Modeling GDP Using Health and Socioeconomic Indicators

Erin Xu, Dora Dong, Shencen Cai, Sharon Lam

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Introduction

Gross domestic product (GDP) is a widely used measure of a country's economic output, representing the total market value of goods and services produced within its borders over a specified period. It serves as a key indicator of national economic performance and enables comparison across countries and time periods. From economic theory, GDP is influenced by components such as consumer spending, government expenditures, investment in capital goods, and net exports. Factors like human capital, infrastructure, technological innovation, and political stability are also vital.

This project applies multiple linear regression (MLR) to investigate the extent to which health-related and socioeconomic factors are associated with GDP, with the research question being: *To what extent do government spending on health and socioeconomic resources affect a country's GDP?* Specifically, country status (developed vs. developing), percentage expenditure on health, polio immunization coverage, income composition of resources, years of schooling, and population are the combination of continuous and categorical predictors used to explain the extent in which they affect GDP in countries around the world. Health spending, represented by percent of a country's expenditure and polio immunization coverage, has been shown to enhance productivity, and income composition and national development status reflect broader socioeconomic conditions. Education and population are also recognized as structural drivers of economic growth because educated workers increases human capital, research and innovation for better products, processes and overall economic advancement.

As economic theory suggests a positive relationship between GDP and improved development indicators, and estimating a linear model allows us to quantify the individual contribution of each predictor to GDP while controlling for the others, a positive relationship between GDP and indicated predictors can be expected. The focus of this analysis is on interpretability, to understand how each predictor relates to economic output and to support evidence-based approaches to development and policy planning.

Data description

The dataset used in this project is titled *Life Expectancy* (WHO), sourced from *Kaggle* (Kumar, 2018). Its primary usage is for health data analysis. Data collectors combined publicly available data from the *World Health Organization* (WHO) and the *United Nations* (UN), which were gathered through national health departments, structured questionnaires, and annual statistical submissions by participating countries (World Health Organization, n.d.; United Nations, n.d.). The sample comprises over 1,600 complete observations, focusing on education, demographic, and socioeconomic indicators relevant to economic growth.

While the dataset was initially intended to examine factors affecting life expectancy, this project selects 7 of the original 22 variables that align with economic theory, which emphasizes the importance of education, health, and human capital in supporting sustained increases in GDP.

The preliminary model is prone to multiple violations of model assumption, but multiple linear regression is still an appropriate method for analysis, as the scatterplots of the response and each predictor show a

huge potential for linear association, constant error variance, and uncorrelated and normal errors, through diagnostic procedures like predictor transformations.

Table 1: Variables used in the model

Variable	**Description**	**Type**
GDP	Gross Domestic Product per capita (USD)	Response variable
Status	Developed or Developing status	Categorical variable
Percentage expenditure	Expenditure on health as a percentage of Gross Domestic Product per capita (%)	Continuous variable
Polio	Polio immunization coverage among 1-year-olds (%)	Continuous variable
Population	Population of the country	Continuous variable
Income composition of resources	Human Development Index in terms of income composition (index from 0 to 1)	Continuous variable
Schooling	Number of years of schooling (years)	Continuous variable

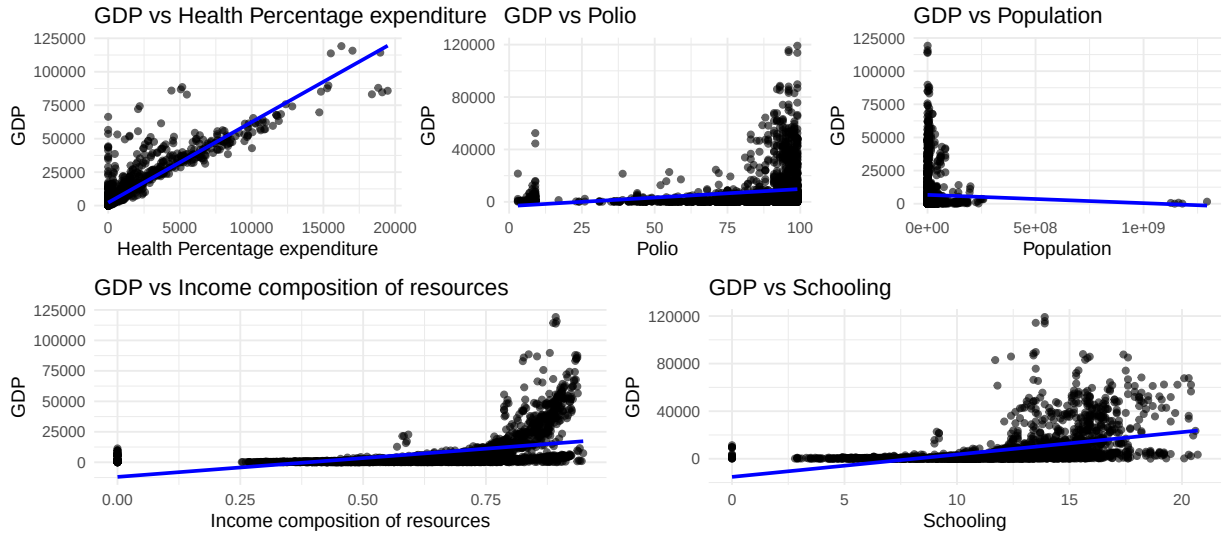
Table 2: Continuous variables summary

Variable	Mean	Std	Min	Q1	Median	Q3	Max
GDP	7483.16	14270.17	1.68	463.94	1766.95	5910.81	119172.74
Percentage expenditure	738.25	1987.91	0.01	4.69	64.91	441.53	19479.91
Polio	82.55	23.43	3.00	78.00	93.00	97.00	99.00
Population	1.28e+07	6.10e+07	34.00	1.96e+05	1.39e+06	7.42e+06	1.29e+09
Income composition of resources	0.63	0.21	0.00	0.49	0.68	0.78	0.95
Schooling	11.99	3.36	0.00	10.10	12.30	14.30	20.70

Table 3: Status (categorical variable) frequency

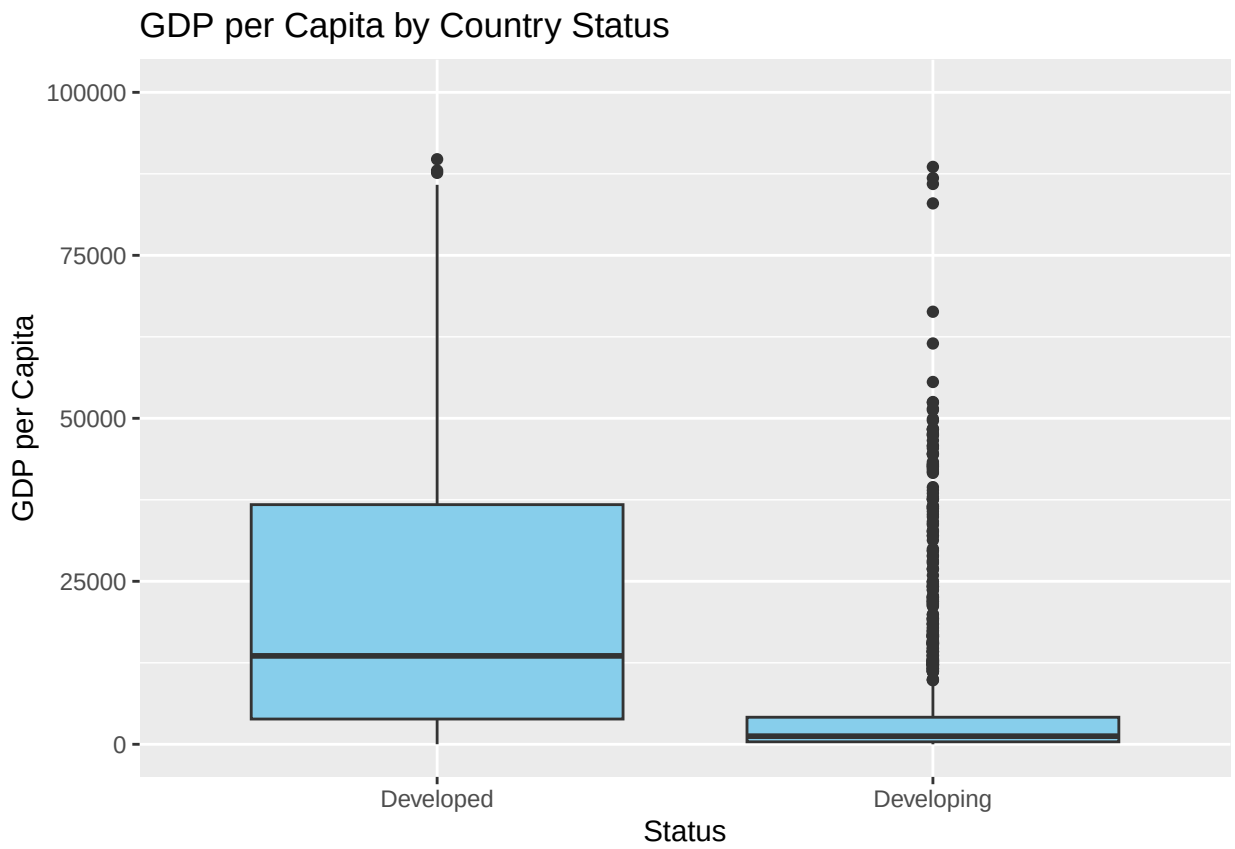
Status	Frequency
Developing	2426
Developed	512
Total	2938

Figure 1: Scatter plots of GDP against numeric predictors



GDP increases as health percentage expenditure does in a rather compelling linear manner, although the clustering near the lower ends of the domain is concerning due to outliers in countries that are experiencing geopolitical turmoil. GDP and polio as well as income composition of resources and schooling demonstrate weaker positive trends, looking more quadratic, most likely with leverage points at the tails. It's clear that there are bad leverage points in GDP and population. In the context of geography and the complexity of individual states, one can suspend their disbelief easily about certain leverage points, but nonetheless, these need to be dealt with to provide a more accurate prediction of GDP with the set predictors at hand.

Figure 2: Histogram of GDP & numeric predictors



GDP, percentage expenditure, and population are strongly right-skewed, with mostly low values. Schooling and income composition are slightly left-skewed, clustering at the high end. Income composition is also bimodal, although there is potential for a bell-curve-like shape. Polio rates are highly left-skewed. Since country status is a categorical predictor, the boxplot graph is better suited to evaluating the normality assumption. Developed countries have a higher median GDP per capital and wider IQR range, which indicates greater variability than developing countries, which violates a model assumption. Also, developing countries appear highly skewed to the right, with most countries clustered at low GDP per capital values. The long tail of outliers stretching upward indicate a few developing countries with relatively high GDPs. In context, these outlier countries like Malaysia, Mexico, or Turkey are often classified more deeply as upper-middle-income economies (World Bank) because they clearly act as outliers compared to the rest of the developing world.

Primary model results and diagnostics

We propose the following multiple linear regression model:

$$\begin{aligned} GDP &= \mathbb{E}[\log(GDP)] + e \\ &= b_0 + b_1 \cdot \text{PercentageExpenditure} + b_2 \cdot \text{Polio} + b_3 \cdot \text{Population} \\ &\quad + b_4 \cdot \text{IncomeCompositionOfResources} + b_5 \cdot \text{Schooling} + b_6 \cdot \text{Status} \end{aligned}$$

Get the response and predictors:

```
##
## Call:
## lm(formula = response ~ Status + x0 + x1 + x2 + x3 + x4, data = all_data)
```

```
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -6.3838 -0.6281  0.3300  0.8680  2.4999
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)       3.656e+00  2.280e-01  16.037  < 2e-16 ***
## StatusDeveloping  5.719e-02  1.064e-01   0.538    0.591
## x0                3.862e-04  2.030e-05  19.019  < 2e-16 ***
## x1               -7.981e-04  1.459e-03  -0.547    0.585
## x2               -1.866e-10  4.348e-10  -0.429    0.668
## x3                1.398e+00  2.733e-01   5.115 3.51e-07 ***
## x4                2.086e-01  1.871e-02  11.152  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.241 on 1642 degrees of freedom
## Multiple R-squared:  0.5001, Adjusted R-squared:  0.4983
## F-statistic: 273.8 on 6 and 1642 DF,  p-value: < 2.2e-16
```

We estimate the deterministic model as:

$$\begin{aligned}\hat{GDP} = \exp(&\hat{b_0} + \hat{b_1} \cdot \text{PercentageExpenditure} + \hat{b_2} \cdot \text{Polio} + \hat{b_3} \cdot \text{Population} \\ &+ \hat{b_4} \cdot \text{IncomeCompositionOfResources} + \hat{b_5} \cdot \text{Schooling} + \hat{b_6} \cdot \text{Status})\end{aligned}$$

Initially, the distribution of GDP was heavily right-skewed due to a small number of countries with disproportionately large economies. Residual plots also showed signs of heteroscedasticity, violating regression assumptions. To address this, we applied a log transformation to the response variable, which preserved the interpretability of a linear model while improving the spread of residuals.

The adjusted R-squared of the transformed model was 0.9258, indicating that 92.6% of the variation in GDP is explained by the model. Among numerical predictors, percentage expenditure on health and schooling were both statistically significant ($p < 0.001$), suggesting strong positive relationships with GDP. This supports the idea that education and health investment enhance human capital and economic productivity (Radcliffe, Raghupathi). For the categorical predictor Status (Developed vs. Developing), the p-value was approximately 0.0038, indicating that developed countries tend to have significantly higher GDPs after accounting for other variables. In contrast, polio immunization and population size were not statistically significant, implying weaker associations.

The residual plots assess linearity and constant variance assumptions. Residuals were mostly centered around zero, but a slight V-shape indicates some remaining heteroscedasticity, especially at the lower and higher ends of fitted GDP. This suggests more stable residuals in middle-income countries, while richer and poorer countries show more unpredictable patterns. For example, the U.S., Qatar, and Luxembourg all have high GDPs, but for very different reasons (tech, gas, or tax policy). Similarly, lower-income countries may have inconsistent or less reliable data.

The Q-Q plot showed that residuals were somewhat normal, but skewed left. Residuals versus individual predictors showed random scatter for income composition and schooling, but some structure for expenditure, population, and polio, suggesting potential nonlinearities.

Overall, the model shows evidence that educational and economic factors influence GDP, though remaining issues with heteroscedasticity and non-normal residuals should be better resolved, as these violations weaken ordinary least squares (OLS) model accuracy. Employing further transformations like Box-Cox, investigating covariance, colinearity, the removal of bad leverage points and outliers, comparison of different models through F-test and analysis of variance (ANOVA), or even exploring weighted least squares (WLS) are key stratagem to confidently predict the expected GDP in a country.

Figure 3: Linearity and homoscedasticity graphs

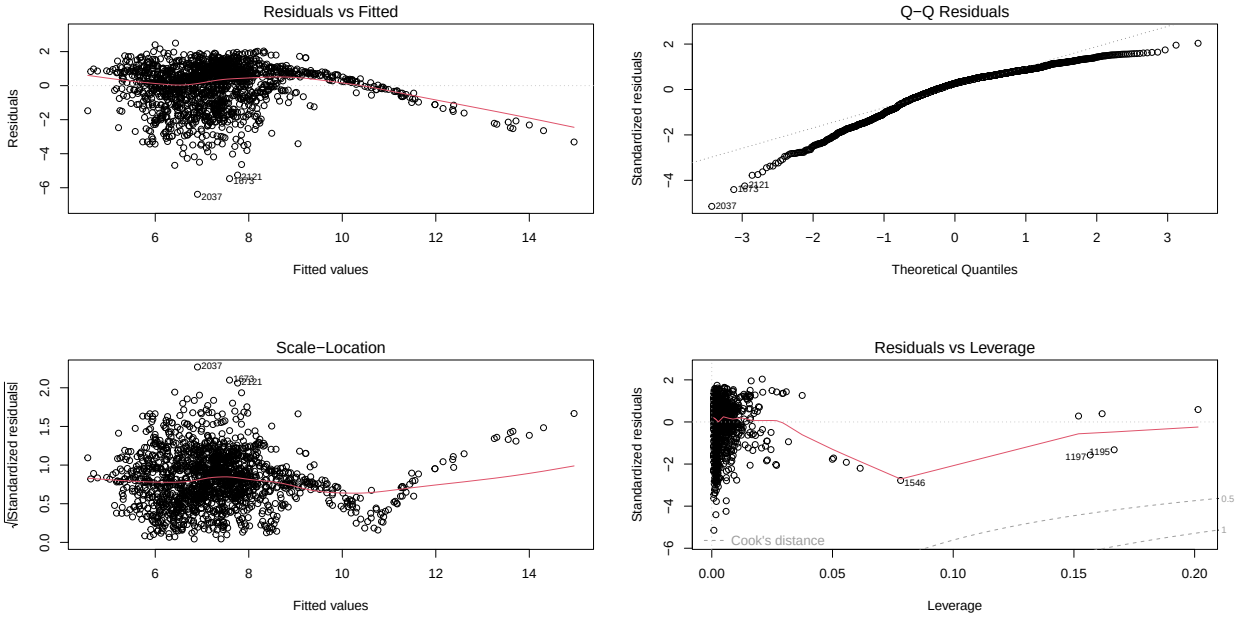


Figure 4: Residual vs each predictor

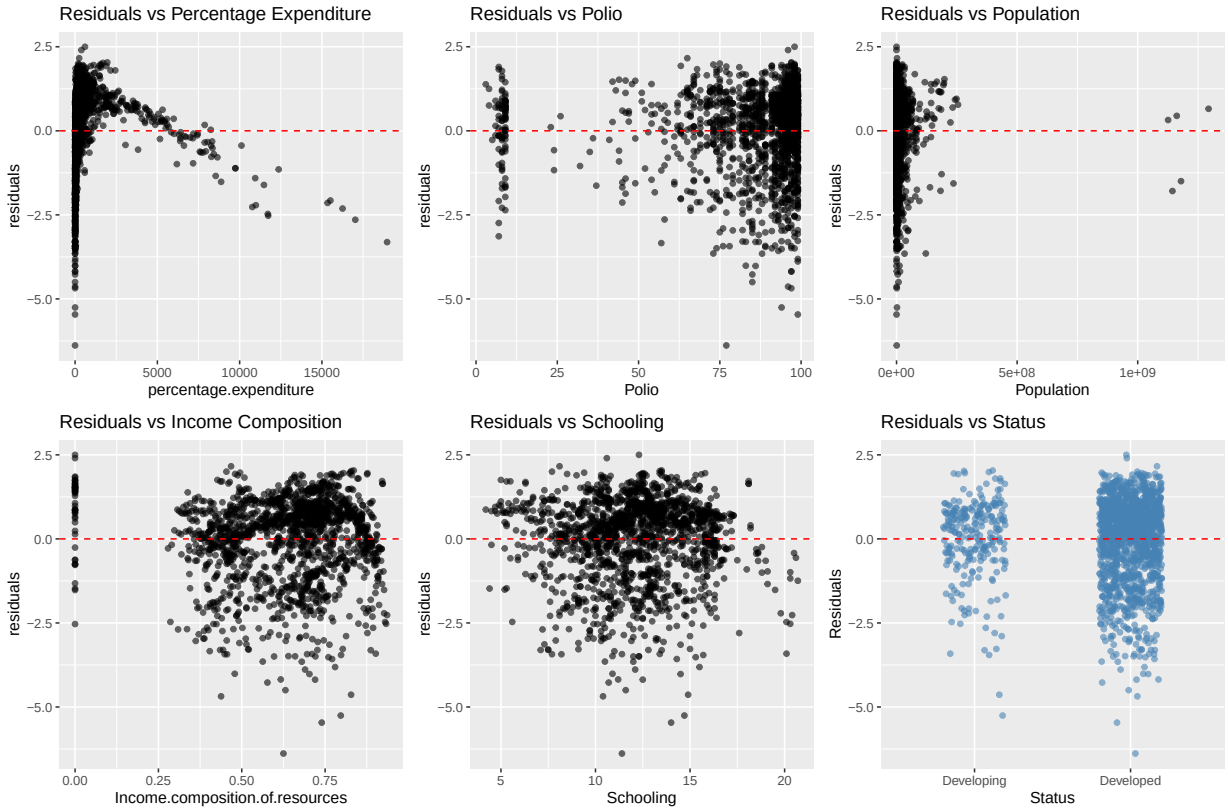
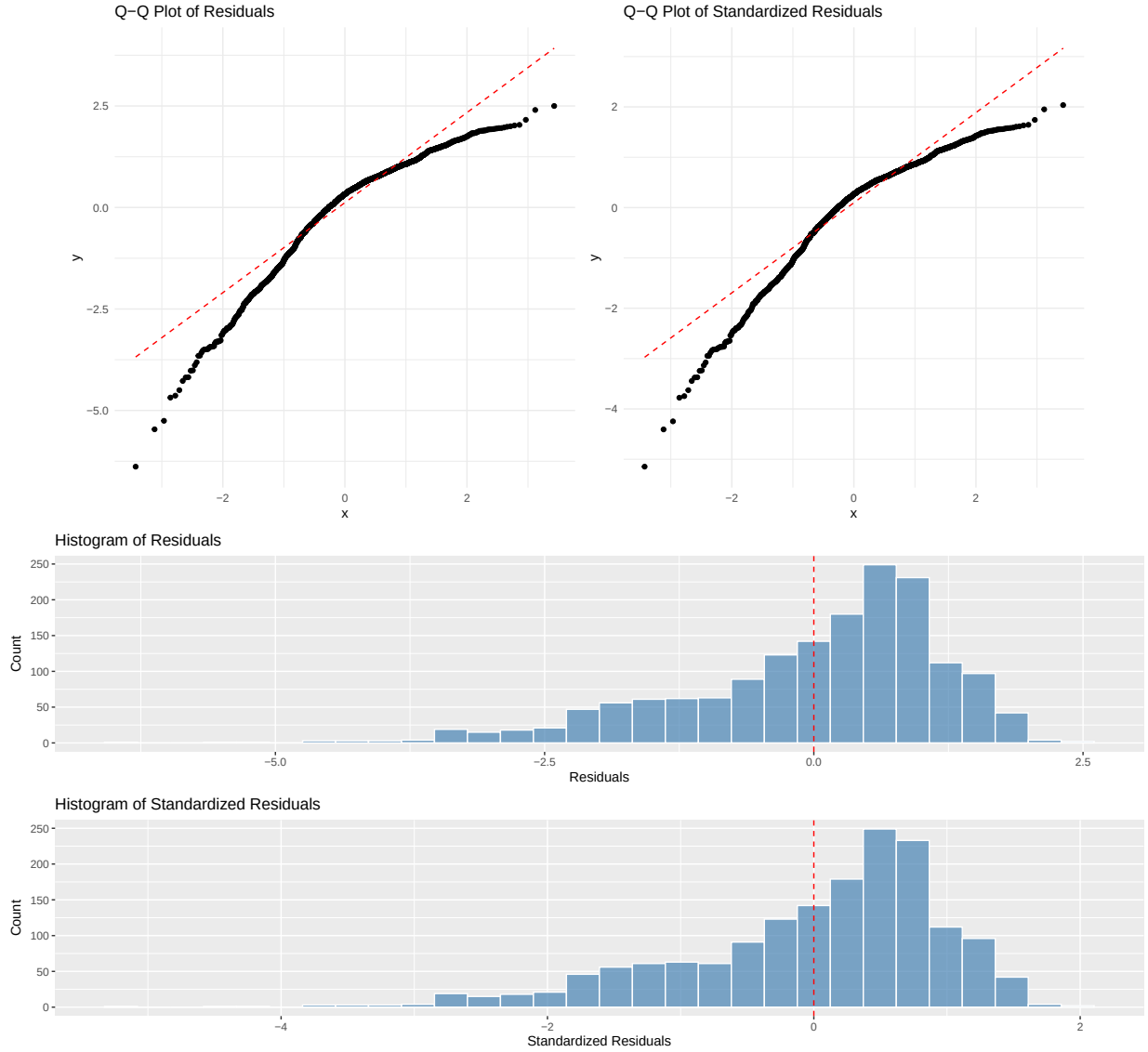


Figure 5: Normality graphs



Model selection

From the conclusion in preliminary model diagnostics, the model violated linear regression assumptions and would benefit from modifications.

We first fitted a full model using all available predictors from the dataset without transformation. We then performed best subset selection and stepwise selection. Stepwise selection was done using *step*() based on Akaike Information Criterion (AIC) and Bayesian Information Critertion (BIC) which filtered the complexity and goodness of fit of the model. Best subset selection was done using *regsubsets*() from the **leaps** package, which tries all combinations of up to 10 predictors and evaluates them based on adjusted R^2. This is **Model 1**. The main issue here was the predictor choice that had been determined by the criterion: Both total expenditure on health and percentage expenditure on health were included in the model, however this is not meaningful as these predictors are just different perspectives of health and GDP spending. Therefore,

population replaced the percentage expenditure since population had previously a strong indication on its influence of GDP, and this became **Model 2**.

Then, since this model violated normality of residuals and heteroscedasticity, **Model 3** is the variable transformation of **Model 2**, where Box-Cox was applied to the response, with the result of maximized log-likelihood power parameter $\lambda = 0.101$. This significantly improved the normality and variance stability of the residuals, however, a curvature on the residual and fitted values plot was still observed.

In order to address the remaining violation, **Model 4** applies transformations on the predictors. Polio and population scatterplots from the introduction exploratory data analysis indicated a potential nonlinear relationship with GDP, therefore, a quadratic transformation was applied to these two predictors, although improvement on normality violations were not representative in diagnostic graphs.

Therefore, **Model 5** and **Model 6** are the combination of both response and predictor transformations. For these two final candidate models, multicollinearity in the predictors was also assessed through the Variance Inflation Factor (VIF). Both candidates returned VIF values of below 5, a strong indication that multicollinearity was not a concern in either model. In lieu of the research question, multicollinearity is unlikely to be a major concern as these predictors capture distinct phenomena that measure different social mechanisms. Also, predictors that were already expressed as a percentage of a population removes the common size factor that would otherwise cause co-linearity in cross-country data.

Model 6 is **Model 5** with an additional observation: Before transforming the population variable, the residual vs. leverage plot exhibited several points with high leverage. This would indicate influence on the fitted line to stray from the population line. As a result, a logarithmic transformation was applied on the population predictor here. This transformation substantially reduced the number and magnitude of bad high-leverage points and indicates that the model became less sensitive to extreme values in the predictors.

Table 5: Diagnostic metrics for Models 5 and 6

Metric	Model 5	Model 6
R^2	0.4209	0.4249
Adjusted R^2	0.4188	0.4288
AIC	8085.524	8074.323
BIC	8128.788	8117.587

Table 6: Explanation of transformed variables

Transformation	Variable(s)	Motivation
Box–Cox ($\lambda \approx 0.101$)	Response: `GDP`	Heavy right-skew and non-constant variance in raw GDP; log-like Box–Cox stabilizes variance and improves normality.
Quadratic term	`Polio`^{2}, `Schooling`^{2}, `Total.expenditure`^{2}	Scatterplots showed curvature; adding a squared term captures diminishing returns visible in the data.
Log scale	Population to log(Population)	Original residual-vs-leverage plot had extreme leverage for the largest countries; the log scale compresses the range and removes those high-influence points without discarding data.

All other predictors remained on their natural scale because residual plots and VIF values (< 5) did not indicate further non-linearity or multicollinearity problems.

Table 7: Influential Observations and Outliers | Detection Tool | Flagged IDs | Action Taken| |———————-|———————-|———————————-| | Leverage (`hatvalues`) | 126, 2121, 92, 1233| High-leverage points detected. **Retained** if not extreme, as removal caused curvature and worsened model fit — suggesting genuine structure. | | Cook's Distance | 126, 2121, 92, 1233| Points showed influence on the fitted line. **Reviewed** alongside other diagnostics. | | DFFITS | 126, 2121, 92, 1233| Consistent with Cook's D. Points flagged for high impact on predicted values. **Kept** unless they also violated residual assumptions. | | Studentized Residuals | Same as above | Observations with |residual| > 4 considered **outliers**. These were **removed**, likely due to data entry issues or extreme geopolitical context. |

After removal of the clear outliers, diagnostics (Figure 3 & 4) showed homoscedastic residuals and no further influential cases above conventional cut-offs.

Table 9: ANOVA Table

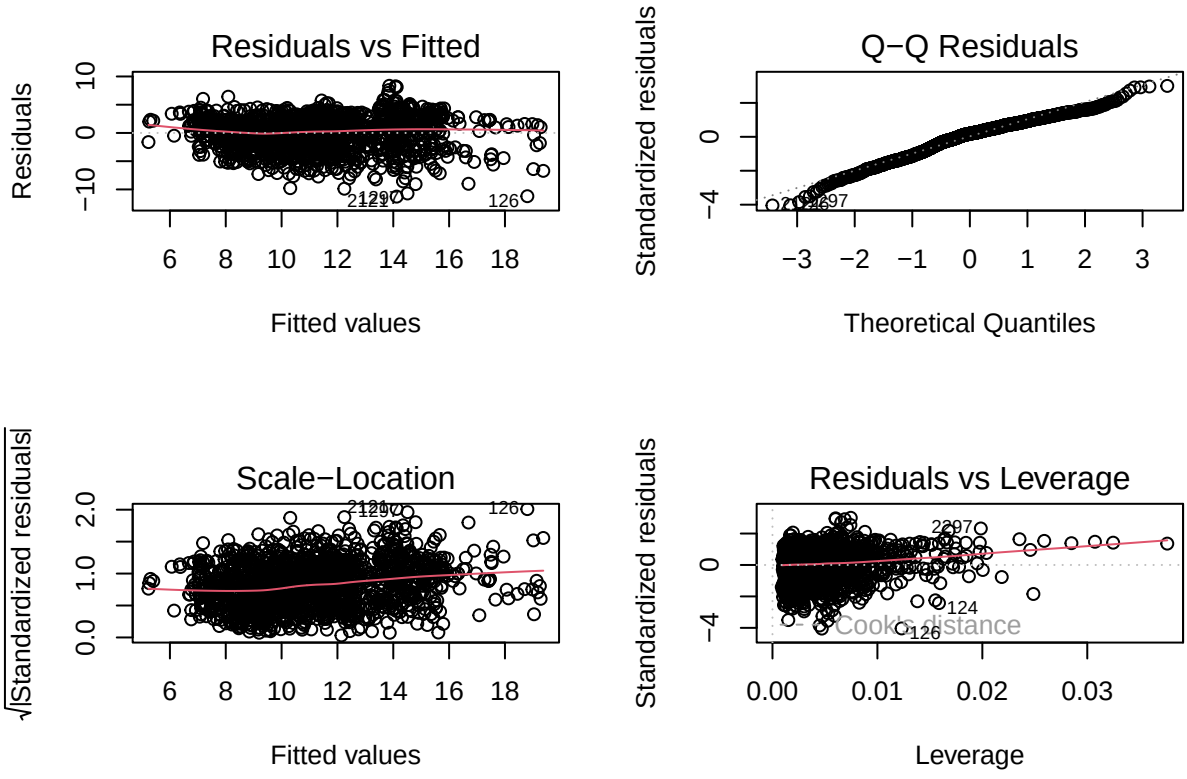
Predictor	Df	Sum Sq	Mean Sq	F value	Pr($> F$)
Status	1	3194.3	3194.3	584.3467	2.2e-16
Total expenditure^2	1	308.6	308.6	52.9796	5.7e-13
Polio	1	682.4	682.4	117.1461	2.2e-16
log-population	1	10.3	10.3	1.7096	0.1836
Income composition	1	4114.7	4114.7	706.3467	2.2e-16
Schooling^2	1	75.9	75.9	13.0305	0.000317
Residuals	1416	8248.6	5.8	—	—

In addition to examining diagnostic plots, overall fit and complexity of the final two models were evaluated with certain metrics. **Model 6** has a larger Adjusted R^2 value and smaller AIC and BIC values. To assess the influence of individual observations, Cook's distance, difference in fits (DFFITS) and leverage values were examined. Removing outliers improved the normality and homoscedasticity of residuals ($126, 2121, 92, 1233$). However removing high leverage or high influence points led to curvature in the residuals vs fitted plot and deviations from normality in the Q-Q plot. This suggests that these points may contain genuine structure in the data necessary for the model to adequately capture relationships. Therefore, we decided to only remove clear outliers based on standardized residuals, while retaining leverage and influential points.

Based on best meeting these criteria, and solving violation assumptions, **Model 6** is our final model for inference and interpretation of GDP by health and socioeconomic predictors.

```
##
## Call:
## lm(formula = bc_GDP ~ Status + I(Total.expenditure^2) + Polio +
##     I(log(Population)) + Income.composition.of.resources + I(Schooling^2),
##     data = all_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -11.2678  -1.8229   0.5069   1.9800   8.3447
##
## Coefficients:
##                                Estimate Std. Error t value Pr(>|t|)
## (Intercept)                    6.227949   0.603082  10.327  < 2e-16 ***
## StatusDeveloping              -1.175649   0.235843  -4.985 6.86e-07 ***
## I(Total.expenditure^2)         0.003817   0.002451   1.557    0.120
## Polio                         -0.003145   0.003273  -0.961    0.337
## I(log(Population))            -0.001182   0.025241  -0.047    0.963
```

```
## Income.composition.of.resources  4.273179   0.596040   7.169 1.14e-12 ***
## I(Schooling^2)                   0.021669   0.001756  12.342  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.792 on 1642 degrees of freedom
## Multiple R-squared:  0.4249, Adjusted R-squared:  0.4228
## F-statistic: 202.2 on 6 and 1642 DF,  p-value: < 2.2e-16
```

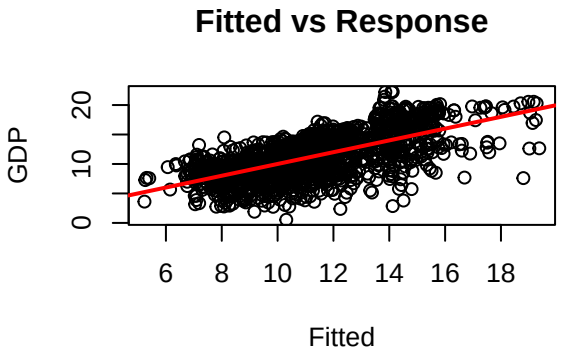


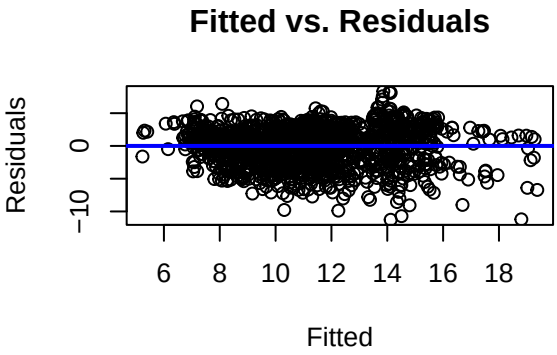

```
##                          Status          I(Total.expenditure^2)
##                        1.473847                        1.102295
##                           Polio              I(log(Population))
##                        1.141679                        1.017460
## Income.composition.of.resources                I(Schooling^2)
##                        2.518552                        2.985993
```

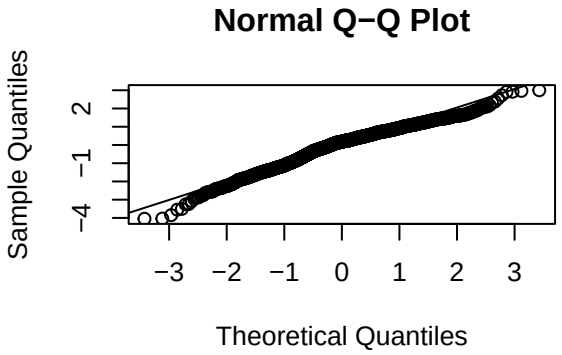
```
##        df       AIC
## model1  8 31226.955
## model2  8 34906.658
## model3  8  8085.575
## model4  8 34818.269
## model5  8  8085.524
## model6  8  8074.323
```

```
##        df       BIC
```

```
## model1  8 31270.218
## model2  8 34949.922
## model3  8  8128.838
## model4  8 34861.533
## model5  8  8128.788
## model6  8  8117.587
```



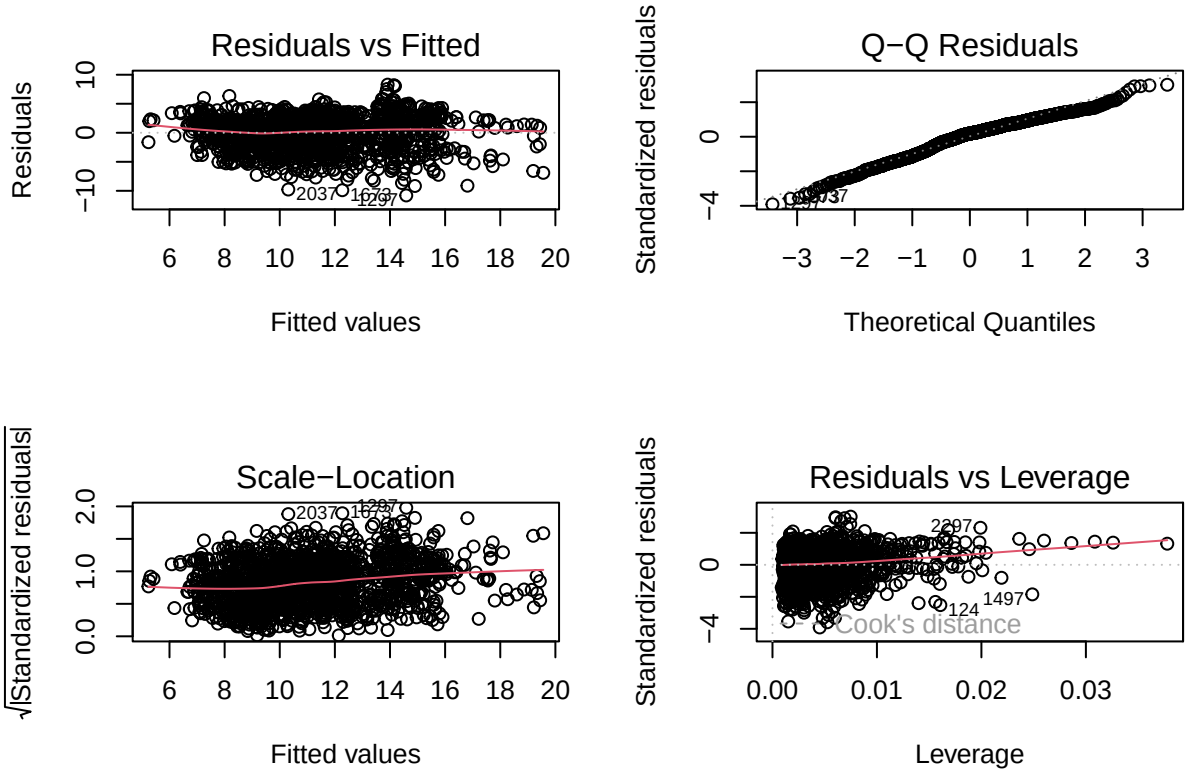





```
##
## Call:
## lm(formula = bc_GDP ~ Status + I(Total.expenditure^2) + Polio +
##     I(log(Population)) + Income.composition.of.resources + I(Schooling^2),
##     data = clean_data6)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -10.7965  -1.8298   0.4982   1.9687   8.2887
##
## Coefficients:
##                                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)                      6.329789   0.597670  10.591  < 2e-16 ***
## StatusDeveloping                -1.245231   0.234032  -5.321 1.18e-07 ***
## I(Total.expenditure^2)           0.003577   0.002429   1.473    0.141
## Polio                           -0.003347   0.003242  -1.032    0.302
## I(log(Population))              -0.002211   0.025005  -0.088    0.930
## Income.composition.of.resources  4.154936   0.591220   7.028 3.07e-12 ***
## I(Schooling^2)                   0.022231   0.001746  12.733  < 2e-16 ***
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.765 on 1640 degrees of freedom
## Multiple R-squared:  0.4343, Adjusted R-squared:  0.4322
## F-statistic: 209.8 on 6 and 1640 DF,  p-value: < 2.2e-16

## Analysis of Variance Table
##
## Response: bc_GDP
##                                  Df  Sum Sq Mean Sq  F value    Pr(>F)
## Status                            1  4376.3  4376.3 572.3355 < 2.2e-16 ***
## I(Total.expenditure^2)            1   271.9   271.9  35.5587 3.025e-09 ***
## Polio                             1   292.1   292.1  38.1981 8.048e-10 ***
## I(log(Population))                1     4.7     4.7   0.6124     0.434
## Income.composition.of.resources   1  3441.1  3441.1 450.0292 < 2.2e-16 ***
## I(Schooling^2)                    1  1239.6  1239.6 162.1216 < 2.2e-16 ***
## Residuals                      1640 12540.1     7.6
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```



Final model inference and results

Discussion and conclusion ‘

Author contributions

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