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A Statistical Analysis and Strategic Recommendations on Global Educational Investment and Poverty Reduction

[1]*Aadit Jain, [2]Hyunseo Aiden Ryou, [3]Junseo Andy Ryou, [4]Pukaphol Thienpreecha, [5]Robert Morrison

[1,3,4,5] Student, Rancho Bernardo High School

[2] Student, College of Arts and Sciences, University of Pennsylvania

https://orcid.org/0009-0002-4805-3665

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Abstract

Purpose: This study examines the relationship between educational funding and poverty alleviation worldwide. By analyzing data from 1960 to 2023, encompassing 71 countries, it aims to understand how increasing educational investment impacts poverty rates.

Methodology: The analysis utilized data from the World Bank's World Development Indicators. Data cleaning was performed using Excel, while statistical analyses were conducted using Python's sci-kit-learn, SciPy, NumPy, Matplotlib, and IBM's SPSS. The methodologies included a normal model setup, Gaussian Process Regression (GPR), linear regression, hypothesis testing, and confidence interval computation to establish correlations and predict outcomes.

Findings: The study discovered a negative correlation between education funding and poverty rates. Specifically, a 1% increase in educational spending as a percentage of GDP correlates with a 3.09% reduction in poverty rates. The 95% confidence interval of [-4.979, -1.201] and the hypothesis test with a p value of 0.002 on the slope of the regression line further reinforce the observed negative trend. GPR predictions indicate that the decrease in poverty rate changes from about 5% to 10% of population as educational funding rises from 0% to 1.5% of GDP. The likelihood of annual poverty rate increase stands at 40.46%, with a potential 0.4052% rise in such cases.

Unique contribution to theory, practice, and policy: This study recommends progressive educational funding reforms, targeted tax credits for educational investments, and strategic educational programs aligned with labor market needs. Policy implications suggest a multilateral approach involving governments, corporations, and citizens to foster substantial improvements in education and poverty reduction efforts. These findings advocate for data-driven policy reforms to optimize the socio-economic benefits of educational funding globally.

Keywords: *Poverty Alleviation, World Bank, Educational Funding, Global Education Trends.*

1.0 INTRODUCTIONANDBACKGROUND

A compelling body of research reinforces the relationship between educational investment and poverty alleviation. The "Journal of Public Economics findings," suggests that greater educational funding per capita tends to result in enhanced educational outcomes, particularly in underprivileged districts [1]. This improved educational performance is crucial in breaking the cycle of poverty. Furthermore, the interplay between poverty is multifaceted, with economic disparity. A study featured in the journal "Economies" indicates that poverty and income inequality bears a positive relationship as observed across 34 provinces in Indonesia [2]. Thus, the evidence supports the premise that bolstering educational funding can reduce poverty.

The scope and industry of our project are global as the audience of our statistical analysis is governments and legislators from nations across the globe. This is indicated by our inclusive data collection, gathering data from more than 71 nations around the world with diverse economic and geographical locations. With our recommendations and data, we hope to convince governments that specific actions can be taken to the already existing educational funding policies to scale the impact of poverty reduction through education.

Our problem statement is insufficient educational investment, exacerbated by recent global crises, threatens to deepen poverty rates, particularly among students from low-income backgrounds, necessitating multifaceted policy reforms and strategic educational funding enhancements. This analysis is done to study the hypothesized negative correlation between educational funding per capita and poverty rates. The risk of the increasing poverty rate is mainly due to the recent COVID-19 pandemic, wars, global warming, lack of jobs, and a poor healthcare system. Lack of educational resources can hinder access to quality education and limit social mobility, contributing to sustained poverty and possibly elevating it. Those most vulnerable to this risk are students and families from low-income backgrounds and communities, facing increased poverty rates in the long term. Risk mitigation could involve enhanced educational funding in pivotal areas, policy reforms to counteract income inequality, tax credit programs to fund education, and a 3-way collaboration between the citizen, corporation, and nation to revolutionize education. These strategies are grounded in the belief that education is a powerful tool for poverty alleviation and that increased education spending can lead to a decrease in poverty.

2.0 DATA METHODOLOGY

World Development Indicators - The World Bank Group:

https://databank.worldbank.org/home

- Credibility: The World Bank is an international financial institution that is backed by 189 member countries, making their data very reliable and heavily relied upon by large institutions. However, we do have missing data (especially from 1960s1980s in developing countries), forcing us to use differences between data points rather than absolute values.

- Importance to project: After searching for metrics about poverty rates and education data, many different sources were linked to the World Bank database's World Development Indicators. As the most extensive and accurate data source available, we sourced our modeling and simulation data from this source.
- Categorizing Data: The dataset helps define historical trends by including data from at least the past ten years (poverty and education data include data for the past 63 years). While the historical data can be used to project future trends using linear regression, the missing data makes it harder to perform reliable linear regression to forecast future outcomes and trends. The dataset effectively separates outcomes by providing data for each country of the world. The severity of risk can easily be characterized by looking at differences between poverty rates in a certain span of time and seeing whether we see an increase in poverty over that span. While the frequency of risk isn't that explicit, multiple differences between poverty rates can be used to create probability distributions like the normal model, binomial model, student-t model, Bernoulli model, etc
- Poverty headcount ratio at $2.15 a day (2017 PPP) (% of population):

– Motivation: In order to model the effect of education spending on poverty, we needed data that counted the poverty ratio for every country that was adjusted for inflation for fairness. We also used this dataset to model future risk if we didn't increase education data.

– Parameters: We took all data points from each country from the years 19602023. This dataset allowed us to link the education spending as a percent of GDP to poverty to perform a linear regression. We were able to find the change in poverty headcount ratio by taking the earliest and latest existing data point for each country and subtracting them, as well as the years between the data points to find the average change of poverty headcount ratio per year for each country. For risk modeling, we took each consecutive data point and subtracted them from each other, and divided them by the number of years past, in order to find the average change in poverty headcount ratio between each data point.

– Purpose: By performing a linear regression analysis we were able to look at the correlation between the government expenditure on education and poverty headcount ratio. In addition, by calculating the mean and standard deviation of the changes in poverty headcount ratio by year, we can model the future risk of poverty and probability of severe increase in poverty.

- Government expenditure on education, total (% of GDP):

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- Motivation: In order to model poverty by change of education data, we had to use an education - funding data type. We used % of GDP as our final indicator, as it was scaled by a country's actual wealth and thus could partially account for the difference between a country's economic status.
- Parameters: We took all data points from each country from the years 19602023. We took the earliest and latest data point from each country, and used it as our independent variable in linear regression.
- Purpose: By performing a linear regression analysis we were able to look at the correlation between the government expenditure on education and poverty headcount ratio.

3.0 MATHEMATICSMETHODOLOGY

We utilized the following three models to conduct our analyses:

- Normal Model Distribution
- Linear Regression
- Gaussian Process Regression

Normal Model Distribution

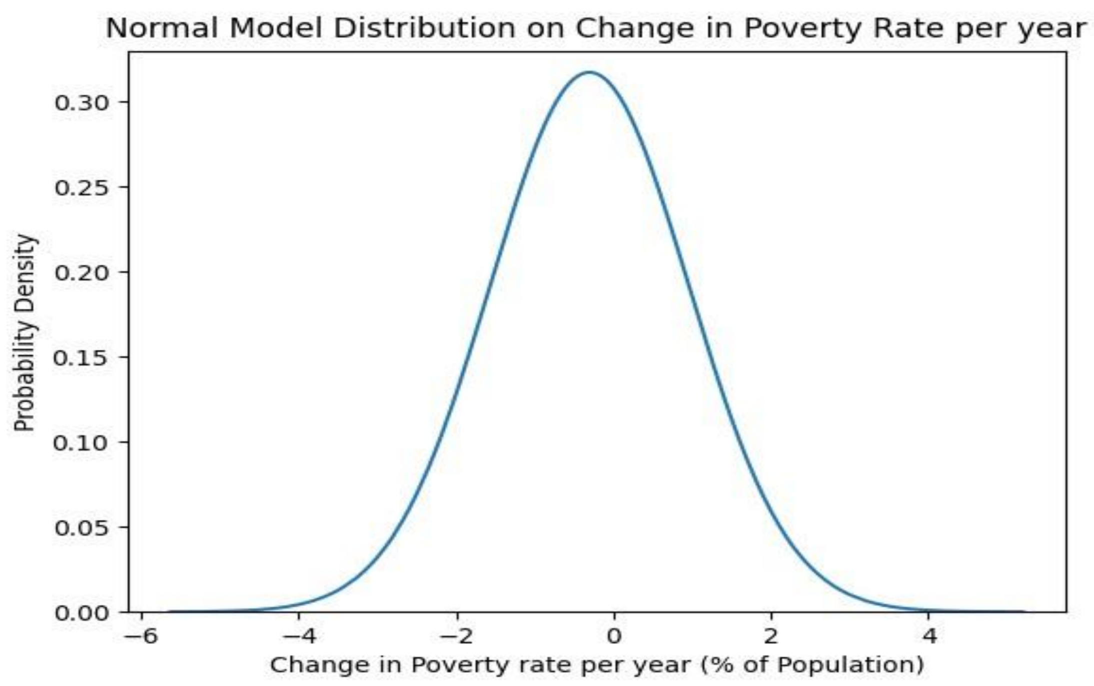

Figure 1: Normal Model

- Description: Utilizing the World Bank Poverty Data, we found the average change in poverty per year by subtracting consecutive points and dividing the difference by the number of years passed. The years passed were sometimes huge and other times they were quite small. Each country was treated as a separate entity but each country itself had multiple average changes in poverty per year since our data had a long range of years(1960 - 2023). We found the mean(-0.30373%) and standard deviation(1.258270%) of the average changes in poverty to construct a normal model in python. The normal model is bell-shaped and symmetric about the mean. The x-axis is the change in poverty rate per year and the y-axis is the probability density function, telling us the frequency with which a certain change in poverty rate occurs. The normal model allows us to compute the frequency and expected value associated with poverty increasing, which is defined as our risk.
- Assumptions: We assumed that the average change in poverty per year represents the actual change in poverty per year. Another assumption we made is that the average changes in poverty per year were symmetrically distributed about the mean and the distribution resembles a bell. Lastly, we have also assumed that the normal distribution for change in poverty rate per year we have constructed will be the same for the future as well.
- Accuracy: The following histogram (Figure 2) of the average change in poverty rates shows that the distribution is fairly symmetric and resembles the shape of a bell, justifying the use of a normal model. We also removed some outliers to construct the normal model, allowing the distribution of average change in poverty per year to more closely resemble the shape of a normal model. The use of average change of poverty per year is justified as it helps encapsulate the general trend of change in poverty when the years passed is quite big and also considers small-term changes in poverty when the years passed is small.

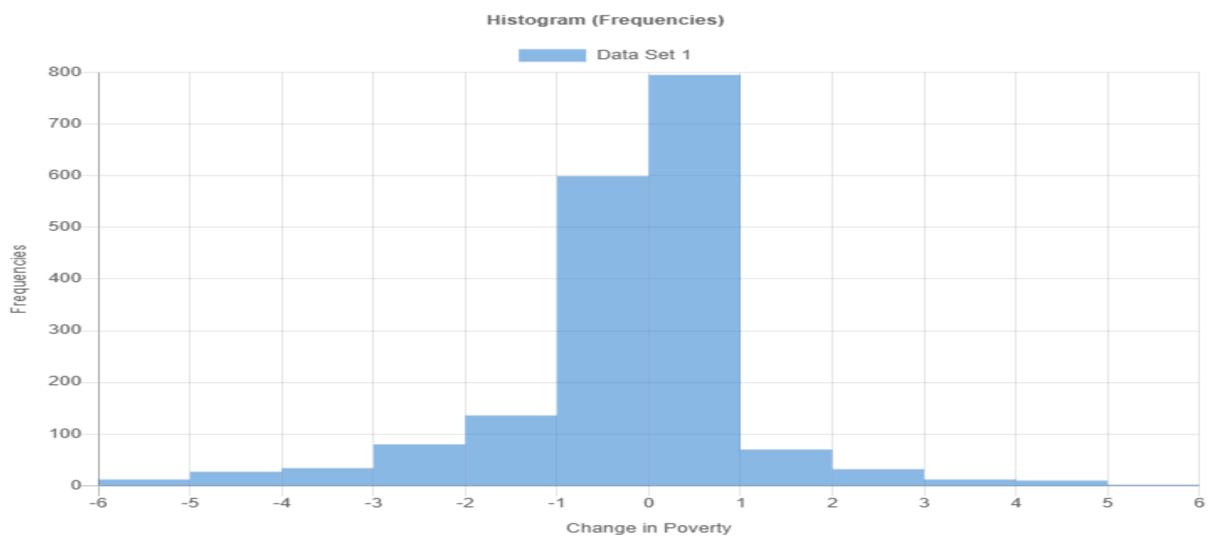

Figure 2: Histogram

- Trends and changes over time: The normal model is quite responding to trends and changes over time as it uses average change in poverty per year which accounts for both long-term(years passed is big) and short-term(years passed is small) change in poverty. It is considering both general trends over a long span and short term fluctuations that could be random.

Linear Regression

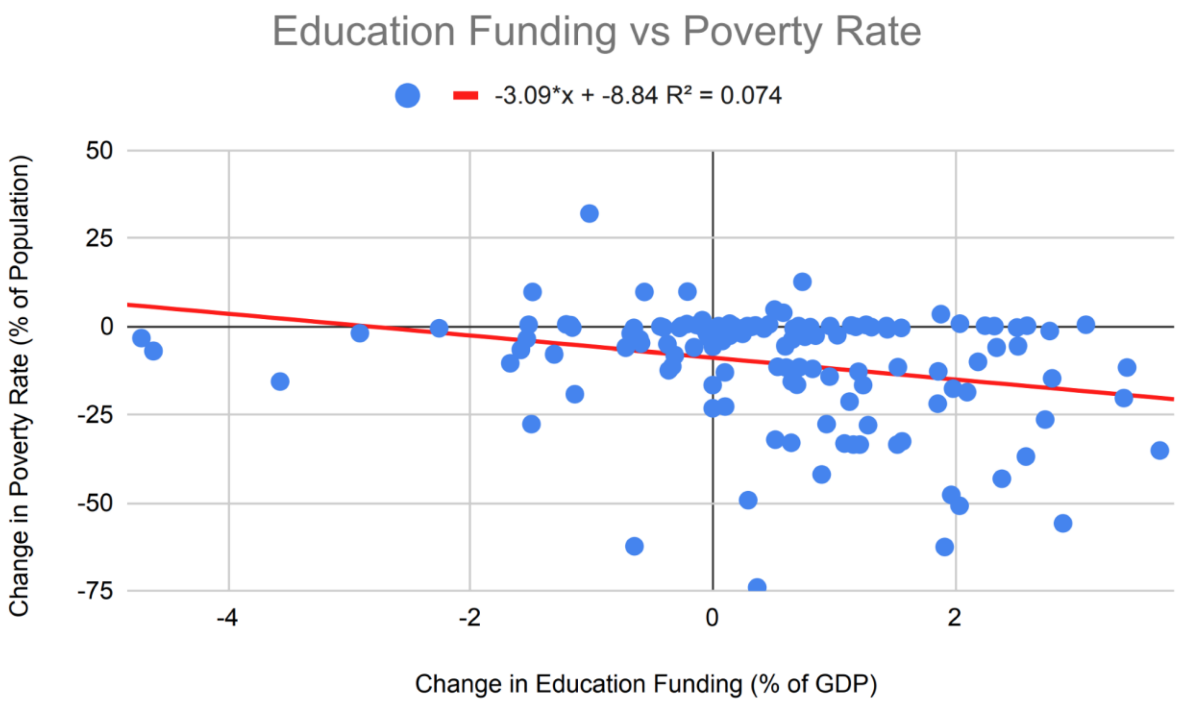

Figure 3: Linear Regression

- Description: For each country, we found the earliest and latest year where data for both education funding and poverty rate existed. We took the difference between the latest and earliest data points for both education and poverty. The x-axis is change in education funding and the y-axis is change in poverty rate. After plotting the x and y data points on a scatter plot (where each country is a single point), we did linear regression to find the line of best fit which is shown at the top of the graph. The slope of -3.09 indicates that as education funding increases by 1% of GDP, poverty rates tend to decrease by 3.09% of population, and as education funding decreases by 1% of GDP, poverty rates tend to increase by 3.09% of population. We also got the R value (0.272) which tells us how the strong the association is between change in education and change in poverty and the R^2 (0.074 or 7.4%) which tells us that 7.4% of the variation in change in poverty is accounted for by its regression with change in education funding.

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- Assumptions: We have assumed that there exists a linear relationship between change in education funding and change in poverty and the line of best fit that we have computed would hold true (be the same) for the future as well.
- Accuracy: The residual plot (Figure 4) for the linear regression is quite random which justifies the assumption that there exists a linear relationship between change in education funding and change in poverty rate. While the R value (0.272) is quite low and indicates a weak association, it still justifies the linear regression as R > 0 (R = 0 indicates no association) which indicates some association. We also conducted a two-tailed hypothesis test on the slope of the regression line with $H_0 : \beta = 0$ and $H_a : \beta , 0$. The p-value obtained was 0.002 (Figure 5). At $\alpha = 0.05$, there is sufficient evidence that there exists a significant linear relationship between change in education funding and change in poverty as $0.002 < 0.05$. Furthermore, we also computed a two-tailed 95% confidence interval for the slope of the regression line (Figure 5) and the confidence interval obtained was [-4.979,-1.201]. Since the confidence interval consists entirely of negative values, the negative trend observed in the linear regression is justified. The confidence interval also suggests that increasing education funding by 1% of GDP could decrease poverty rates by up to 4.979% of population, and decreasing education funding by 1% of GDP could increase poverty rates by up to 4.979% of population.

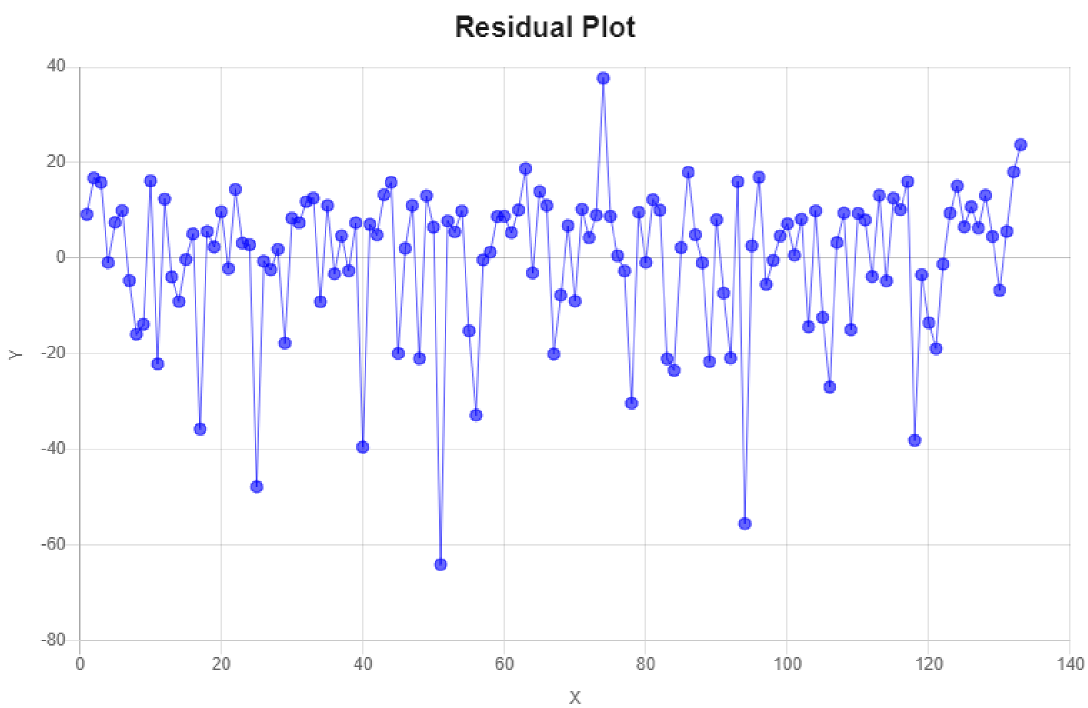

Figure 4: Residual Plot

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Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95.0% Confidence Interval for B Lower Bound	95.0% Confidence Interval for B Upper Bound
1	(Constant)	-8.842	1.454		-6.080	<.001	-11.719	-5.965
	EdFunding	-3.090	.955	-.272	-3.237	.002	-4.979	-1.201

Figure 5: Linear Regression Hypothesis Testing and Confidence Interval

- Trends and changes over time: The linear regression is quite responding to trends and changes over time as both the x and y axes data points represent long term changes and encapsulate the long-term trend. The linear regression doesn't contain short-term fluctuations present in the data which could be more random.

Gaussian Process Regression

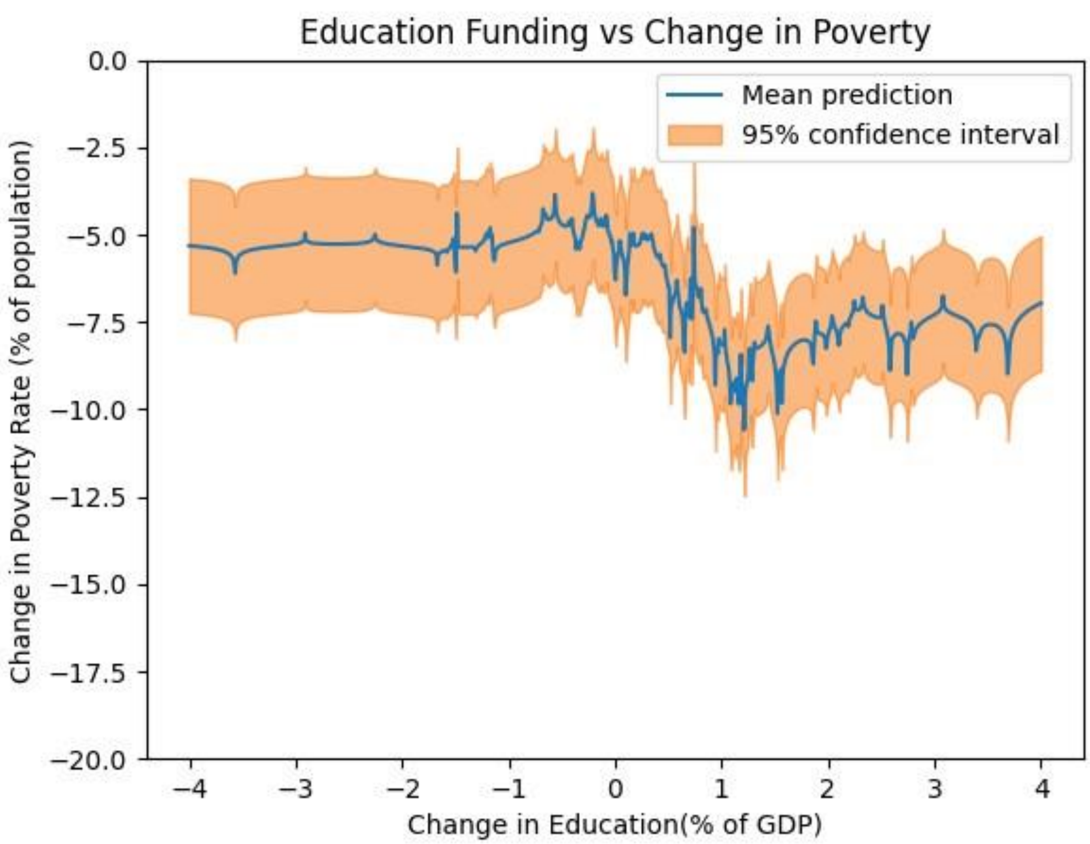

Figure 6: Gaussian Process Regression

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- Description: The Gaussian Process Regression(GPR) [5] is a coded simulation in python whose x and y axes and inputs are the same as the one used in the Linear Regression, except for some extreme values that were removed in the simulation. We use the Rational Quadratic Kernel (RQ Kernel) [6] for our simulation. The RQ Kernel is a common kernel in Machine learning that involves taking an infinite sum of exponentiated quadratic kernels with varying length scales. It measures similarity between pairs of data points using the Euclidean Distance between input vectors. Based on the inputs, GPR is able to predict the change in poverty based on change in education. It also builds a 95% confidence interval around each mean prediction of change in poverty, giving us the possible range of values of change in poverty for a certain value of change in education.
- Assumptions: By using the RQ Kernel, we assumed that the relationship between change in education funding and change in poverty would be smooth. GPR also assumes that the relationship between these two variables follows a Gaussian Process (a statistics model giving a probability distribution over possible functions). We have also assumed that the inputs to our simulation would remain the same in the future as well.
- Accuracy: The simulation is quite accurate as the RQ Kernel captures varying degrees of interactions between the variables, accounting for a lot of combinations. GPR provides predictions through probabilistic distributions over possible function values rather than probabilistic predictions over individual values, allowing us to consider more uncertainty while making predictions. Lastly, GPR takes into account our input data for the simulation and different hyperparameters have to be adjusted accordingly to create a reliable simulation. Hence, GPR is making predictions by capturing patterns and trends from the input data.
- Trends and changes over time: Like the linear regression model, this one is respondent to trends and changes over time as it uses data points that represent the long-term changes and trends instead of the short-term ones.

4.0 RISKANALYSIS

The risk we are researching is the increase of poverty in countries. Poverty increase is a combination of multiple factors such as lack of employment, pandemics or sudden natural disasters, lack of education and healthcare access, inflation, etc. Not only is the mitigation of poverty such as in the case of the homeless population in Los Angeles a moral imperative, but it will also equip businesses and corporations with a larger and more robust workforce. Reducing poverty and hence homelessness will help ensure more safety and cleanliness in cities while keeping individuals healthy. This, in turn, will help reduce extreme health-care costs. Moreover, poverty alleviation programs that train individuals to develop vocational skills will allow impoverished individuals to find jobs and be recruited. Additionally, lifting individuals out of poverty will enlarge the consumer market by bringing in more potential customers as individuals have more income to spend whether it be on their living expenses or recreational activities.

Since our data is symmetric and resembles the shape of a bell, we used a normal model to create a distribution for risk (poverty increasing). Each value of % change in poverty rate per year has a different probability of happening according to the normal PDF function. Values closer to the mean have a higher probability of happening while as we go farther from the mean, the chance of that particular % change in poverty happening becomes lower.

Summary statistics for % change in poverty per year - compiled data from all countries 1960-2023:

Descriptive Statistics

	N	Range	Minimum	Maximum	Mean	Std. Deviation	Variance
ChangeinPoverty	1809	10.825	-5.625	5.200	-.30373	1.258270	1.583
Valid N (listwise)	1809						

Figure 7: Descriptive Statistics

Normal model of % change in poverty per year - compiled data from all countries

1960-2023:

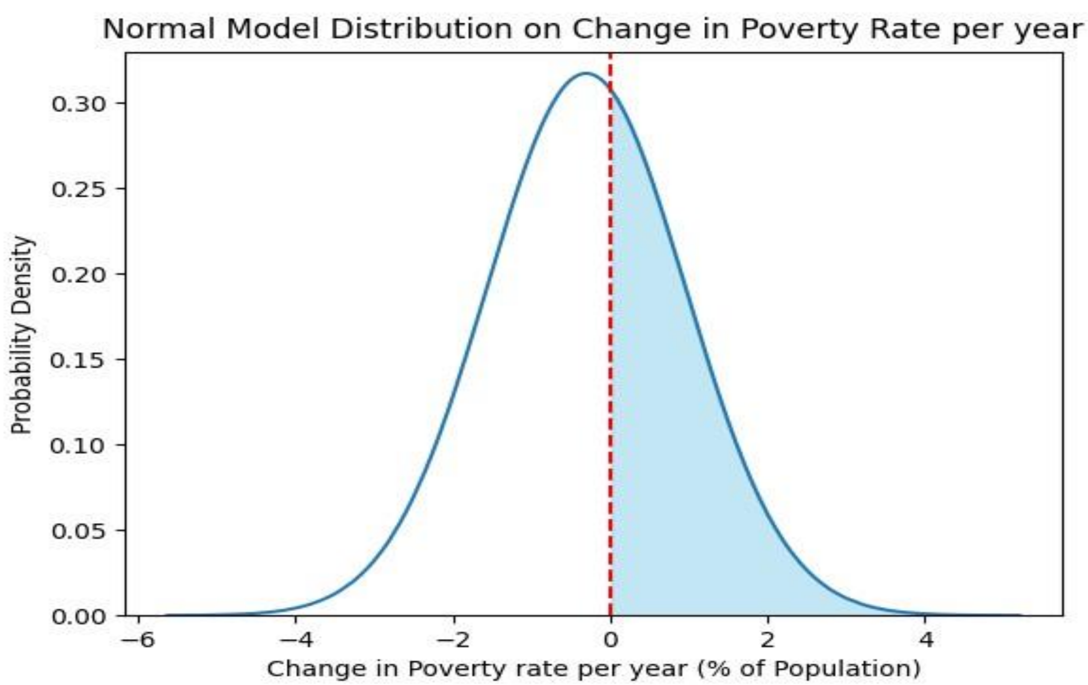

Figure 8: Normal Model for Risk Analysis

If we look at the risk of poverty increasing in a certain year, we get the following values:

- Frequency of risk(represented by the shaded area in the normal model) - 40.46% chance of poverty rate increasing
- Severity of risk - Change in Poverty rate per year being greater than 0%
- Expected value of risk- 0.4052 % increase in poverty per year

The frequency of risk as a % was computed using the normal Cumulative Density Function (CDF):

$$F = (1 - CDF(0)) \times 100 \qquad (1)$$

F represents the Frequency of Risk.

The expected value of risk was computed using the normal Probability Density Function(PDF):

$$E = \sum x_i \times PDF(x_i) \qquad (2)$$

E represents the Expected Value of Risk and x_i represents a data point whose change in poverty per year was greater than 0%.

Using the Expected Value and Frequency of Risk, we can interpret that there is a 40.46% chance of poverty rate increasing in a certain year and if poverty rate increases, then we'll likely see a 0.4052% increase in poverty rate.

Since our normal model encapsulates both long-term and short-term trends by using extensive data from 1960-2023, we believe that this normal model would be valid for the future as well. We believe that the long-term and short-term changes considered by our normal model would experience minimal change in the future, unless there is some sudden event such as a pandemic or a natural disaster. Hence the risk associated with poverty increasing would experience minimal change over time and the frequency, severity, and expected value of risk over time would be quite similar to the ones we have computed.

Our model assumes that year-to-year, risk will be equal for all countries, thus not accounting for external factors such as political instability, a volatile economy, or social unrest. However, it suffices for the purposes of defining risk for a basis for our general simulation.

5.0 RECOMMENDATIONS

The relationship between poverty and educational funding exhibits a complex interplay, as underscored by a visual analysis of international data trends gathered from more than 71 countries (see Figures 3 and 6). This complexity is reflected in our data, where changes in education funding as a percentage of GDP display a noticeable trend against changes in poverty rates, suggesting a nuanced dynamical relationship to be addressed with government policies.

The challenge at hand is the hypothesized inverse correlation between educational investment and poverty. Insufficient funding in education compounds the risks of poverty, particularly in economically disenfranchised areas. Our analysis, depicted in the scatter plot and regression line of Figure 3, illustrates a modest negative correlation (R = 0.272), indicating that as educational funding increases by 1% of GDP, poverty rates tend to decrease by 3.09 %. Moreover, the R^2 value (0.074) indicates that 7.4% of the decrease in poverty can be attributed to its regression with a change in education funding, indicating that an increase in education spending could make a significant impact on decreasing poverty rates. The significance of the linear relationship between change in education funding and change in poverty rates is solidified by the hypothesis test, where we obtained the p-value of 0.002. The 95% confidence interval obtained for the slope of the regression line was [-4.979,-1.201], which provides support for the observed negative trend and suggests that increasing education funding by 1% of GDP could decrease poverty rates by up to 4.979% of population. This trend echoes the recent findings of Purwono and his team of researchers who identified a positive relationship between poverty and income inequality across various regions

[2].

The Gaussian Process Regression (GPR) further supports this trend by showing that as education funding increases from 0% to about 1.5% of GDP, the decrease in poverty rate changes from about 5% to 10% of population. However, the change in poverty rate remains quite stagnant if education funding increases more than 1.5% of GDP. This indicates that simply increasing education funding after a certain threshold doesn't suffice and we need to look at more strategic educational investments.

From our data analysis and the literature review of relevant journals for poverty alleviation, we would like to suggest the following multilateral recommendations:

- Progressive Educational Funding Reform:

– Strategy Details: This reform involves a dynamic funding policy that adapts to the varying needs of districts based on their poverty levels and current educational performance, with the goal of equalizing opportunities. This approach is substantiated by the data in Figure 3 (which shows a negative trend) and the confidence interval for the slope of the regression line in Figure 5 (which consists entirely of negative values), suggesting that increased funding in certain regions could amplify its impact on poverty reduction. This strategy is data-driven and will require the bench marking of the performances of schools across the nation and allocating the funds to schools. With this model, schools will be categorized by their student demographics, poverty levels, and educational performance metrics.

- Implementation Plan: A policy reformulation is needed where state and federal education budgets are allocated not by uniform percentage increases but by a progressive equity-focused index that prioritizes underfunded schools. This model will need the collaboration of policymakers and data scientists to create a database of school data around the nation. Semi-supervised machine learning models could be trained to categorize schools that reach a specific poverty level or educational performance that will categorize them as needing more funding than schools that are already well off.
- Challenges and Metrics: Implementing such a reform poses challenges, including potential resistance from well-funded areas and the need for accurate data to inform the equity index. Success can be measured by monitoring changes in educational outcomes through standardized and poverty rates in the targeted areas over time.

• Targeted Tax Credits for Educational Investment:

- Strategy Details: The creation of tax credit programs would incentivize individuals and corporations to direct their investments toward educational improvements in impoverished areas. We drew this inspiration from the progressive cap and trade model for carbon reduction where human motivation is used for a sustainable development goal and in this case, education. By ensuring tax liability reduction, we aim to create a financial incentive for individuals and corporations to help alleviate poverty through education and create a more equitable society. The aim is to capitalize on the trend seen in Figure 6, where the confidence intervals suggest that strategic investment can lead to significant decreases in poverty rates. We drew inspiration from the empirical work of Schanzenbach et al. who found that targeted financial incentives such as tax reduction can stimulate investment in underfunded educational sectors [3].
- Implementation Plan: The government should establish a tiered tax credit system that provides larger credits for investments in high-need areas. These credits would be applicable to expenditures on educational infrastructure, scholarships, and teacher training programs, and would require collaboration between data analysts, tax authorities, and educational departments to monitor and evaluate the impact. As our data includes more than 71 nations from diverse economic and geographical backgrounds, we encourage a tax credit that is dynamic and versatile and varies from nation to nation.
- Challenges and Metrics: The challenge lies in structuring the credits to ensure they benefit the intended areas without exploitation by individuals and corporations. The impact of these credits can be studied by the data of private investment funneled into educational initiatives and the subsequent changes in local educational statistics and poverty levels. Private investment can be

measured by the collaboration of educational institutions to keep track of individuals and corporations that donate money to their respective institutions. Yearly, schools will be required to report their data to tax authorities and data analysts.

- Economic Diversification through Education:

– Strategy Details: By directing funds towards programs that are responsive to the changing labor market, particularly in STEM fields, the aim is to directly connect education with employability and economic growth. Investing in educational programs that align with the skill demands of the burgeoning sectors of the economy is the strategic investment needed to break the wall of the 1.5% change in education spending–poverty rates stagnation seen after that. Educational programs may come in the form of STEM courses, Career Technical Development courses (CTD), and IB courses. Additionally, it could provide an incentive for schools to modernize their education to fit with the real-time needs of the economy and population. This method is drawn from the work of educational expert Moretti who shows that investing in education to match the skill demands of the labor market leads to economic revitalization and poverty reduction [4]. This strategy would be a seismic shift in especially the lives of current low-income students as they would be given opportunities to develop marketable skills for their future careers.

– Implementation Plan: The creation of partnerships between educational institutions, local governments, and industries is crucial. These partnerships would develop curricula and training programs that are directly aligned with local economic development plans. In fact, these partnerships already exist in certain nations. For example, Norththrop Grunman provides an internship opportunity to partnering high schools in San Diego. Opportunities such as these provide students with the hands-on experience needed for employment. Additionally, establishing education-to-employment pipelines would ensure that the skills acquired in educational settings translate into tangible employment opportunities.

– Challenges and Metrics: The primary challenge is ensuring these programs remain responsive to rapidly evolving industry needs. The effectiveness of this strategy can be assessed by tracking the employment rates of program graduates and the economic growth of the involved regions via the use of classification machine learning models and data analysis.

In crafting these recommendations, we aim to weave a coherent narrative that not only presents a clear and quantifiable plan but also paints an inspiring vision of the future. These strategies are designed to resonate with stakeholders by showcasing the transformative potential of education funding as an instrument of social and economic upliftment internationally for low-income individuals, corporations, educational institutions like schools and colleges, and governments. Through pragmatic planning, legislative action, and community engagement, education funding can be a powerful catalyst for reducing poverty, as our analysis and the corroborating academic research compellingly suggest.

6.0 ACKNOWLEDGEMENTS

This study was conducted in part of the Modelling the Future Challenge hosted by the

Actuarial Foundation where it earned the title of finalist as one of the top 15 across the United States. We would like to acknowledge their guidance and mentorship for the creation of this paper. The Modeling the Future Challenge is a prestigious, real-world competition for high school students combining math modeling, data analysis, and risk management. Here, we conduct our own research project modeling real-world data to analyze risks and make recommendations to companies, industry groups, governments, or organizations.

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