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Income Differences Among Nations: Measuring the Effects of Human Capital on Total Factor Productivity (TFP)

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Abstract

In the past two centuries, long-term economic growth has been defined by The Great Divergence, where the gap of income distribution has widened as a result of some nations experiencing modern economic growth while others have remained stagnant in their economic well-being. This panel data research examines differences in income across countries by applying development accounting to analyze differences in per capita gross domestic product (GDP) and predict each country’s total factor productivity (TFP). Data from the Penn World Tables were collected and categorized into groups based on GDP per capita to create a sample of 144 countries in 10-year intervals from the years 1990-2019. Variables gathered from the Penn World Tables included engaged persons, capital stock, real GDP, and a human capital index. Through observing empirical evidence with economic data, significant evidence supports the hypothesis that human capital is influential in a country’s total factor productivity. Results of various analyses illustrate the significant impact income class has on the correlation between human capital and total factor productivity.

Keywords: The Great Divergence, development accounting, per capita gross domestic product, total factor productivity, Gross National Income, human capital index
Introduction

For decades, economists have been studying the sources of large income gaps among nations. According to standard economic theory, per capita income differences across countries are due to differences in capital per worker and differences in total factor productivity. While prosperity can certainly be attributed to accumulation of capital and labor, the inexplicable portion of economic growth is typically reflected in advances in technologies and production processes known as total factor productivity.

Empirical studies demonstrate that total factor productivity is more important in explaining differences in income across countries than differences in capital per worker. There are many factors that could lead to total factor productivity differences, and it is likely that a combination of these factors widens the gap between the rich and poor nations. While it is difficult to measure the effects of every possible factor that contributes to a country’s total factor productivity, studying one element that influences it can provide insight into why some countries prosper while others do not.

This paper focuses on just one of these factors—how human capital acquired through schooling influences a country’s TFP. This type of human capital, refers to the knowledge, skills, and experience possessed by individuals that contribute to their ability to be productive in society. By conducting this research, I expect to find accounting for education through the measurement of human capital reduced TFP differences across countries within income groups will be reduced, proving level of education is highly influential in the productivity parameter when comparing per capita income across nations.

The outline for the rest of this paper is as follows. Section 1 provides a literature review of the current discussion surrounding the issue, specifically stating the potential factors experts
deem as most influential to TFP. Section 2 provides the theory and procedure, including how research was conducted, the time frame, and sample selection. Section 3 presents the data selection. Section 4 provides results and interprets them. Section 5 explains potential limitations, discusses the implications of the results, and concludes. Section 6 is the appendix containing data and tables referenced in the other sections.

1 Literature Review

When studying the residual factor in a nation’s output, it is vital to include the context of global historical economic growth. Deaton (2013) argues that economic growth during the Industrial Revolution birthed what he termed “the Great Divergence.” The economic inequality that resulted from the 19th century propelled rich countries to become richer, thus creating a cycle where economic growth caused income inequality and this inequality perpetuates economic growth for nations that progress at the expense of another. After the burst of the Industrial Revolution, Europe pulled away from Asia in its annual per capita income (Broadberry 2021); however sustained growth came as a result of other factors. While increases in capital and labor certainly advanced economies, there seems to be a lingering cause of high productivity within a nation recently explored by scientists who argue differing sources of progress. The potential factors are discussed below.

Education

It is apparent some countries more efficiently use capital and labor to produce goods and services. One cause of this, according to Jones (2021), is the human capital people acquire through schooling. “The average number of years American adults have spent in school is just
under 13, while the average in the poorest countries is about 4” (Jones 2021). He discusses the potential explanation for differences in wealth across nations in the context of TFP through the lens of education and how patterns have shown increases in wages resulting from additional years of schooling. Alvi and Ahmed (2015) support this claim, stating “…[the] poor state of human capital in underdeveloped countries is a major challenge to economic growth and development” (Alvi and Ahmed 2015, 110). This relationship is usually represented using Robert Lucas’s (1988) model that ties the rate of return on education to the number of years spent in school.

Political Institutions

National governments’ political institutions set in place can also largely influence how productive a nation is. In Acemoglu, Johnson, and Robinson (2001) they describe how political institutions can be inclusive or extractive. Inclusive institutions are characterized by shared power, diverse representation, and equal opportunity, while extractive institutions consolidate power and prevent economic growth. The same argument is presented in Deaton (2013), as he claims inequality is a consequence of power, affecting progress, and ultimately, people’s ability to be productive. Jones (2021) agrees with this sentiment, using North and South Korea as an example that denounces geography or culture to be a driving force in differences in TFP, but rather claiming it is differences in government policies and regulations that either inhibit or inspire economic growth. Ellington and Ferrarini (2017), exploring Jones’s point more deeply by examining the development of economies in the Korean peninsula over time. They emphasize the importance of investing in human capital and engaging in international trade by denouncing North Korea’s “Juche,” or self-reliant economy that has failed due to its command-and-control
policies under communism. Gross domestic product remains staggeringly low when the country cannot keep up with the pace of global trade and industrialization. Furthermore, people lack incentive to advance production when they lack personal rights. “In the absence of a stable government that protects property rights and allows individuals to freely move in and out of markets, economic growth and prosperity are not possible over the long run” (Ellington and Ferrarini 2017, 9).

*Geography*

Although argued less frequently than human capital or institutions, some scholars aver that geography is the driving factor to explain the differences in TFP across countries. “Location and climate have large effects on income levels and income growth through their effects on transport costs, disease burdens, and agricultural productivity, among other channels. Geography also seems to affect economic policy choices (Gallup, Sachs and Mellinger).” Additionally, continents like Africa experience a cyclical challenge with heat and productivity. Economic implications may engender less output in hotter nations. Letta (2019), for instance, found, “…there is a negative and 5% significant impact of temperature shocks in hot countries, with a net effect of about -1 percentage point on the annual TFP growth.” These conditions are conducive for an issue that feeds itself—“workers in poverty are particularly at risk when heat stress reduces productivity… [and due to heat, in 1995,] productivity loss [was] equivalent to more than 3 million full-time jobs” (International Labor Organization, 2019).
Culture

Culture, too, can impact productivity. There are two approaches to the term culture in this sense, one being the values of work-life balance, and the other being the cultivation of creativity through an entrepreneurial mindset to enhance productivity and increase output. The controversial topic of work-life balance presents contradictory arguments in relation to the cost and benefit of trading work hours for leisure hours. Several reports, however, show countries being just as, if not more, productive having 4-day work weeks and/or working less than 40 hours per week. The United Arab Emirates switched federal employees to a permanent 4.5-day work week. They found it to “boost productivity and improve work-life balance” (O’Loughlin, 2023). In addition to work culture being defined by the number of hours at labor, it can also be expressed through a nation’s emphasis on creative outlet. The Creativity Productivity Index measures economic development by encouraging innovation and creativity. A report by The Economist Intelligence Unit claims “there is a clear and strong positive relationship between creative inputs and the resulting outputs. The correlation coefficient is 0.93 and the variations across countries explain up to 86% of the variation in creative outputs” (Economist Intelligence Unit 2014).

2 Theory

Background

Total factor productivity is how efficiently a country turns its inputs into outputs. Using development accounting, a specific economic model, differences in per capita GDP can be examined across countries. Models often over predict how rich countries are. Consideration of education is crucial to how efficient an economy is because people’s intellectual competitiveness
plays a significant role in productivity. The limitations of other research originate from its methodology. Other models do not adjust for an influential variable in total factor productivity—like climate, health, or gender inequality—or just look at a particular point in time. By adjusting the model for differences in school across nations using the Penn World Tables human capital index, a more accurate representations of wealth discrepancies can be given.

The Cobb-Douglas production function can be used to predict economic well-being in a country, where K and L represent capital and labor, respectively. In development accounting, output per worker is desirable for measurement of a nation’s economic well-being. This can be solved by dividing the function by the labor force. This method can be repeated for all countries, and using a base country, we can divide a country’s per capita GDP by another’s to get each value in common terms relative to the United States (US). In this study, the US will be used as the denominator, meaning each value will be relative to the United States. TFP can be computed by taking the actual per capita GDP and dividing it by the predicted value.

Confirmation of the hypothesis that education greatly impacts a nation's productivity holds significant implications for policymakers aiming to address the existing shortcomings and enhance economic equality across countries. By acknowledging this relationship and accepting education as a catalyst for development, policymakers can focus on implementing policies to improve education in low-income countries, valuable on multiple dimensions. Policymakers can allocate more resources towards building and maintaining educational institutions, ensuring that schools have proper facilities, equipment, and materials. Additionally, countries may find investing in teacher training programs, or promoting innovative teaching methods to be useful in providing quality education and harness the potential of technology in delivering education.
Procedure

Development accounting was the main tool applied in this project. The process begins assuming that each country’s output can be represented by a Cobb-Douglas production function:

\[ Y = A \cdot K^\alpha \cdot L^{1-\alpha} \]

A is the country’s level of total factor productivity, K is the stock of physical capital, and L is the number of workers in the economy. In order to compare countries of different populations, we focus on output per worker, and so we divide the production function by the number of worker:

\[ \frac{Y}{L} = \frac{A \cdot K^\alpha \cdot L^{1-\alpha}}{L} \]

Letting lowercase letter stand for per-worker values, we can write the production function as

\[ y = A \cdot k^\alpha \]

That is, output per worker is a function of total factor productivity and capital per worker.

This is where development accounting is applicable to this project. Suppose we have two countries, the United States and South Korea. If the production function applies to both countries, then the reason why the nations’ GDP per worker will differ is due to (1) differences in total factor productivity, (2) differences in capital per worker, and/or (3) differences in the parameter \( \alpha \). Gollin (2002) demonstrated that \( \alpha \) is, for development accounting purposes, the same across countries (equal to about 0.33) and so income differences boil down to differences in A and/or k.

We now face a problem: national income accounts contain data on y and k, and sources such as the Penn World Table even compute these data in common measures of international dollars. We do not, however, have data on total factor productivity. Here is where Hall and Jones (1999) made an important contribution to growth theory. They noted that if we choose a country
(e.g. the US) as a base case, we can compare any particular country with the U the base case by taking the ratio of their production functions:

\[
\frac{y}{y_{US}} = \frac{A \times k^\alpha}{A_{US} \times k_{US}^\alpha}
\]

Once these ratios were established, the difference between actual output per person and predicted output per person is assessable. In particular, we can re-write this ratio as

\[
\frac{A}{A_{US}} = \frac{y}{y_{US}} \frac{k}{k_{US}}^\alpha
\]

In plain language, the numerator on the right hand side is the actual ratio of a country’s income per person to the US, while the denominator is the predicted value of this ratio without any differences in total factor productivity. The left-hand side is now an estimate of the ratio of a given country’s total factor productivity to the US level of total factor productivity.

We can bring human capital into the picture in the same way as Hall and Jones (1999) do so. Suppose that what we originally called total factor productivity, A, actually composed of two factors: true total factor productivity (A) and human capital (h). We can then re-write our equations as

\[
\frac{y}{y_{US}} = \frac{A \times h \times k^\alpha}{A_{US} \times h_{US} \times k_{US}^\alpha}
\]

and

\[
\frac{A}{A_{US}} = \frac{y}{y_{US}} \frac{h}{h_{US}} \frac{k}{k_{US}}^\alpha
\]
3 Data

Sample Selection & Timeline

Data was pulled from the Penn World Tables for 144 countries over four time periods for a total of 576 observations. Research was conducted for the years 1990-2019 in 10-year intervals (1990, 2000, 2010, 2019) for both parts of this experiment. By observing several decades, results can be “averaged” as certain moments in time are characterized by historical events, falsely representing a country’s economic well-being. One objective of performing panel data research in this study is to demonstrate how countries display growth when observed over time, showing both TFP differences among countries and development within countries within the last four decades.

Classification

Data was organized by income cohort. The thresholds were benchmarked to the World Bank’s Analytical Classifications presented in the World Development Indicators. The World Bank has classified countries into 4 categories since 1987: low-income countries, lower-middle-income countries, upper-middle-income countries, and high-income countries. They are grouped based on their gross national income (GNI) per capita. In my panel data, we investigate 4 incremental time periods—1990, 2000, 2010, and 2019.

Table 1 shows the criteria for classification of each country. As one can see, the criteria changes over time. It is important to note that these are changes in real dollars, not just nominal dollars, so the goal posts are moving over time. This must be taken into consideration when assessing the significance of this variable in the regression.

Table 1
Countries shift in and out of income groups over the four time periods making it important to update the classification every ten years. Due to the various changes of countries’ GNI over time, we must account for the fluctuations by individually assigning each country to an income cohort at each time interval for each criterion given by the World Bank using dummy variables.

**Calculation of Human Capital Index (HCI)**

The Human Capital Index found in the Penn World Tables is draw directly from chapter 3 of Charles Jones’ *Introduction to Economic Growth*. Because the mathematical process to determine how different economies acquire different intellectual abilities and skills is quite intense and complex, this section will briefly describe how HCI is computed. First, we recognize that humans accumulate human capital by spending time learning skills in place of working in the labor force. By combining concepts of the Solow model and the Cobb-Douglas production function, a balanced growth path can be determined explaining that some countries are richer because they have a high investment rate in accumulation of skills. Also assumed is that the growth rate is identical across countries to prevent interminable income gap. While we know this cannot be true, this assumption is crucial in including the calculation of technology, which is a catalyst for humans to acquire new skills, into the HCI. Thus, countries that invest more resources into accumulation of skills are richer, and therefore, present a higher HCI.

<table>
<thead>
<tr>
<th>Analytical Classifications</th>
<th>1990</th>
<th>2000</th>
<th>2010</th>
<th>2019</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low Income</td>
<td>&lt;= 580</td>
<td>&lt;= 755</td>
<td>&lt;= 995</td>
<td>&lt;= 1,025</td>
</tr>
<tr>
<td>Lower-Middle Income</td>
<td>581-2,335</td>
<td>756-2,995</td>
<td>996-3,945</td>
<td>1,026-3,995</td>
</tr>
<tr>
<td>Upper-Middle Income</td>
<td>2,336-6,000</td>
<td>2,996-9,265</td>
<td>3,946-12,195</td>
<td>3,996-12,375</td>
</tr>
<tr>
<td>High Income</td>
<td>&gt; 6,000</td>
<td>&gt; 9,265</td>
<td>&gt; 12,195</td>
<td>&gt; 12,375</td>
</tr>
</tbody>
</table>
4 Empirical Results

In this section, we will present the key findings of the study and discuss their implications in the context of existing literature and theory. The key findings are first presented in a bivariate analysis where variables are paired and the relationship between them is observed. The second section provides results from a regression analysis where multiple variables are accounted for in one statistical test.

Bivariate Analysis

Using data from the Penn World Tables and the World Bank, a bivariate correlation between human capital (HC) and total factor productivity (TFP) across income groups over time was conducted to examine the relationship between these variables. Specifically, we took the natural log of each data point, so relationships can be expressed in percentages as opposed to units.\(^1\) Mathematically, we have

\[
\text{Implied TFP} = (HCl) \times x + b
\]

The graphs below show the data on TFP and HCI for each time period.

---

\(^1\) A unit of human capital and total factor productivity is difficult to quantify (and is actually the ultimate goal of this research...to quantify the effects of human capital on total factor productivity) but expressing the correlations in percentages permits more comparable results and a digestible analysis.
Upper-Middle Income Economies Over Time 1990-2019

Implied TFP vs Human Capital Index

- 1990
- 2000
- 2010
- 2019
To conduct this experiment, a systematic random sample was used to select which countries were to be observed. Countries were listed in random order. Then, the listed country corresponding to the number rolled on a six-sided fair die was chosen along with every \( n \)th term following depending on the size of each income category determined the country selected for observation.

6 countries were chosen from low-income group—Burundi, Sudan, Zambia, Ethiopia, Liberia, and Uganda—11 from the lower-middle income group—Ukraine, Pakistan, Philippines, Kenya, Honduras, Iran, Indonesia, Zimbabwe, Egypt, Bangladesh, and Morocco—11 from the upper-middle income group—Albania, China, Belize, Ecuador, Brazil, Argentina, Colombia, Costa Rica, Thailand, Mexico, and Dominican Republic—and 16 from the high-income group—Canada, Denmark, Norway, France, Spain, Germany, Japan, Italy, Iceland, Bahrain, Singapore, Australia, Saudi Arabia, Austria, Sweden, and Poland.

Table 2 summarizes the findings of this exercise across all time periods and income groups.

<table>
<thead>
<tr>
<th>Compilation of Bivariate Correlational Slopes by Cohort Over Time</th>
<th>1990</th>
<th>2000</th>
<th>2010</th>
<th>2019</th>
<th>Average Income Cohort</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low Income</td>
<td>0.118</td>
<td>0.548</td>
<td>0.912</td>
<td>0.555</td>
<td>0.533</td>
</tr>
<tr>
<td>Lower-Middle Income</td>
<td>0.845</td>
<td>-0.454</td>
<td>0.197</td>
<td>0.168</td>
<td>0.189</td>
</tr>
<tr>
<td>Upper-Middle Income</td>
<td>-0.114</td>
<td>-0.235</td>
<td>-0.481</td>
<td>-1.219</td>
<td>-0.512</td>
</tr>
<tr>
<td>High Income</td>
<td>-0.801</td>
<td>-0.678</td>
<td>-0.330</td>
<td>0.114</td>
<td>-0.424</td>
</tr>
<tr>
<td>Average for Time Period</td>
<td>0.012</td>
<td>-0.205</td>
<td>0.075</td>
<td>-0.096</td>
<td></td>
</tr>
</tbody>
</table>

The correlation between HC and TFP is extremely weak for all time periods and income groups and is even negative roughly half the time. On the surface, this contradicts my hypothesis that HC is a large driving factor to the increase in productivity over time.
Delving deeper into each income group, we see that across all time periods reported, the low-income group displays a positive correlation between HC and TFP. Using the low-income group in 2010 as an example, each number in the table can be interpreted as the following: a 1% increase in HC leads to a 0.912% increase in TFP. All contributions to human capital in the low-income cohort of countries contribute to an increase in TFP.

Within the lower-middle income group, the pattern is similar, however, the correlation presents itself as less than ½% increased contribution to TFP except for in the year 1990. Furthermore, the correlation between the variables presents itself negative in 2000, which is interesting considering all other time periods were positive, although weak. In this income cohort, it can be observed that HC as a contributor to TFP weakens over time.

Upper-middle income countries demonstrate a negative correlation between human capital and TFP over time. Furthermore, the relationship gets increasingly negative over time. High income countries are also mostly negatively correlative; however, they increase over time, ending with a positive value in 2019.

Now, if we consider all income cohorts and look at them across individual time periods, observe there is little pattern deducible from the data as the average correlation alternates positive and negative for the four time periods. What this tells us is that there certainly driving factors beyond HC

This leaves a large gap in the interpretation of this data that may be filled in through more in-depth analysis. The next step will be to run a regression using TFP as the dependent variable again but using multiple independent variables. Instead of conducting a simple bivariate analysis where only one independent variable can be used as a driver, this regression will aggregately
account for human capital, income cohort, and time period to assess the strength of each variable in its effect on TFP.

**Regression Analysis without Interaction Variable**

My empirical analysis will consist of a logarithmic regression where human capital, year, and income group are my independent variables and TFP is my dependent variable. Dummy variables were used for year and income group as those values are ordinal. When using dummy variables, one variable must be dropped to avoid the issue of collinearity, which occurs when there is perfect correlation or redundancy among predictor variables. Dropping one variable ensures that there is a reference category against which the other dummy variables can be compared. This approach helps to avoid multicollinearity and ensures reliable and meaningful interpretation of the regression coefficients for the dummy variables. Additionally, a natural log transformation of the data measures elasticity—how responsive the TFP is to changes in HCI. The purpose of converting the values to $\log(x)$ and $\log(y)$ is to simplify units to percentages. The equation below connects back to the original developmental accounting equation in that the variable, $A$, we had solved for is now the dependent variable in our regression equation.

$$\ln(TFP)_{it} = \alpha_{it} + \beta_1 \ln(HC)_{it} + \beta_2 (year)_{it} + \beta_3 (income\ group)_{it} + \epsilon$$

Table 3 presents the results of this regression.
Table 3

<table>
<thead>
<tr>
<th>Regression Results</th>
<th>Coefficient</th>
<th>P-Value (at 95% Conf. Interval)</th>
</tr>
</thead>
<tbody>
<tr>
<td>lnHCl</td>
<td>-0.222</td>
<td>0.110</td>
</tr>
<tr>
<td>Income Class</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lower-Middle</td>
<td>0.123</td>
<td>0.032</td>
</tr>
<tr>
<td>Upper-Middle</td>
<td>0.322</td>
<td>0.000</td>
</tr>
<tr>
<td>High</td>
<td>0.437</td>
<td>0.000</td>
</tr>
<tr>
<td>Year</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2000</td>
<td>-0.987</td>
<td>0.000</td>
</tr>
<tr>
<td>2010</td>
<td>-0.260</td>
<td>0.000</td>
</tr>
<tr>
<td>2019</td>
<td>-0.401</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Some interesting findings in Table 3 are, first, that income class is certainly impactful to total factor productivity. All 3 income classes are statistically significant at the 95% confidence interval because their P-values are each ≤ 0.05. This means that income level is correlated to the amount of output a nation has.

Second, the variable year shows that, on average, TFP increases across the whole dataset every year shown in Table 3. Lastly the coefficient for human capital presents as a negative correlation to TFP, however this value is not statistically significant at the 95% confidence level as its P-value is 0.11. From these preliminary results we can determine there may potentially be no correlation between human capital and total factor productivity. These results justify the need for a more in-depth analysis which will be performed using another regression analysis, but this analysis will contain an interaction variable between human capital and income class.

Regression Analysis with Interaction Variable
I performed a final regression analysis in which I introduced an interaction variable between human capital and income class. In this case, I continued using the log-on-log approach, the use of dummy variables, and the examination of data across four different time periods. However, in this case I ran the regressions for each year separately rather than using dummy variables.

The key distinction in this analysis is the inclusion of a unique independent variable - the product of the human capital index assigned to each country within each time period and their respective income class. This analysis aims to investigate the impact of human capital on total factor productivity within each income class. The regression equation below excludes the independent variables ln(HC) and income group to avoid multicollinearity.

\[
\ln (\text{TFP})_{it} = \alpha_{it} + \beta_1 (\ln(\text{HC}) \times \text{IncClass})_{it} + \epsilon
\]

Table 4 presents the results organized by year across the horizontal axis and income class along the vertical axis. It is crucial to mention that, due to the utilization of dummy variables, only three income classes are included in the analysis, as one group must be omitted, again, to avoid multicollinearity. In this regression, the Low-Income class was omitted for this purpose.

**Table 4**

| Regression Results when Human Capital interacts with Income Class |
|---------------------|-----------------|-----------------|-----------------|-----------------|
|                     | 1990            | 2000            | 2010            | 2019            |
| **Lower-Middle**    |                 |                 |                 |                 |
| Coefficient         | -2.632          | -2.769          | -2.271          | -0.793          |
| P-value             | 0.000           | 0.000           | 0.000           | 0.070           |
| **Upper-Middle**    |                 |                 |                 |                 |
| Coefficient         | -0.913          | -1.132          | -0.898          | -0.002          |
| P-value             | 0.000           | 0.000           | 0.000           | 0.994           |
| **High**            |                 |                 |                 |                 |
| Coefficient         | 0.160           | 0.079           | 0.161           | 0.691           |
| P-value             | 0.183           | 0.530           | 0.150           | 0.000           |
| Intercept           | -0.296          | -0.342          | -0.498          | -1.216          |
| *Interpretation     | 74%             | 71%             | 61%             | 30%             |

*Level of TFP relative to the US
The intercept serves as a useful baseline for our analysis, representing the average level of total factor productivity compared to the US in each year. In the log-on-log regression utilized, the intercepts can be interpreted as percentages when raised to the power of ‘e,’ effectively undoing the logarithmic transformation. By expressing each country's total factor productivity as a ratio relative to the US, we can understand the average level of productivity as a percentage of that of the US. Consider the intercept in the year 1990.

\[ e^{-0.296} \approx 0.74 = 74\% \]

This suggests that, on average in 1990, countries exhibited total factor productivity at 74% of that of the US.

Moreover, the coefficients indicate the degree to which the gap between countries and the US widens or narrows as we explore the interaction between human capital and total factor productivity, with each coefficient representing an elasticity. The approach of using ratios denominated in US terms and a log-on-log regression allows for this interpretation. Taking the Upper-Middle income category in 2000 as an example: A coefficient of -1.132 means that a 1% increase in human capital (specifically, the human capital index) reduces the gap by 1.132%.

The analysis indicates that variations in human capital impact poorer countries significantly more than wealthier ones, showing that an increase in human capital in countries with lower GDP per worker has a more substantial effect compared to those with GDP levels closer to that of the US. This effect is most pronounced in the Lower-Middle and Upper-Middle income groups, with statistical significance across those categories, whereas significance is limited to 2019 in the High-income group.

Overall, the findings suggest that narrowing the gap in total factor productivity relative to the US becomes increasingly challenging across higher income categories. In essence, lower
income classes demonstrate heightened responsiveness to changes in human capital, supporting the hypothesis that addressing educational disparities among countries leads to a reduction in the gap between total factor productivity levels. This trend underscores the pivotal role of human capital in driving total factor productivity.

5 Conclusions

Revisiting the Hypothesis

These results provide strong evidence supporting the notion that human capital plays a significant role in driving differences in total factor productivity. By adjusting for human capital, we can more accurately measure the true impact of various factors on productivity levels. The classification of income class was crucial in this process to reveal that the impact of human capital (or the lack of) is particularly important in poor countries. This suggests that investments in improving human capital, such as education and training programs, can lead to significant improvements in overall productivity. By understanding and leveraging the impact of human capital on productivity, organizations and economies can strive towards more sustainable growth and success.

Potential Limitations

This research on total factor productivity has several potential limitations that may affect its findings. One such limitation is the study's limited time frame, which ranges from 1990 to 2019. This may exclude long-term trends and structural shifts in global economic growth and productivity, potentially leading to inconclusive results. Additionally, as previously mentioned, there may be impact on TFP from other factors. The research acknowledges that factors like
geography, culture, and political institutions can also influence productivity and economic growth. These factors are briefly discussed but not thoroughly explored, leaving room for other significant determinants of TFP to be overlooked. Furthermore, the reliance on data from the Penn World Tables and the World Bank exposes the research to measurement errors or discrepancies. Additionally, the simplified models used to estimate TFP, such as the Cobb-Douglas production function, may oversimplify the complex interplay between labor, capital, human capital, and technology. As a result, the study may overlook critical determinants of TFP, possibly leading to an omission of significant factors impacting that value. The impact of these potential gaps and biases in the research may compromise the ability to establish causal links between human capital and TFP. These limitations suggest the need for further research to establish causal relationships between various factors and the greater output of TFP.

Further Direction for Research

In order to further refine and expand upon the findings of this study, several directions for future research can be considered. Exploring the differences in total factor productivity by continent or region could provide valuable insights into regional variations and the impact of geographic factors on productivity levels. Additionally, examining productivity levels based on religion or political institution could offer a deeper understanding of how cultural and governance factors influence productivity outcomes. Furthermore, gathering data from further back in history could help to establish long-term trends and provide a more comprehensive overview of productivity dynamics over time. Additionally, developing a more precise instrument to represent income levels could enhance the accuracy of the analysis by better defining the income class variable. By incorporating these suggestions into future research,
experts can continue to advance our understanding of the complex relationship between human capital, total factor productivity, and various contextual factors.
References


