The Effect of Economic Growth on Health: A Case Study of the United Kingdom (1960-2015)

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Abstract

The study conducted in this report has explored the connection between economic growth and how health had been impacted in the United Kingdom. This mainly focused on Infant Mortality Rate(IMR) from 1960 to 2015. Data of health expenditure from 2000 to 2015 has also been used for analysis. Machine learning techniques, including Linear Regression, Polynomial Regression, and Random Forest models were used to gather the impact of Gross Domestic Product (GDP) per capita and also for the 2000-2015 period, health expenditure as a percentage of GDP on IMR. The analysis has revealed a significant inverse correlation between GDP per capita and IMR, with the relationship showing non-linear characteristics. Health expenditure was also found to be a significant factor in more recent years. The findings of this analysis aim to provide insights into the difficult interchange of economic factors and public health by demonstrating the utility of data-driven approaches in this domain of health and wealth.

Contents

1 Introduction

This project takes a look at an important question, how does a country's money situation affect the health of its people around the country? We are focusing specifically on the one country, that is, the United Kingdom (UK), and looking at data we have from 1960, all the way to 2015. It's very fascinating to see how things have changed over such a long period of time, especially in a country like the UK that has seen a lot of economic ups and downs but has always cared about making sure people are healthy.

Instead of just using the usual ways to study this, we are trying something a bit different by using what i have learned about data science and machine learning in my first semester. The idea is that by using these computer based tools to look at the numbers, we might uncover new patterns or understand the connection between money and health in a clearer way. We will see if these modern data tools like machine learning algorithms can give us a fresh look at this old question.

One common idea out there that I would like to introduce is called the Preston curve [1]. Normally, this idea says that countries with more money usually have people who live longer and are healthier. But, it also says that once a country gets pretty wealthy(developed country), just getting even richer doesn't make as big a difference to health as it does for poorer countries. This is a good point to start with, but it doesn't always tell the full story for one specific country over many years or when we look at specific health measures. That's why we are going deeper into the UK's data.

Our main goal here is to use these data science methods to check the link between the UK's wealth which is measured by a factor called Gross Domestic Product (GDP) per person and a really important health sign called the Infant Mortality Rate (IMR). IMR denotes us about how many babies out of every thousand born don't make it to their first birthday. It's a sensitive indicator of how good a country's overall health and care systems are. We will look at this for the whole 1960-2015 period. Then, to get a more recent picture, we will also look at how much the UK spent on healthcare (as a part of its GDP) from 2000 to 2015, and see if that, along with GDP, had a noticeable effect on IMR.

By focusing on the UK, we hope to get a better idea of how money and health have been linked in a developed country. We think what we find could be useful for people who make decisions about healthcare and for anyone interested in how data can help us understand public health. The next parts of this report will explain the data we used, the methods we tried, what we found, and what it all might mean.

2 Literature Review

When we explore the connection between a country's economic health and the well being of its people, it's a subject that many have looked into. A key idea often discussed is the "Preston curve," introduced by Samuel Preston in 1975. This concept generally shows that as a country becomes wealthier (with a higher GDP) its population tends to live longer and experience better health. However, the biggest health gains from economic growth are usually seen in poorer nations. Once a country reaches a certain level of establishment in economic sector, simply increasing wealth doesn't bring about the same dramatic improvements in health, suggesting other factors become more critical [1]. Preston's work highlighted that the relationship is not fixed. Shifts in the curve over time suggested that factors beyond income such as technological advancements and public health knowledge also play crucial roles.

In the context of the United Kingdom, a report was read by me on the Marmot Review in 2010 led by Sir Michael Marmot has provided significant insights. This comprehensive study highlighted the strong links between social and economic conditions and health outcomes in England. It has highlighted that health inequalities are often tied to imbalance in income, education, and living conditions, indicating that a nation's overall GDP doesn't tell the whole story about individual and community health [2].

The review argued for a social gradient in health where health outcomes improve incrementally with socioeconomic status, suggesting that policies should aim to reduce these imbalance across the entire population, not just focus on the most unprivileged.

More recently, the rise of data science and machine learning has offered new ways to analyze these tough relationships and also these models makes an easier life for business across the globe. The modern analytical techniques has the ability to examine large datasets which helps to uncover patterns and insights that might have been previously hidden. These approaches can help identify key factors influencing public health and the effectiveness of different interventions. For instance, machine learning can model non-linear relationships and interactions between variables that traditional linear models might miss offering a more subtle understanding of how economic factors translate into health outcomes.

For this project, the primary data on economic indicators (like GDP per capita) and health outcomes (like Infant Mortality Rate) for the UK was sourced from the World Bank's World Development Indicators database [3]. This rich dataset allows for a longitudinal look at how these factors have evolved and interacted over several decades. The specific dataset and any preliminary explorations or related work for this analysis can also be found at the my GitHub repository [4]. The World Bank data is widely used in economic and health research due to its widely coverage and standardized definitions making cross country and time-series analyses possible.

Our study aims to apply some of these data-driven approaches to the UK's historical data, focusing on understanding the specific relationship between economic growth and infant mortality, and how health expenditure might play a role in more recent years. By leveraging these methods, we hope to contribute to the existing body of literature by providing a detailed case study of a developed nation, potentially revealing patterns that are specific to high-income contexts where the basic determinants of health are largely met, and where the focus shifts to the efficiency and equity of health systems and the impact of more targeted investments.

3 Data and Methodology

To investigate the influence of economic factors on health outcomes within the United Kingdom, my study employs a methodology centered on the analysis of longitudinal data using machine learning techniques. This section outlines the data sources, the data preparation procedures, the selected machine learning models and the metrics used for model evaluation.

3.1 Information We Used

The analysis in this study is based on two primary datasets. First, we had a main set of information from a file named `longitudinal_data.csv`, covering the years from 1960 to 2015 for the United Kingdom. This information included a few key things. One was the Gross Domestic Product (GDP) for each person, measured in current US dollars. This tells us about the country's overall money situation each year. I have understood this to be sourced from the World Bank with its special code being `NY.GDP.PCAP.CD` and also this dataset was given as a primary resource in the assessment guidelines in minerva and it also stated that its taken from world bank. Another key piece of information was the Infant Mortality Rate (IMR), which is the number of babies out of every 1,000 born alive who die before their first birthday. This is a common way to measure how healthy a country's people are and how good its health care system is. This was also understood to be from the World Bank, with the code `SP.DYN.IMRT.IN`. The information also included the year, so we could see how things changed over time.

Secondly to get a better idea about how spending on health care might be involved, we gathered information about how much the UK spent on health as a part of its total GDP. We used a python library called `wbgapi` to get this information directly from the World Bank. This information was for the years 2000 to 2015, and its World Bank code is `SH.XPD.CHEX.GD.ZS`. This specific indicator, current health expenditure as a percentage of GDP, provides a measure of the societal resources allocated to health functions, regardless of the source of funding.

3.2 Getting the Information Ready

Prior to the application of machine learning models, a careful data preparation phase was undertaken. This process consisted of several critical steps to ensure the integrity and suitability of the data for analysis. The initial step involved data cleaning where both datasets were checked for missing values. Any year showing missing data for either GDP per capita or IMR was excluded to maintain the integrity of the subsequent modeling. A similar procedure was applied to the health expenditure data. Simultaneously, variable names were standardized for clarity and ease of interpretation. For instance, the World Bank indicator `NY.GDP.PCAP.CD` was relabeled to the more intuitive `GDP_per_capita`, and `SP.DYN.IMRT.IN` became `IMR`. Further, all numerical data were verified to ensure correct formatting for consistent processing for primarily confirming their treatment as numeric rather than text data. Lastly, the two datasets were merged. The primary dataset (containing GDP and IMR) was integrated with the health expenditure data using the `Year` variable as the common key. Given that the health expenditure data spanned only from 2000 to 2015, the resultant combined dataset was consequently restricted to this period, incorporating GDP per capita, IMR, and health expenditure as a percentage of GDP for these years. This temporal restriction for the combined analysis is important to note, as it focuses the investigation of health expenditure's role to a more recent period.

3.3 Machine Learning Methods

We used three different machine learning methods to look at the connection between the money-related information and IMR. We did this in two main parts. First, we looked at how GDP per person related to IMR from 1960 to 2015. Second, we looked at how GDP per person and health spending together related to IMR from 2000 to 2015.

The first method was Linear Regression. We used this to see if there was a simple, straight-line connection between our money related factors (like GDP per person, or GDP per person and health spending) and IMR. Linear regression assumes a linear relationship between the independent variable(s) and the dependent variable, providing a straightforward interpretation of the effect size through its coefficients.

The second method was Polynomial Regression. We used this because sometimes the connection between things isn't a straight line. This method can find curved relationships. We used a curve of degree 2, which is a common choice, allowing for a single bend in the relationship curve. This is particularly relevant when considering concepts like the Preston curve, which inherently suggests a non-linear association.

The third method was a Random Forest Regressor. This is a more advanced method that can find even more complicated, non-straight-line connections and can also tell us how different factors might work together. It is an ensemble learning method that operates by constructing a multitude of decision trees at training time and outputting the mean prediction of the individual trees. It also helps us see which money-related factors were more important in predicting IMR through its feature importance scores. When we used this method, we also used a tool called `StandardScaler` to make sure all our numbers were on a similar scale, which helps the Random Forest work better by preventing features with larger magnitudes from dominating the model. We set up the Random Forest to use 100 decision trees, with each tree not going too deep (a maximum depth of 5) and making sure each final branch had at least 2 pieces of information (min samples leaf = 2). These hyperparameters were chosen to balance model complexity and prevent overfitting.

For all these methods, when we needed to teach the machine learning model and then test it, we split our information. Most of it (usually 80% for the 1960-2015 dataset, or 75% for the smaller 2000-2015 set) was used to teach the model (training set). The rest (20% or 25%) was kept aside to test how well the model learned (test set). We used a setting called `random_state` (set to 42) to make sure that if we ran the work again, we would get the same results, ensuring reproducibility of the model training and evaluation process.

3.4 Checking How Well the Methods Worked

To see how well each machine learning method did, we used two common measures. One was Mean Squared Error (MSE), which tells us, on average, how far off the model's predictions were from the real IMR numbers; a lower MSE means the model did a better job. It is calculated as the average of the squared differences between the predicted and actual values. The other was the R-squared (R^2) Score, which tells us how much of the change in IMR can be explained by the money-related factors we put into the model; an R^2 score closer to 1 means the model explained a lot of the change and was a good fit. An R^2 of 0 indicates the model does no better than predicting the mean of the dependent variable, while an R^2 of 1 indicates a perfect fit. For the Random Forest method, we also looked at how important each money-related factor was in helping the model predict IMR. This is typically measured by the mean decrease in impurity (MDI), where features that contribute more to reducing impurity (or error) in the decision trees are considered more important.

3.5 Tools and Keeping Track

I did all my information preparation and machine learning work using the Python programming language (version 3.11). I used common tools like Pandas for handling information, NumPy for number work, Scikit-learn for the machine learning methods, and Matplotlib and Seaborn for making graphs. All the computer code we wrote for this is saved in a GitHub repository [4]. This means anyone can look at my code to see exactly what I did and try it themselves, promoting transparency and reproducibility in research.

4 Results and Analysis

This section presents the key findings derived from the analytical exploration of economic growth, health expenditure, and infant mortality rate (IMR) within the United Kingdom. The initial phase of our analysis involved a visual examination of long-term trends using time-series plots for Gross Domestic Product (GDP) per capita and Infant Mortality Rate (IMR) spanning the period from 1960 to 2015. These visualizations are crucial for understanding the historical context before delving into more complex modeling.

Observing the trajectory of GDP per capita in the United Kingdom, as depicted in Figure 1, reveals a story of consistent and substantial economic expansion over the 55-year period. The graph shows an upward trend, starting from a GDP per capita of approximately USD 1,380 in 1960 and rising to over USD 44,000 by 2015. This represents more than a 30-fold increase in nominal terms. While the growth is generally persistent, there are visible fluctuations, including periods of more rapid acceleration (e.g., the 1980s and late 1990s) and instances of slower growth or minor dips, likely corresponding to broader economic cycles and events such as the oil crises of the 1970s or the financial crisis of 2008-2009.

This sustained increase in national wealth provides the foundational economic context for potential improvements in public health infrastructure, education, sanitation, and living standards, which are often linked to health outcomes.

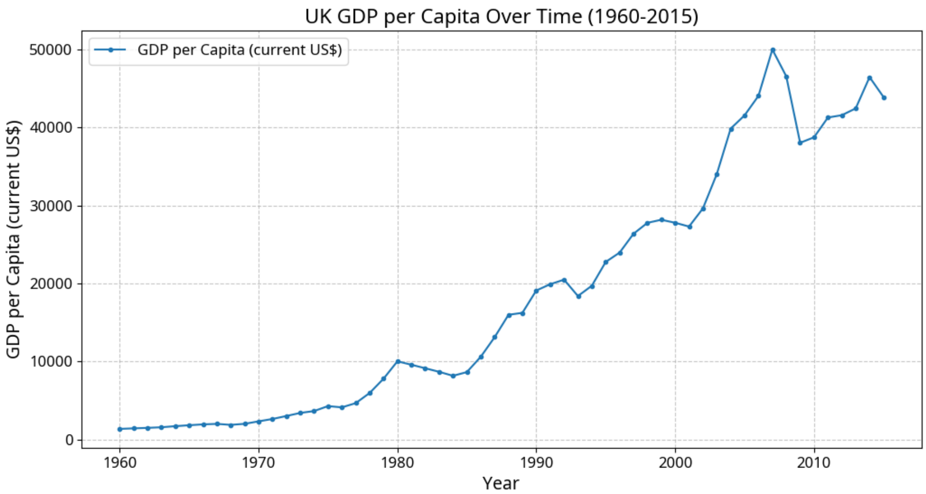

Figure 1: UK GDP per Capita Over Time (1960-2015)

Concurrently, the trend in infant health within the UK shown in Figure 2, illustrates a dramatic and highly positive transformation. The Infant Mortality Rate, which stood at a concerning 22.9 deaths per 1,000 live births in 1960, experienced a steep and continuous decline throughout the subsequent decades. By 2015, the IMR had fallen to approximately 3.9 deaths per 1,000 live births, a reduction of nearly 83%. This remarkable reduction signifies profound advancements in pediatric care, maternal health services, widespread immunization programs, improvements in sanitation and nutrition, and overall public health measures. The rate of decline appears sharper in the earlier decades (1960s-1980s), gradually becoming more modest as the IMR approached very low levels, a common pattern as countries eliminate the more easily preventable causes of infant mortality and further reductions require more advanced and often costly invlovement.

Focusing on the more recent period from 2000 to 2015, Figure 3 presents the trend in UK's health expenditure as a percentage of its GDP. The graph indicates a general upward trend in this allocation, starting from around 7.16% in 2000 and rising to approximately 9.8% by 2015, with some fluctuations. Notably, there was a significant increase in the early 2000s, followed by a period of more stability and then a slight rise towards the end of the period. This suggests an increasing prioritization of healthcare spending relative to the overall size of the economy during these years, possibly reflecting policy decisions to invest more in the National Health Service (NHS) and respond to growing healthcare demands from an aging population and technological advancements. This trend is important as it allows us to investigate whether this increased financial commitment to health, alongside general economic growth, had a discernible impact on health outcomes like IMR in the 21st century.

To quantify the relationship between economic growth and infant mortality over the long term (1960-

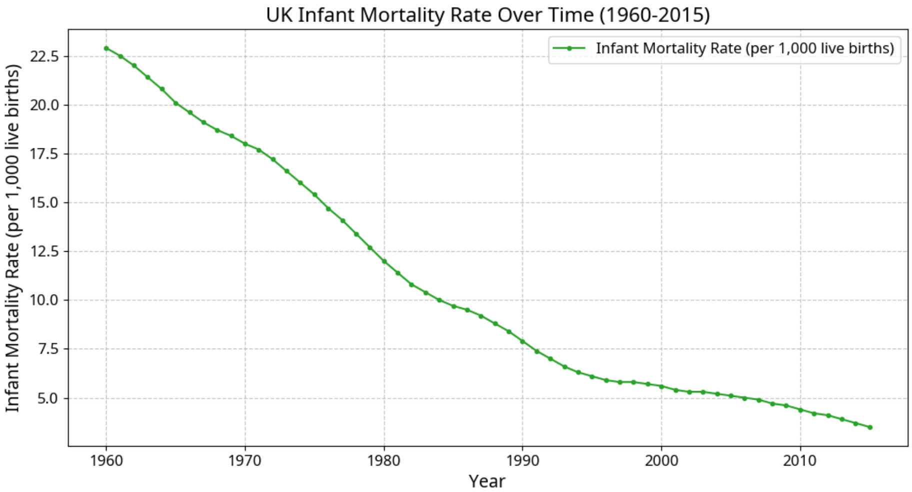

Figure 2: UK Infant Mortality Rate Over Time (1960-2015)

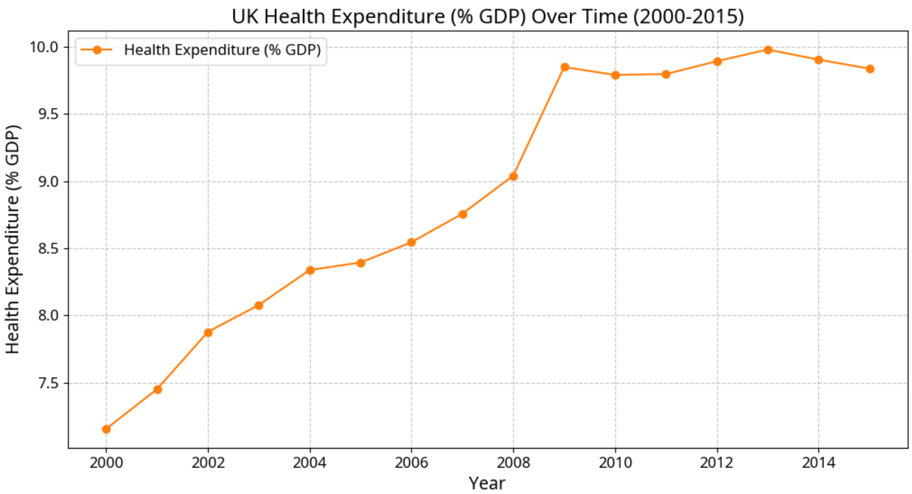

Figure 3: UK Health Expenditure (% GDP) Over Time (2000-2015)

2015), regression models were applied. A linear regression model predicting IMR from GDP per capita yielded an R^2 value of approximately 0.746. This indicates that roughly 74.6% of the variance in IMR over this 55-year period could be statistically explained by changes in GDP per capita. The Mean Squared Error (MSE) was approximately 12.00, which represents the average squared difference between the observed actual IMR and the IMR predicted by the model. This relationship is visualized in Figure 4. The scatter plot shows data points for each year, with GDP per capita on the x-axis and IMR on the y-axis. The overlaid red regression line clearly depicts a negative correlation: as GDP per capita increases, IMR tends to decrease. While the linear model captures this general trend, the scatter of points, particularly the slight curve suggested by the density of points, suggests that a simple straight line might not perfectly represent the nuances of this relationship across all levels of GDP.

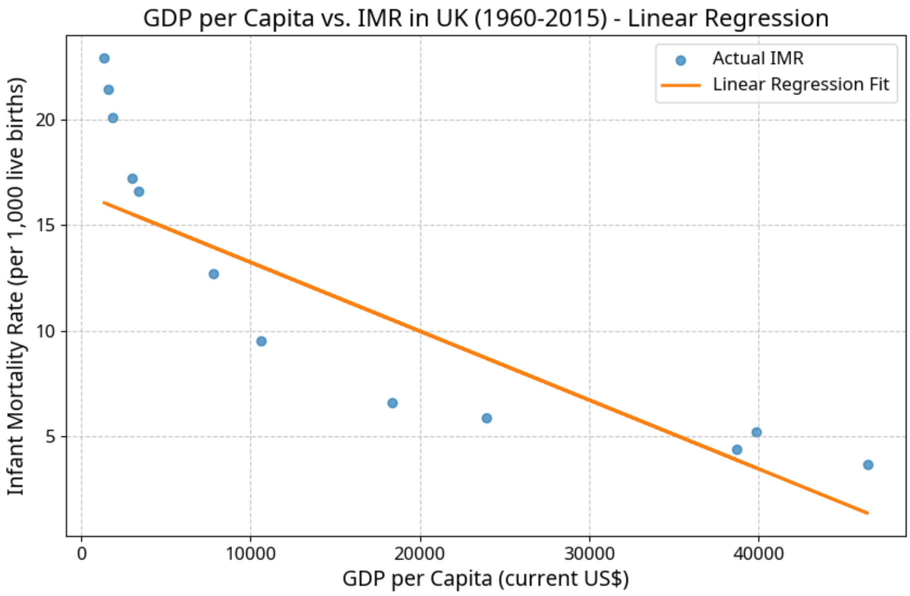

Figure 4: GDP per Capita vs. IMR in UK (1960-2015) - Linear Regression

A second degree polynomial regression model was also fitted to explore potential non-linearities. This model generally showed an improved fit with a higher R^2 value of approximately 0.927 and a lower MSE of approximately 3.43. The substantial increase in R^2 (from 0.746 to 0.927) and the significant decrease in MSE (from 12.00 to 3.43) suggest that the polynomial model provides a much better representation of the data. Figure 5 illustrates this curvilinear relationship. This suggests that while IMR decreases with rising GDP, the rate of decrease is not constant, it is steeper at lower levels of GDP and flattens out as GDP per capita becomes higher. The curve fits the data points more closely than the straight line, particularly capturing this diminishing return, which aligns with the principles of the Preston curve. This implies that initial economic growth brings rapid improvements in IMR, but as the country becomes wealthier, further increases in GDP have a progressively smaller impact on reducing IMR.

For the period 2000-2015, the analysis has incorporated health expenditure as an additional factor influencing IMR. A multiple linear regression model using both GDP per capita (`GDP_per_capita`) and Health Expenditure as a percentage of GDP (`Health_Expenditure_GDP_Percent`) as predictors for IMR

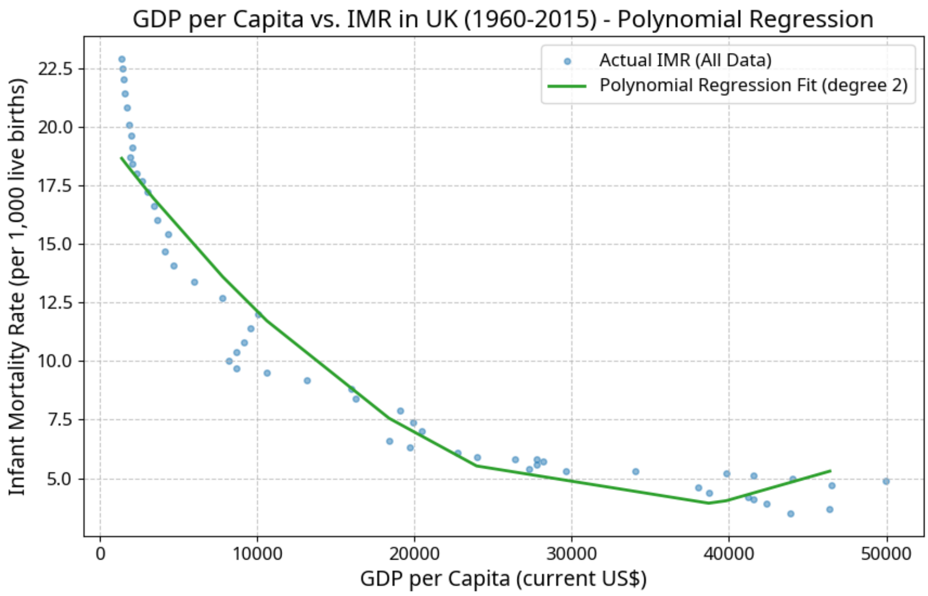

Figure 5: GDP per Capita vs. IMR in UK (1960-2015) - Polynomial Regression (Degree 2)

was developed. This model produced an R^2 value of approximately 0.817 and an MSE of approximately 0.101. The coefficients for `GDP_per_capita` and `Health_Expenditure_GDP_Percent` were approximately -6.86×10^{-6} and -0.641 respectively, with an intercept of about 10.74. These results suggested that holding other factors constant a one unit increase in health expenditure as a percentage of GDP is associated with a decrease of about 0.641 in IMR, while a one dollar increase in GDP per capita is associated with a very small decrease in IMR. This indicates that both higher GDP per capita and higher health expenditure as a percentage of GDP are associated with lower IMR during this period, with health expenditure showing a more considerable coefficient in terms of practical impact on IMR within this model.

To further explore these relationships with a more complex model capable of capturing non-linearities and interactions, a Random Forest Regressor was employed for the 2000-2015 data. This model yielded an R^2 of approximately 0.873 and an MSE of approximately 0.070, indicating a strong predictive performance and an improvement over the multiple linear regression model for this period. Figure 6 shows the actual versus predicted IMR values from the Random Forest model. The points generally aligning along the diagonal line (which represents perfect prediction) signify good prediction accuracy, with most predictions falling close to the actual values.

The feature importance analysis from the Random Forest model is presented in Figure 7. This analysis offered critical insights into the relative contributions of two key factors: `GDP_per_capita` and `Health_Expenditure_GDP_Percent`, in predicting IMR for the 2000-2015 period. The findings indicated that `Health_Expenditure_GDP_Percent` emerged as the dominant factor, holding an importance score of approximately 0.887 (or 88.7%). In contrast, `GDP_per_capita` registered a significantly lower importance score of about 0.113 (or 11.3%). This is a striking finding, suggesting that in this more recent period, for a high-income country like the UK, the proportion of national income dedicated specifically to health expenditure played a significantly more important role in explaining variations in IMR than overall

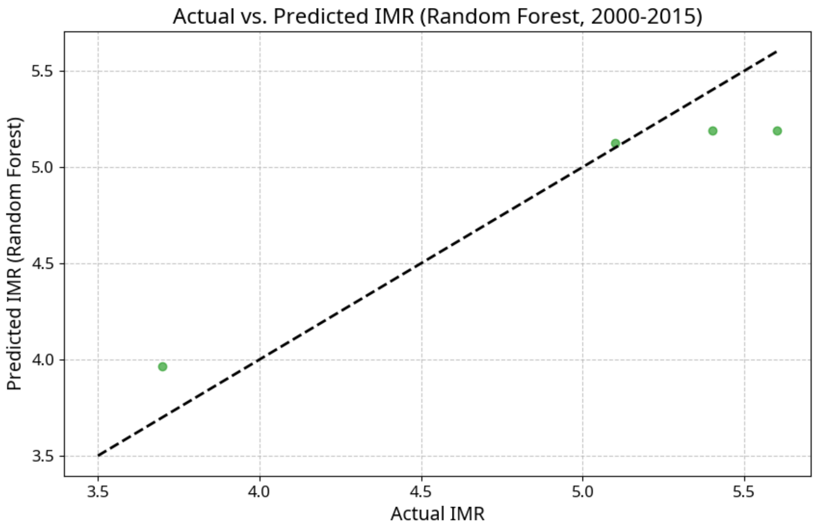

Figure 6: Actual vs. Predicted IMR using Random Forest (2000-2015)

economic wealth (GDP per capita) alone. This implies that how a wealthy country allocates its resources towards health may be more critical for marginal gains in health outcomes like IMR than simply the overall level of wealth.

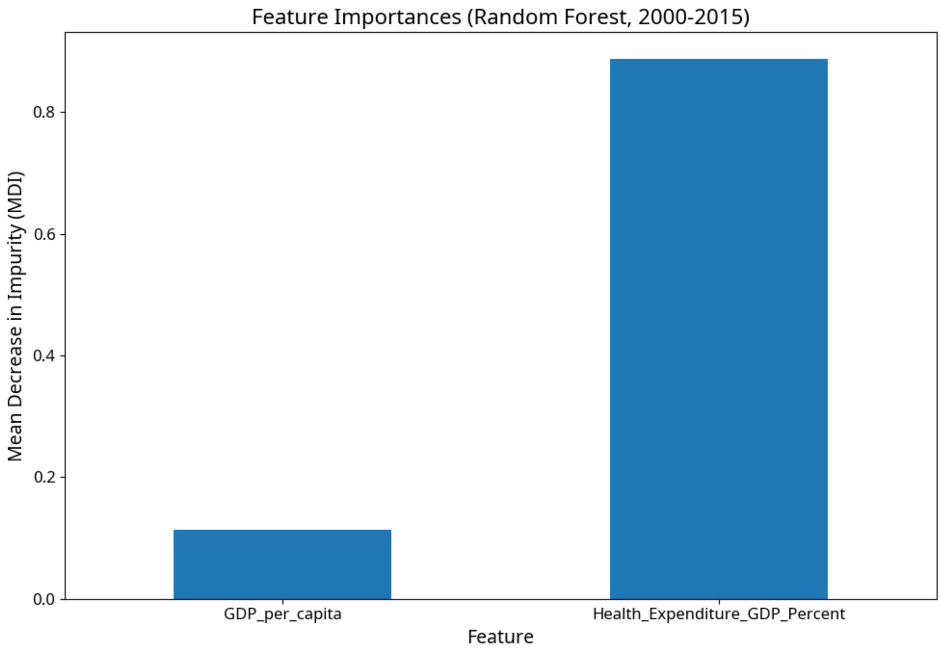

Figure 7: Feature Importances from Random Forest Model (2000-2015)

These findings collectively highlight the strong historical link between economic development and improvements in infant health in the UK. Moreover, the analysis of more recent data underscores the critical role of dedicated health expenditure, suggesting that policy decisions regarding healthcare funding are paramount for achieving further gains in health outcomes, even in affluent nations. The transition from GDP being a primary driver to health expenditure becoming more prominent reflects the evolving nature of health determinants as a country develops.

5 Discussion

The results of this study offer several points for discussion regarding the relationship between economic growth, health expenditure, and infant mortality in the United Kingdom. The long-term analysis (1960-2015) clearly has demonstrated a strong inverse correlation between GDP per capita and IMR, aligning with the general principle of the Preston curve. As the UK's economy grew substantially over these five decades there was a concurrent and dramatic fall in infant mortality. This supports the view that economic development is a main factor of improved population health, likely through many mechanisms such as better nutrition, housing, sanitation, and access to basic medical care that accompany increased national wealth.

The polynomial regression model has been the superior fit ($R^2 \approx 0.927$) compared to the linear model ($R^2 \approx 0.746$) for the 1960-2015 period, suggests that the relationship is not simply linear. The flattening of the curve at higher GDP levels implies that while economic growth is crucial for health improvements especially in earlier stages of development or when emerging from lower income levels, the marginal health gains from further economic growth diminish once a country achieves high income status. This is consistent with what we learn in Preston's observations and suggests that other factors, including the efficiency and equity of the healthcare system, social determinants of health (such as education and social support), and specific public health interventions, become increasingly important in driving health improvements in wealthier nations. Once IMR is already low, further reductions often require tackling more complex and less known causes of infant death, which may not be as responsive to general economic uplift alone.

The analysis of the more recent period (2000-2015), which has incorporated health expenditure as a percentage of GDP, provided further subtle insights. While GDP per capita continued to be a factor associated with lower IMR, the Random Forest model revealed that health expenditure was considerably more influential in predicting IMR during these years, accounting for approximately 88.7% of the feature importance (as seen in Figure 7). This is a significant finding because it suggests that for a developed nation like the UK which already possesses a high baseline level of economic wealth and a relatively low IMR, the specific allocation and potentially the effectiveness of resources towards healthcare are more direct and impactful drivers of marginal improvements in sensitive health indicators like IMR. The general increase in health expenditure as a percentage of GDP observed from 2000 to 2015 (as shown in Figure 3) likely contributed to the continued, albeit more gradual, decline in IMR during this period. This highlights that at higher levels of development, it is not just about having wealth, but how that wealth is strategically invested into the health system.

These findings have important implications for policy. They underscore that while broad economic prosperity lays an foundation for better public health, targeted investment in health services and infrastructure is critical for sustaining and advancing health outcomes, particularly in high-income settings. The Marmot report that i read has highlighted on social determinants and health inequalities also remains relevant here even with high national health expenditure the distribution and accessibility of these resources across different socioeconomic groups can significantly affect overall health statistics and averages. The study shows that focusing on people from underrepresented category might have more positive impact on IMR for a country like UK. This can be a very valuable insight for upcoming years.

It is also important to acknowledge the limitations of this study. The analysis relies on average national data which may not cover significant regional or sub population imbalances in both economic conditions and health outcomes within the UK. While IMR is a great indicator of overall population health and healthcare quality, a broader suite of health metrics (e.g., life expectancy, maternal mortality, prevalence of chronic diseases) could provide a more broad picture of the health impacts of economic factors. Furthermore, the models employed explore correlations and statistical associations establishing direct causality requires more complex study designs, such as those incorporating instrumental variables or natural experiments, to rule out amazing factors or reverse causality. Factors such as education levels (particularly maternal education), environmental quality, lifestyle factors, and the impact of specific public health campaigns or technological advancements in medical care, which were not explicitly included in these models due to data availability for the entire period, also play a crucial role in determining health outcomes and could be interesting variables for our study.

Despite these limitations, the application of machine learning techniques we used has provided a valuable medium through which to examine these relationships. The ability of models like Random Forests to capture non-linear interactions and assess feature importance offers advantages over traditional regression approaches alone, particularly when exploring complex multifactorial issues like public health. The insights gained can help to refine our model for more targeted causal research.

6 Conclusion

This study has shown to explore the effect of economic growth on health in the United Kingdom, using Infant Mortality Rate (IMR) as a key health indicator, by applying data science and machine learning techniques to data spanning from 1960 to 2015. The analysis confirmed a strong historical inverse relationship between GDP per capita and IMR, with economic growth coinciding with substantial reductions in infant deaths. The nature of this relationship appears non-linear, with diminishing returns in health improvements from economic growth alone as the country achieved higher levels of wealth, a finding consistent with the Preston curve. This underscores the fundamental role of economic development in establishing a baseline for population health.

For the more recent period of 2000-2015 having added the health expenditure as a percentage of GDP has revealed its significant role. The Random Forest model has identified that health expenditure as a more dominant predictor of IMR than overall GDP per capita during these years. This highlights that for an economically developed nation like the UK continued improvements in key health indicators such as IMR are strongly linked to direct investment and resource allocation within the healthcare sector itself. It suggests that once a country like UK is established in health sector, it needs a constant investment to sustain it.

The findings underscore the importance of both sustained economic development and robust, well-funded public health systems. While economic prosperity provides the means, strategic health expenditure and policies aimed at equitable access to care are crucial for translating wealth into real health benefits for the population. Our research have shown how the data driven analysis can be beneficial for a country like UK. For example we could see one of the valuable feedback from the analysis is that even during multiple economic crisis in UK the graph of Infant mortality rate remained the same.

Future research could expand on this by incorporating a wider array of socio-economic and environmental variables, also exploring regional variations within the UK to understand the imbalance and employing more advanced analysis techniques to better capture dynamic causal effects and feedback loops between economy and health. From Health point of view, adding variables concerning health like life expectancy would be great deal for the analysis. Investigating the impact of specific health policies or reforms during the study period could also give better valuable insights. However, this study captures a clear indication of the interlink between economic well being and public health highlighting the continued need for focused health investments and policies that address health equity to achieve further progress in population health outcomes.

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