Child Mortality & Health Expenditure: A Cross-Country Analysis

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Abstract

This paper attempts to analyze the effect healthcare expenditure has on child mortality rates. Despite research already being done in this field, child mortality continues to be a problem in the global economy. While the type of relationship between healthcare and child mortality is generally agreed upon in modern economics, the exact change we would expect to see in child mortality from a change in healthcare expenditure is still unknown. Our paper provides further evidence towards what sort of impact we might see by looking at the relationship of these two variables in 105 different countries.

I. Introduction

We live in a world that is plagued with a multitude of health problems, especially in this day and age after the considerable devastation from COVID-19. One of the biggest health problems we as a world face to this day is child mortality. Child mortality refers to the death of children before their fifth birthday. While there is no doubt that the child mortality rate has decreased over the years, unfortunately in 2020, there were 5 million children that died before reaching the age of 5. Child mortality is a topic that researchers have pored over for years, trying to pinpoint its causes and aim for definite solutions.

According to the United Nations Sustainable Development Goals, countries all over the world are supposed to strive to create a healthy living environment for their domestic population, including the most vulnerable, such as children. However, the problems that lead to child morality, such as extreme poverty or unsafe living conditions, can be global at times, making it a difficult situation to resolve. Research still shows that globally, infectious diseases such as pneumonia, malaria, etc. remain the leading causes of death for children under five. Naturally, one of the most impactful ways to combat these diseases that impact the entire nation is to look to the federal government and public health expenditure.

Health expenditure simply measures the final consumption of healthcare goods and services in a given country. Healthcare goods and services encompass a wide range of things whether that be medical equipment, long-term care, public health services, and so on. There is no recommended spending level on health expenditures from any overarching organization as it is a decision that can depend on the situation, the country, and its GDP. However, we would still expect that countries with a higher level of healthcare expenditure would have better overall health outcomes, and therefore lower child mortality.

This study will test our thoughts by performing analyses on cross-sectional data of countries' healthcare expenditures and the level/amount of child mortality apparent in these countries. We believe that countries with higher health expenditures will simply have better equipment, services, health processes, and more that would contribute to the improvement of the overall health of their population. With a healthy population, a country would experience numerous economic benefits, such as increased labor productivity.

We specifically chose “health expenditure” as our independent variable because we wanted to observe how fiscal action could affect child mortality. This separates ourselves from other studies that tend to focus on situations such as poverty, living conditions, disease, etc. In addition, this particular topic is important as studying the relationship between health expenditure and childhood mortality will lead to a better understanding of the direct effects that an increase/decrease in expenditure can lead to and what steps should be taken.

II. Literature Review

A very recent study done by Cardona et al. (2022) estimated the potential loss of life in children under 5 years old that could be attributable to the economic downturns that happened in 2020. The study specifically aims to “address the indirect economic effects of the COVID-19 pandemic by estimating the impact of different economic downturn scenarios on under-5 mortality in low, lower-middle, and upper-middle-income countries” (para. 6). The researchers accessed reputable, credible databases for their research into the relationship between GDP and child mortality with the data being from the World Bank World Development Indicators database and the United Nations World Populations Prospects estimates. Using the data, they performed multilevel mixed effects multivariable regression analysis to ultimately isolate the GDP mortality effect controlling for other variables. In an attempt to be sure that the results accounted for the most possible errors, the researchers also examined the uncertainty range of their estimates. For their baseline projection where there was no reduction in GDP but rather just the original number, they found that the estimated loss of lives for children under 5 would be 19.2 million. However, for scenarios with a GDP reduction of 10% or 15%, there would be 19.8 million and 20.2 million lives lost respectively. For a 15% reduction in GDP, that would be more than an additional 900,000 under-5 lives lost in comparison to the baseline projection. In the end, the study found an estimate that shows the economic downturns of 2020 significantly increased the loss of life among children under 5 years old.

Dhrifi (2018) provided research and insight into the topic of healthcare expenditures, economic growth, and infant mortality. His paper seeks to investigate the effect that healthcare expenditure can have on child mortality through a simultaneous-equation model. The model in the paper consisted of 93 developed and developing countries with data that spanned from 1995-2012. This specific paper was unique in the fact that it not only looked at the direct effects of healthcare expenditures but also the indirect effects of economic growth. After performing the appropriate analyses of the data, the researcher was able to find significant results. The outcomes showed that a per capita income growth does indeed have a significant effect on reducing child mortality, specifically that a 1% increase in per capita income reduces child mortality by 0.76%. The paper goes on to discuss how factors related to economic growth could portray a possible reduction in the child mortality rate. For example, a high economic growth rate would have a considerable effect in reducing poverty or at least alleviating the circumstances of poverty. With this, the paper found that a 1% decrease in the poverty rate decreases the child mortality rate by

1.05%. However, even with these interesting relationships between the tested variables, the main goal of this paper was to test whether health spending can reduce child mortality and how significant of an effect it would be. It was found that a 1% increase in healthcare expenditures could lead to a total effect of a 0.52% decrease in the child mortality rate (0.17% direct impact and 0.35% indirect impact).

Nyamuranga and Shin (2019) were more focused in the sense that they looked at a comparison between specific regions which happened to be the Southern African Development Community (SADC), the Sub-Saharan Africa (SSA) region, and the developing world as a whole. The comparison incorporated public health expenditure and child mortality rates for the countries in those regions. For data, the study used panel data that was taken from the World Development Indicators database for the period of 2000-2013, and the data included 98 developing countries (15 SADC countries). The researchers estimated a dynamic data model of child mortality by using a method of moments technique. There was a statistically significant finding that indicated that public health expenditure did have an effect on reducing infant and under-five mortality rates in developing countries. It also showed that its effect was the strongest in the SADC region. Certainly, this particular study had its limitation in the perspective of being the base literature for our research as it only looked at developing countries. However, it gave a unique insight into how to focus on a certain region, and still provided relevant data on the variables that we ourselves are considering.

There is a significant amount of literature that looks at our topic of interest or any related fields of interest. Many studies and papers perform complex analyses of different datasets to determine the effects of healthcare expenditure, private expenditure, GDP, etc. While there are many pieces of literature that do explore these areas of health expenditure and child mortality, we believe that our paper can still contribute to the space. Our paper, with our individual analysis and databases, could still add a result and perspective that supports other pieces of literature but is nonetheless unique to the area of study. This is why we believe that our work can still be unique to some degree and contribute to the literature in the cross-sectional area of economics, health expenditure, and child mortality.

III. Data

To model the relationship between child mortality and health expenditure, we gathered a sample size of 105 countries. We were determined to have education and average income as our control variables as we expect both variables to have an impact on child mortality. Most current literature related to this topic incorporated some form of GDP/income. Therefore we included income per capita as one of our variables. Literature such as Dhrifi (2018) used variables such as poverty, but we wanted to consider variables that were extensions of those literature variables, notably development and education, so we added primary school completion rate and whether a country is developed as our other two variables. We would expect that countries with high national incomes would have low mortality rates, as parents can afford good healthcare for their children. Countries with high national incomes also tend to be developed countries where taxes are high, allowing government healthcare expenditure to be high (ex: as seen in Germany and the United Kingdom).

We would also expect a close relationship with education. Countries with large national incomes per capita can afford better education, making education more rewarding. Education also leads to health-related technology and practices that would reduce child mortality.

In our data, we had some interesting spreads and statistics. Child mortality rate, health expenditure per capita, and income per capita were heavily skewed to the right, while the percentage of primary school completion was skewed left. These spreads are not surprising. It would seem intuitive that most countries have a few child mortalities a year, with some experiencing unusually high mortality rates. While the average annual child mortality rate was 22 (out of 1,000 live births), Sierra Leone had an extremely high rate of 112. This can be explained by the country's struggles with numerous diseases, such as malaria, that can be extremely fatal to infants. Iceland had a noticeably low mortality rate at 2 per 1,000 live births.

For health expenditure, the highest value by far was by the United States with $10,921 spent on average per capita. This is not surprising given that prices for health services in the United States have recently been extremely high compared to other developed countries. In our data for primary completion rate for the relevant age group, some countries, such as Belarus (108) and Colombia (107) had over 100% completion rates. This is likely due to the way the completion rate is calculated (number of primary completions / number of children in a certain age group), which allows for a completion rate of over 100% by allowing for completion of older/younger ages.

Data was especially limited post-2019, which is why we selected 2019 as the year, as it was the most recent year with data pre-pandemic. This data was gathered by the World Bank, and all data is of 2019.

Table 1: Variable Descriptions

Variable Name	Description	Year	Units	Source
MR	Child mortality rate (before age 5) per 1,000 live births	2019	Number of people	World Bank
HE	Health expenditure per capita	2019	USD	World Bank
Y	Adjusted net national income per capita	2019	USD	World Bank
ECR	The percent of the relevant age group that has completed primary school	2019	Percentage	World Bank
Dev	Development status of countries built from HDI	2019	Dummy: 0 = developing 1 = developed	World Bank

Figure 1: Log Health Expenditure vs Mortality Rate

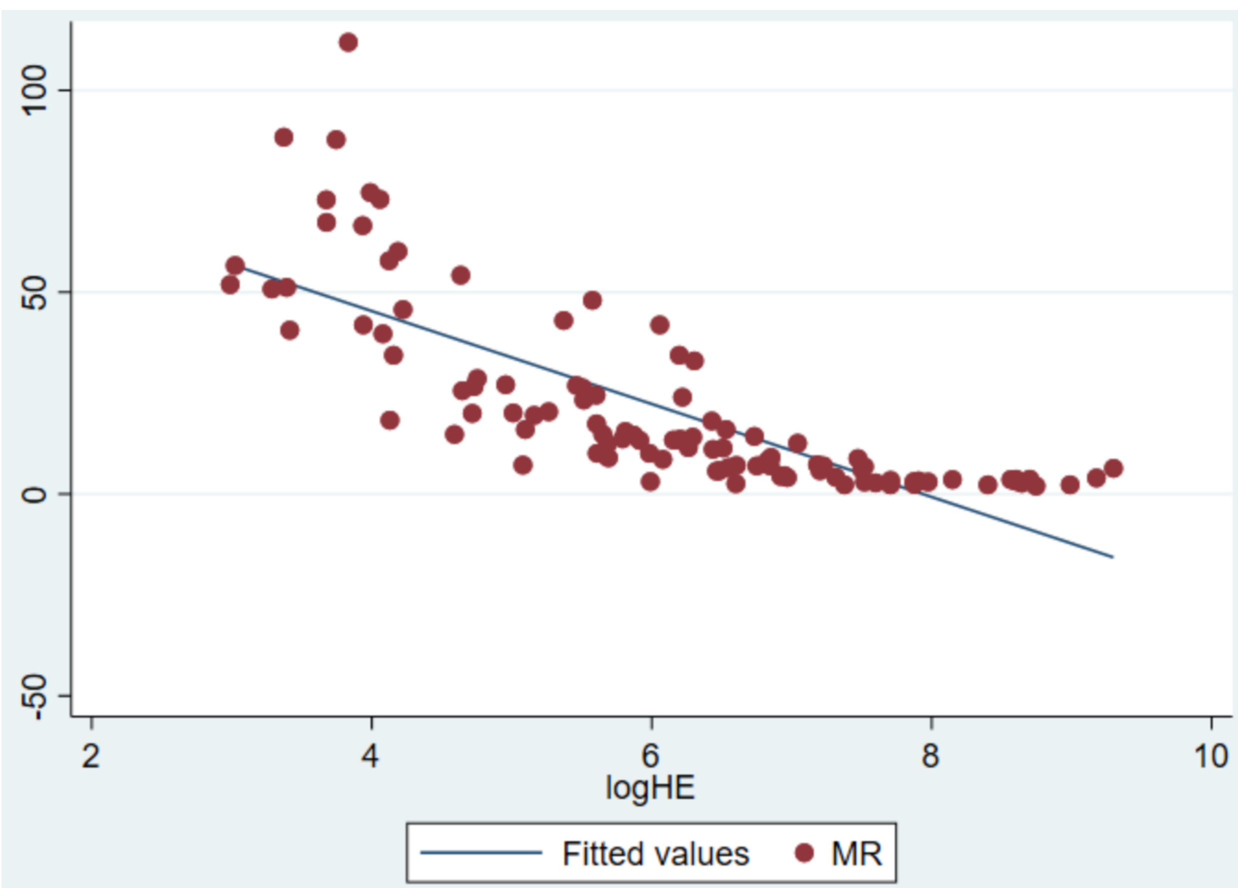

Table 2: Descriptive Statistics

Variable Name	Observations	Mean	Std. Dev.	Min	Max
MR	105	21.7	22.9	2	111.9
HE	105	1237.4	2023.5	19.8	10921.0
Y	105	12754.0	15593.6	165.7	63271.8
ECR	105	93.1	12.4	54.7	111.9
Dev	105	0.5	0.5	0	1

Before running the tests, the Classic Linear Model assumptions must be checked.

1) **Linear in Parameters:** $y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + u$

   β represents the slope parameters. As seen in the equation, these are all kept linear (ex: no β^2).

2) **Random Sampling:**

   The 105 countries used in this sample were all available countries that had data in the four variables we are including in our regression models. It should be noted that there could be some correlation between the countries lacking data and the variables used in our analysis. Therefore, certain regions may be underrepresented, and focusing on this limitation could be an area for future research. Here, however, we will assume that the condition of random sampling is met.

3) **No Perfect Collinearity:**

   As seen in Appendix C and as expected, there is no perfect collinearity between any variables (ex: one is not a scalar of another). Additionally, no variables are constant in this analysis.

4) **Zero Conditional Mean:**

   This condition suggests that $E(u_i x_i) = 0$ for all x values. As seen in Figure 1, the scatter points seem to have the same distribution above and below the line of best fit. The sum of residuals is approximately 0. However, there could be a scenario with this assumption being violated through bias if there is an omitted variable that has a correlation with the included explanatory variables.

5) **Homoscedasticity:**

   Once again, looking at Figure 1, we do not see anything that violates this condition. The variation of y from the line of best fit seems independent of the x values. Therefore, the variation of residuals from 0 would also seem independent of the x values, and there would be constant variance. There could be a possibility of heteroscedasticity appearing, but it would still leave the model unbiased.

6) **Normality**

This assumes the error u is independent of the explanatory variables in the models and is normally distributed with a zero mean and constant variance. To prove/determine this assumption, we plotted both a histogram of residuals to show the normal curve as well as a Q-Q plot. The plotted graphs are shown in Appendix I and J.

IV. Results

Model 1: (Simple Regression)

$$MR = 91.4 - \underset{(.9)}{11.5}(\log HE) + u$$

When we created the simple regression model with child mortality rate and health expenditure, we got an intercept of 91.4 and a slope coefficient of -11.5. Therefore, our model predicts that a country with no health expenditure would have a child mortality rate of 9.14% (91.4 out of 1,000 live births). For every 1 percent increase in health expenditure, the model predicts that child mortality would decrease by 1.15%. It is also nice to note that the standard error is relatively small at 0.9, and the logHE had a p-value of 0.000, demonstrating that it is extremely significant.

Model 2: (Multiple Regression)

$$MR = 149.2 - \underset{(2.9)}{2.9}\log(HE) - \underset{(3.4)}{4.7}\log(Y) - \underset{(0.1)}{.7}(ECR) - \underset{(3.7)}{5.4}(Dev) + u$$

We added all our variables to this model. As seen in the OLS Results table below and Appendix E, health expenditure loses the significance it had in model 1, increasing from a p-value of 0.000 to 0.331. As expected, the slope coefficient for health expenditure decreased; this model predicts that for every 1 percent increase in health expenditure, child mortality will decrease by 2.9 per 1,000 live births. Interestingly, primary completion rate was the only variable that showed significance at the 10% level. This makes sense considering health expenditure, income, and whether a country is developed or not are all likely heavily correlated. As shown in extensions, income and health expenditure were found to be jointly significant.

Model 3: (Multiple Regression)

$$MR = 132.4 - \underset{(1.3)}{6.5}\log(HE) - \underset{(3.4)}{0.7}(ECR) - \underset{(3.6)}{6.3}(Dev) + u$$

Given that health expenditure and income were jointly significant, we decided to remove income from our third model. Health expenditure's p-value once again dropped to a value of 0.000, and its slope increased to 6.5; therefore, our model would predict child mortality to decrease by .65 percent for every 1 percent increase in health expenditure. The primary completion rate remained significant with a p-value of 0.000. Our dummy variable, development, was also significant at a 10% significance level since its p-value was .082.

Model 4: (Multiple Regression)

$$MR = 110.2 - \underset{(3.4)}{5.2}\log(HE) - \underset{(3.9)}{6.4}\log(Y) - \underset{(4.2)}{4.0}(Dev) + u$$

In model 4, we added back the income variable and removed the primary completion rate. Health expenditure was no longer significant and its slope dropped to slightly to 5.2. Interestingly, none of the values were significant at the 10% level. As previously stated, this makes sense given that income and health expenditure are jointly significant.

OLS Results

Independent Variables	(1)	(2)	(3)	(4)
logHE	-11.5*** (.9)	-2.9 (2.9)	-6.5*** (1.3)	-5.2 (3.4)
logY	--	-4.7 (3.4)	--	-6.4 (3.9)
ECR	--	-0.7*** (0.1)	-0.7*** (3.4)	--
Dev	--	-5.4 (3.7)	-6.3* (3.6)	-4.0 (4.2)

*Significant at *10%, **5%, and ***1%*

Given the relatively large sample size and three control variables, these models furthers the notion that health expenditure decreases child mortality. This conclusion is not surprising, as it has already been thoroughly supported by previous research. As healthcare expenditure increases, people have better access to healthcare. With this better access to healthcare, children have an improved chance to fend off disease, survive otherwise fatal injuries, and so on. Therefore, it becomes more important to try and estimate the exact effect healthcare expenditure has on child mortality. This will allow for a more efficient fiscal policy. Our model suggests that healthcare expenditure has a moderate effect on child mortality. Additionally, healthcare expenditure would have impacts on other age groups, which is beyond the scope of this study.

V. Extensions

I. Robustness Test

As discussed before, there are individual parts of the regression models that may be correlated, so it was important that we did a “robustness check” to examine how those regression coefficients change by dropping certain regressors, especially correlated ones. Both logY and logHE have been chosen as the ones to be dropped because of the high correlation shown in Appendix C.

The null hypothesis for this robustness test is shown below:

$$H_o : \beta_1 = \beta_2 = 0$$

We chose Model 2 to be our unrestricted model as it was the multiple regression model that contained all of our tested variables. The equation formed below, in Appendix H, will be created by dropping the stated variables from above. Thus, our F-test will be conducted using these unrestricted and restricted models.

__Restricted Multiple Regression:__

MR = 124.59 - 1.01(ECR) - 18.55(Dev) + u
(10.61) (.118) (2.94)

The calculations for the F-test of joint significance are as follows:

$$F = \frac{\left(\frac{SSRr \; - \; SSRur}{q}\right)}{\left(\frac{SSRur}{n-k-1}\right)} = \frac{\left(\frac{20336.96 \; - \; 14974.12}{2}\right)}{\left(\frac{14974.12}{105-4-1}\right)} = 17.91$$

The critical value of the F test (with the appropriate degrees of freedom) is around 4.85 at a 1% significance level. Our calculated F statistic of 17.91 was much higher than the critical value which allows us to reject our null hypothesis. Thus, we can see that the two dropped variables of logY and logHE were not highly significant on their own but are jointly significant, most likely due to their high level of correlation. Our 3rd model in Appendix F removes logY in an attempt to deal with this collinearity. In the future, these variables should be carefully and appropriately considered together.

II. Different Functional Forms

Quadratic Multiple Regression Form:

$$\mathbf{MR = 165.65 - (1.6 * 10^{-7})(HE2) - 8.9(logY) - 0.7(ECR) - 5.5(Dev) + u}$$
$$\qquad\qquad (8 * 10^{-8}) \qquad\quad (1.6) \qquad (.1) \qquad (3.6)$$

Further information about this model is provided in Appendix K. Instead of taking the natural logarithm of health expenditure per capita, we took its quadratic (HE^2). This yielded interesting results as the significance of the health expenditure variable sharply rose as the p-value dropped from 0.331 in Model 2 to 0.050. Even more interesting was that the R^2 value was much higher than expected at around 0.73. This value was higher than all of our other models, so with this model, the data fit the regression model well. In the future, it could be appropriate to use HE^2 in different models.

III. Dummy Variables

In our data segment, we introduced our dummy variable, developed, which assigned a 1 to developed countries and 0 to developing countries. For this, we used the World Bank's data on the Human Development Index (measured from 0 - 1) of countries to build our dummy variable using the said 0.8 as a threshold for developed vs. developing. For all of our models written in the paper and presented in the Appendix, we used the developed variable, so our multiple regression models have already taken the dummy variable into account. It was interesting to see the significance level of the dummy variable change as we removed some variables/added others and the effect of being a developed vs. developing country on the child mortality rate.

VI. Conclusions

With the multiple regression models, we noticed that our main independent variable, *logHE*, had a negative coefficient which was in line with our initial hypothesis that an increase in health expenditure would decrease the child mortality rate. While the coefficients support our logical assumption of a negative correlation between health expenditure and child mortality rate, the significance levels for logHE vary throughout the models, and our highest significance is with a t-statistic of -4.98 and a p-value of 0.00 in model 3. Through our robustness tests, though there may be multicollinearity issues that may ruin our CLM, we were able to find where that issue may occur and account for it by dropping one of the jointly significant variables. The models still had an R-squared value greater than 0.6.

In terms of limitations, having more recent data from 2021 would have allowed our results to be more up-to-date with current global trends and the impact of the pandemic. There was also an issue of missing data for individual countries which limited our sample size and the quality of data that we were able to access. In addition, we would have liked to have a dataset that filtered child mortality incidents by cause of death so that we could clean out the data that did not relate to a health/healthcare issue death.

Ultimately, this paper only looks at the main relationship between health expenditure and child mortality rate. One future area of research would be to consider another variable as the main independent variable while controlling for other ideas. We believe that the Human Development Index would be an interesting variable to consider in relation to the child mortality rate. Of course, another avenue to research would be to simply continue with health expenditure but add even more relevant control variables to obtain a better model. With this paper being written as a cross-country analysis from aggregated 2019 data, there is no understanding of how these trends would continue over time. Thus, future work could also consider doing a time series analysis which would overall provide a better understanding of the relationship between child mortality rate and healthcare expenditure.

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Appendix:

Appendix A: List of Countries

Afghanistan	United Arab Emi	Argentina	Armenia	Austria	Azerbaijan	Burundi	Benin	Burkina Faso
Bulgaria	Bahrain	Belarus	Belize	Bolivia	Barbados	Brunei Darussala	Bhutan	Switzerland
Chile	Cameroon	Colombia	Costa Rica	Cyprus	Czechia	Germany	Djibouti	Denmark
Dominican Repu	Algeria	Ecuador	Egypt, Arab Rep.	Spain	Estonia	Ethiopia	Finland	Fiji
Gabon	Georgia	Gambia, The	Greece	Guatemala	Croatia	Hungary	India	Ireland
Iran, Islamic Rep	Iceland	Israel	Italy	Jamaica	Jordan	Kazakhstan	Kyrgyz Republic	Cambodia
Korea, Rep.	Kuwait	Lao PDR	St. Lucia	Sri Lanka	Morocco	Moldova	Madagascar	Maldives
Mexico	Montenegro	Mongolia	Mozambique	Mauritania	Mauritius	Malawi	Malaysia	Namibia
Norway	Oman	Pakistan	Peru	Philippines	Poland	Portugal	Qatar	Romania
Russian Federati	Rwanda	Saudi Arabia	Senegal	Singapore	Solomon Islands	Sierra Leone	Serbia	Suriname
Slovak Republic	Slovenia	Sweden	Eswatini	Seychelles	Togo	Thailand	Turkiye	United States
Uzbekistan	St. Vincent and t	Vanuatu	Samoa	South Africa	Zimbabwe			

Appendix B: STATA Summaries

. summ

Variable	Obs	Mean	Std. dev.	Min	Max
MR	105	21.71143	22.93122	2	111.9
HE	105	1237.437	2023.545	19.84998	10921.01
Y	105	12754.02	15593.57	165.7095	63271.76
ECR	105	93.11184	12.44786	54.72869	111.9388
Dev	105	.4571429	.5005491	0	1

Appendix C: Correlation Matrix

. correlate
(obs=105)

	MR	HE	Y	ECR	Dev
MR	1.0000				
HE	-0.4194	1.0000			
Y	-0.5147	0.9155	1.0000		
ECR	-0.7191	0.2916	0.3582	1.0000	
Dev	-0.6342	0.5434	0.6638	0.4167	1.0000

Appendix D: Model 1

```
. regress MR logHE
```

Source	SS	df	MS
Model	33483.5509	1	33483.5509
Residual	21203.8954	103	205.863062
Total	54687.4463	104	525.84083

Number of obs	=	105
F(1, 103)	=	162.65
Prob > F	=	0.0000
R-squared	=	0.6123
Adj R-squared	=	0.6085
Root MSE	=	14.348

MR	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
logHE	-11.51254	.9027022	-12.75	0.000	-13.30283	-9.72224
_cons	91.38184	5.639476	16.20	0.000	80.19727	102.5664

Appendix E: Model 2

```
. regress MR logHE logY ECR Dev
```

Source	SS	df	MS
Model	39713.327	4	9928.33174
Residual	14974.1193	100	149.741193
Total	54687.4463	104	525.84083

Number of obs	=	105
F(4, 100)	=	66.30
Prob > F	=	0.0000
R-squared	=	0.7262
Adj R-squared	=	0.7152
Root MSE	=	12.237

MR	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
logHE	-2.874157	2.945168	-0.98	0.331	-8.717286	2.968972
logY	-4.673436	3.388886	-1.38	0.171	-11.39689	2.050018
ECR	-.7200582	.1203208	-5.98	0.000	-.9587713	-.4813452
Dev	-5.375954	3.660771	-1.47	0.145	-12.63882	1.886912
_cons	149.1778	15.51815	9.61	0.000	118.3902	179.9653

Appendix F: Model 3

```
. regress MR logHE ECR Dev
```

Source	SS	df	MS			
Model	39428.5533	3	13142.8511	Number of obs	=	105
Residual	15258.893	101	151.078148	F(3, 101)	=	86.99
Total	54687.4463	104	525.84083	Prob > F	=	0.0000
				R-squared	=	0.7210
				Adj R-squared	=	0.7127
				Root MSE	=	12.291

MR	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
logHE	-6.516561	1.308814	-4.98	0.000	-9.112895	-3.920226
ECR	-.7341297	.1204214	-6.10	0.000	-.9730133	-.4952461
Dev	-6.346672	3.608461	-1.76	0.082	-13.50489	.8115442
_cons	132.4052	9.680793	13.68	0.000	113.2011	151.6093

Appendix G: Model 4

```
. regress MR logHE logY Dev
```

Source	SS	df	MS			
Model	34350.4844	3	11450.1615	Number of obs	=	105
Residual	20336.9619	101	201.356058	F(3, 101)	=	56.87
Total	54687.4463	104	525.84083	Prob > F	=	0.0000
				R-squared	=	0.6281
				Adj R-squared	=	0.6171
				Root MSE	=	14.19

MR	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
logHE	-5.15862	3.386435	-1.52	0.131	-11.8764	1.559157
logY	-6.393335	3.915628	-1.63	0.106	-14.16089	1.374217
Dev	-4.027141	4.237011	-0.95	0.344	-12.43223	4.377949
_cons	110.2702	16.33959	6.75	0.000	77.8569	142.6836

Appendix H: Restricted Regression Model

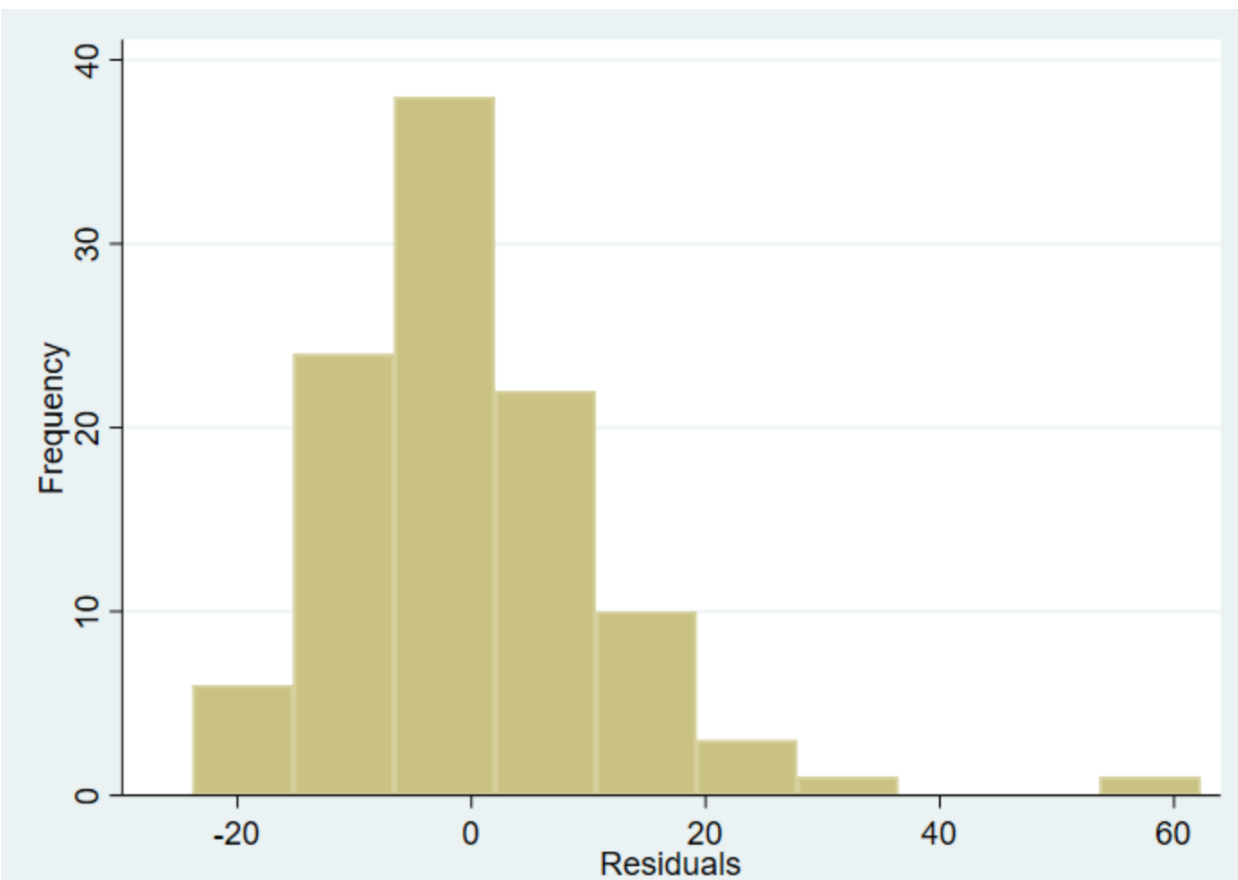
```
. regress MR ECR Dev
```

Source	SS	df	MS
Model	35683.2865	2	17841.6432
Residual	19004.1598	102	186.315293
Total	54687.4463	104	525.84083

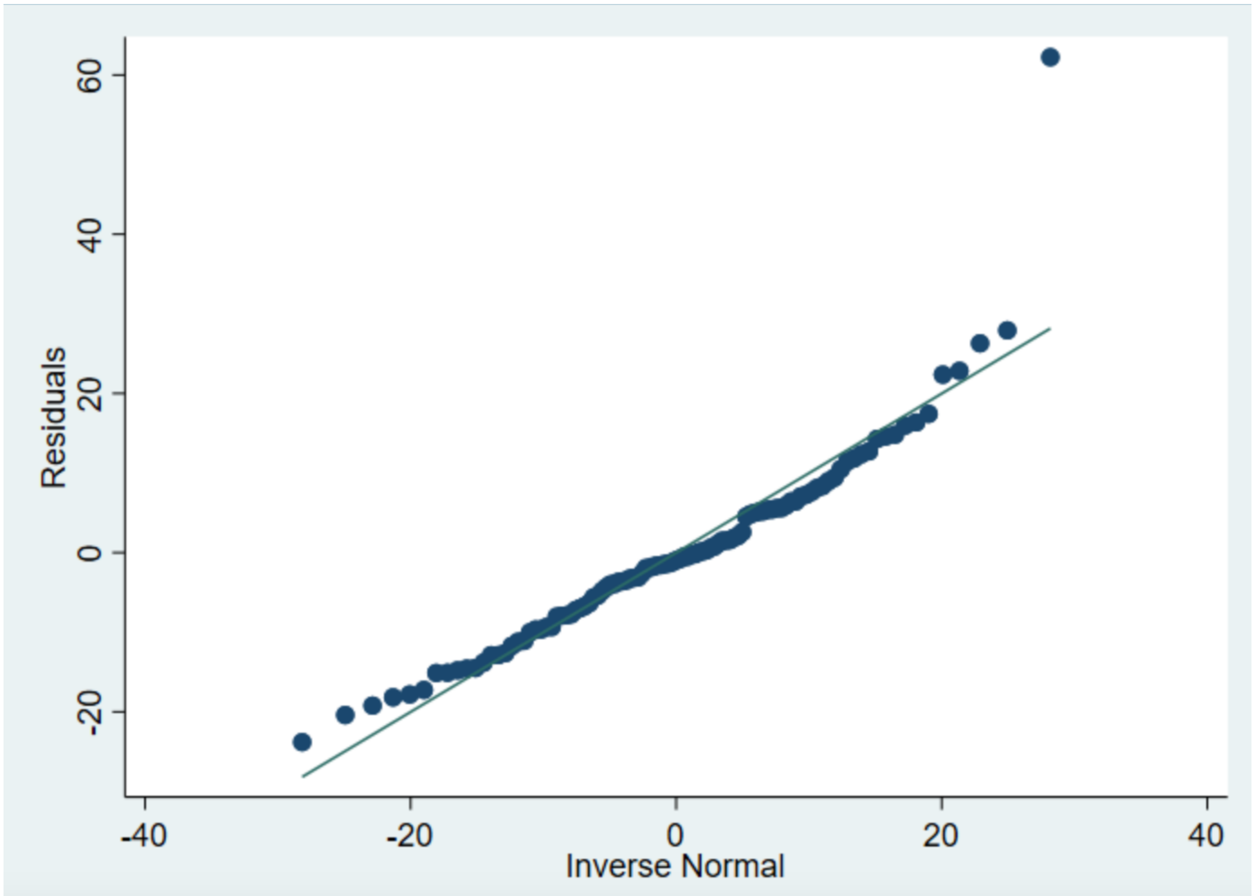
Number of obs	=	105
F(2, 102)	=	95.76
Prob > F	=	0.0000
R-squared	=	0.6525
Adj R-squared	=	0.6457
Root MSE	=	13.65

MR	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
ECR	-1.013858	.1182835	-8.57	0.000	-1.248472	-.779243
Dev	-18.54759	2.941521	-6.31	0.000	-24.38208	-12.71309
_cons	124.5925	10.60848	11.74	0.000	103.5506	145.6343

Appendix I: Histogram of Residuals



Appendix J: Q-Q Plot of Residuals



Appendix K: Quadratic Model

```
. regress MR HE2 logY ECR Dev
```

Source	SS	df	MS
Model	40140.8052	4	10035.2013
Residual	14546.6411	100	145.466411
Total	54687.4463	104	525.84083

Number of obs	=	105
F(4, 100)	=	68.99
Prob > F	=	0.0000
R-squared	=	0.7340
Adj R-squared	=	0.7234
Root MSE	=	12.061

MR	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
HE2	1.58e-07	7.97e-08	1.98	0.050	-3.44e-10	3.16e-07
logY	-8.91746	1.612647	-5.53	0.000	-12.1169	-5.718014
ECR	-.6970026	.1191694	-5.85	0.000	-.9334313	-.4605739
Dev	-5.491132	3.584704	-1.53	0.129	-12.60308	1.620818
_cons	165.6503	11.97233	13.84	0.000	141.8975	189.403