66
Cov. Estimator:	Clustered		
		F-statistic:	445.62
Entities:	80	P-value	0.0000
Avg Obs:	22.000	Distribution:	F(7,1752)
Min Obs:	22.000		
Max Obs:	22.000	F-statistic (robust):	45.230
		P-value	0.0000
Time periods:	22	Distribution:	F(7,1752)
Avg Obs:	80.000		
Min Obs:	80.000		
Max Obs:	80.000		

Parameter Estimates

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
Intercept	0.1610	0.0561	2.8700	0.0042	0.0510	0.2710
log_gdp_per_capita	−0.7487	0.0845	−8.8650	0.0000	−0.9144	−0.5831
sqrt_health_expenditure	−0.1709	0.0342	−5.0018	0.0000	−0.2380	−0.1039
log_reflected_dpt3_immunization	−0.0095	0.0160	−0.5969	0.5506	−0.0409	0.0218
log_reflected_secondary_education	−0.0772	0.0336	−2.3006	0.0215	−0.1430	−0.0114
logit_water_services	−0.0748	0.0593	−1.2612	0.2074	−0.1912	0.0415
log_population_density	−0.1640	0.0703	−2.3317	0.0198	−0.3019	−0.0261
log_gdp_per_capita:Income_High	−0.4146	0.1246	−3.3267	0.0009	−0.6590	−0.1702

Figure 11: Regression results for simple Random Effects

The random effects model permits each country to have a country -specific baseline while maintaining a common relationship between GDP and mortality. By explicitly controlling for time-invariant country heterogeneity, the model isolates the effect of measured variables. This approach successfully reveals the underlying pattern: the GDP $\times$ Income interaction term becomes statistically significant at the 0.05 level ($p = 0.0009$) as indicated in Figure 11, indicating that accounting for country-level differences uncovers the genuine relationship obscured by pooled OLS.

While the random effects model improves our results significantly, a key limitation remains: it assumes that unmeasured country characteristics (such as institutional quality or healthcare system development) are unrelated to GDP, which is unrealistic. In reality, countries with well-developed institutions (educational, health, governmental) tend to have both higher GDP and better health outcomes. Ignoring these factors potentially introduces bias in our estimates.

Simple random effects mixes the within-country and between-country effects of how GDP affects child mortality. Our hypothesis about diminishing returns in low-income countries specifically concerns the between-country aspect—that low-income countries as a group experience stronger mortality reductions from economic growth compared to high-income countries. So it is valuable to split the two effects using Mundlak's approach to isolate the between-country relationship that our hypothesis addresses.

C Random Effects Model using Mundlak Approach: Diagnostics

We assessed normality assumptions for our Random Effects Mundlak model at two levels: within-country residuals and between-country residuals.

Figure X shows Q-Q plots and histograms for both components. Both plots follow reasonable normality with only minor tail deviations, these diagnostics support the validity of our model-based inference.

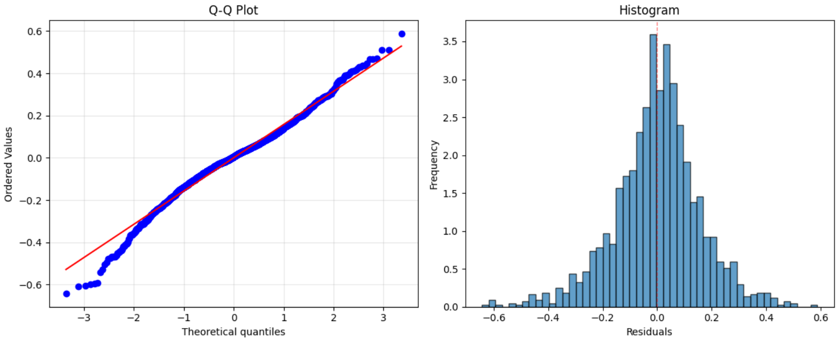

Figure 12: Within-country residuals

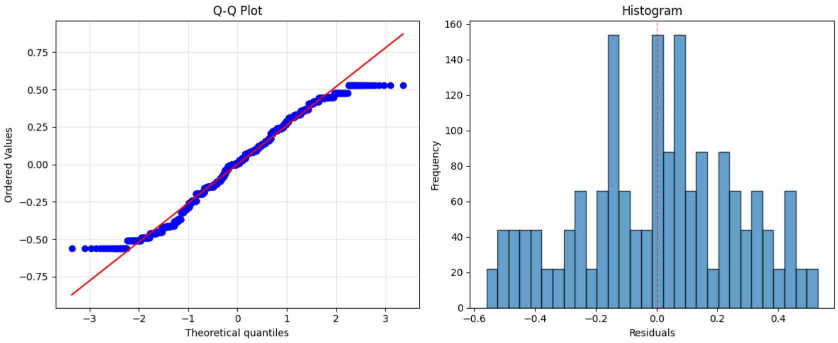

Figure 13: Between-country residuals

The plots on the left of Figure 13 are Q-Q plots, they show quantile-quantile comparisons and align pretty well with line with the 45 degree slope thereby demonstrating theoretical normal distribution; the histograms on the right display empirical normal distributions.

D Interpretation of Within vs. Between Effects

The larger within-country effect for low-income countries compared to the between-country effect requires explanation. Between-country effects reflect structural, long-run differences—they compare countries' average GDP and mortality over the entire 22-year period. Within-country effects capture year-to-year GDP growth and its immediate impact on mortality. Because within-country variation is more volatile (annual changes rather than averages), the coefficient magnitude is larger, yielding more prominent mortality reductions for the same percentage GDP increase.