Average working hours and Productivity: An analysis across countries and time

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I. Abstract

Working plays a major role in our life. Many studies found that working hours have declined considerably over the last 50 years, but cross-country analysis of differences in working hours has been limited due to unavailability of a comprehensive dataset for multiple countries. Utilising cross-country data from Bick et al. (2018) and panel data from the Penn World Table, we assessed the global trend for average working hours, whether average working hours are different between higher-income and low-income countries, and whether average working hours are associated with GDP per capita, employment rates, average year of schooling, gender equality, and human capital. Our cross-country analysis found that average hours worked per adult are substantially higher in low-income countries than in high-income countries, at around 7 hours. The pattern of decreasing hours with aggregate income holds for both men and women, for adults of all ages and education levels. Regarding data across time, the global trend for working hours is decreasing; however, it's different across continents and countries according to Naïve Bayes analysis. We estimate a 3.67-hour average difference in cross-country average working hours per week.

II. Introduction

We spend most of our day working and most of our life going to work. One fundamental observation in the field of macroeconomics is the significant variation in per capita aggregate income among nations (Caselli, 2005). However, there is limited research on average working hours and their indications for country welfare and productivity level. Average working hours directly impact labor productivity; hence, it is one of the most crucial keys to understand productivity differences across countries.

Keeping that in mind, this project aims to answer these following questions:

- What are the trends for cross-country average working hours throughout the years?
- Are average hours worked higher for adults in high-income countries or for adults in low-income countries?
- Is there a statistically significant relationship between hours worked and GDP per capita, wages, employment rates, average year of schooling, gender equality, and human capital?

and utilise our findings to shed some insights into the nature of labour productivity.

III. Background

1. Related literature

Prior to our analysis, Bick et al. (2018) conducted a study in which they examined how the number of hours worked varies with income levels across different countries, including those with varying income levels. Most previous research on the subject of average hours worked across countries has tended to focus on high-income nations, particularly the United States and European countries (Bick, Brüggemann, and Fuchs-Schündeln, 2019). This may be due to limited data from lower-income countries, and challenges in harmonizing data as data collection methods from countries outside Europe and North America may not be as standardized.

There have also been studies aiming to understand changes in working hours over time, although these have largely focused on high-income countries as well. For instance, McGrattan and Rogerson (2004) and Ohanian et al. (2008) have investigated changes in working hours among OECD countries over time, while Ramey and Francis (2009) have concentrated on the long-term decline in working hours in the United States. Aguiar and Hurst (2007) and Costa (2000) have examined historical variations in working hours relative to income within the United States, and Huberman and Minns (2007) have explored these patterns for several OECD countries. However, the existing evidence on working hours in developing countries is notably scarce. Caselli (2005) examined data on working hours from the International Labor Organization (ILO) for 28 countries, although only two of these countries fall within the lower half of the world income distribution. Additionally, Gollin, Lagakos, and Waugh (2014) conducted a comparative analysis of average working hours among employees in the agricultural and nonagricultural sectors in a broad range of countries using nationally representative surveys. It is worth noting that their data is comparable within sectors for each country but may not be directly comparable across countries. Many studies have utilized data from the Penn World Table to investigate average working hours, namely Jones and Klenow (2016), who consider hours worked in their study of welfare differences across countries.

2. Data collection

Surveys are the primary way to collect data on working hours. They are typically conducted by national statistical agencies. There are two main types: labor force surveys and establishment surveys.

Establishment surveys gather information on employment and reported working hours, primarily provided by employers. These surveys often focus on paid or contractual hours and typically exclude self-employment, informal labor, and certain smaller businesses. However, establishment surveys align more closely with the methodology used to calculate GDP, rendering them valuable for the examination of labor productivity. The Penn World Table acquires its labor data from establishment surveys.

Conversely, labour force surveys collect data on employment status and actual hours worked by directly querying the workers themselves. These surveys encompass hours worked in all economic sectors, including both formal and informal employment, whether full-time or part-time, and even encompass self-employment and unpaid family labor. The dataset constructed by Bick, et al. (2018), was based on such surveys, and in some aspects, more closely reflect the reality of working hours in a large set of countries.

In this light, establishment surveys likely report hour paid for, referring to the hours for which employees receive compensation from their employers. On the other hand, labor force surveys capture actual hours worked, representing the time individuals spend engaged in job-related activities contributing to the production of goods and services, as defined by the Australian Bureau of Statistics (ABS). The connection between these two types of hours is illustrated in the diagram below:

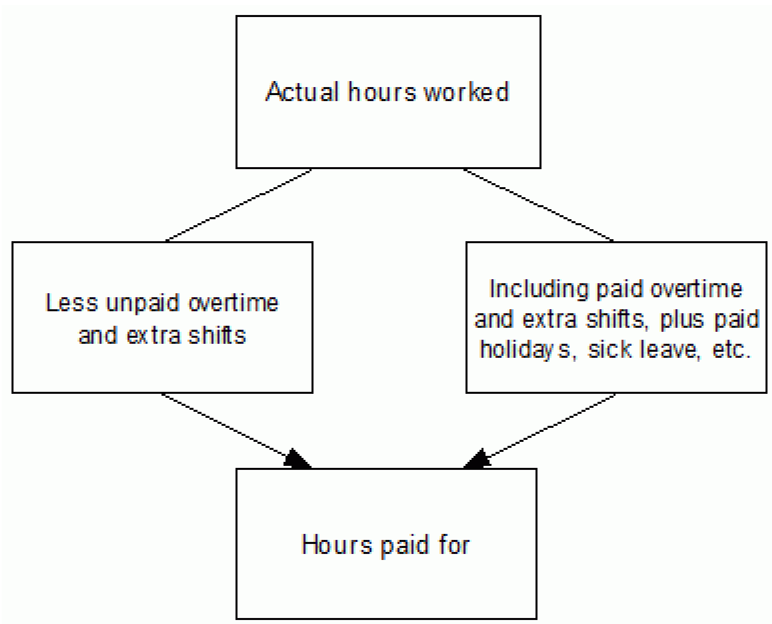


Figure 1: Relationship between actual hours worked and hours paid for

Source: Australian Bureau of Statistics (ABS)

IV. Methods

1. Data sources

a. Cross-country data obtained from Bick et al. (2018)

In our cross-country analysis, we utilized a dataset compiled by Bick et al. This dataset was constructed using nationally representative household surveys gathered from 80 countries with a minimum population of one million. For 32 of the countries in our study, the data were derived from harmonized datasets, which had already undergone standardization efforts to ensure consistency in survey questions. These harmonized datasets include the European Union Labor Force Survey (EULFS), covering 26 countries, and the International Public-Use Microdata Project (IPUMS), encompassing 6 countries. In the case of the remaining 48 countries, the data were obtained from country-specific sources such as censuses, household surveys, or labor force surveys, which includes 19 surveys that were conducted as part of the World Bank's Living Standards Measurement Studies (LSMS). (Bick et al., 2018)

The dataset provides information on the average weekly working hours for various countries as of 2005. In cases where data for 2005 was missing, the dataset includes data from the nearest available year. This approach ensures the best possible comparability between countries at a specific point in time and allows for a more accurate analysis of actual working hours as it takes into consideration both paid and unpaid labor, thereby providing a more realistic representation of average working hours in each country.

In our analysis, we focused mainly on these following variables in the dataset:

Variable	Description
gdppc_e9ry	Expenditure-side real GDP from the PWT
ln gdppc e9ry	Log of real GDP
hwp_a_all	Average hours worked per week
hwp_m_all	Average hours worked per week by male
hwp_f_all	Average hours worked per week by female
hwp_a_[age group]	Average hours worked per week by age groups
hwp_a_[education level]	Average hours worked per week by education levels

Table 1: Variable description for Bick et al. (2018) data

b. The Penn World Table (PWT)

Concerning both temporal and international comparisons, we employed the Penn World Table (PWT), a well-established and widely used data resource for researchers interested in assessing cross-country economic growth and welfare. The PWT is hosted on Dataverse, it can be accessed in its entirety through the following doi: 10.34894/QT5BCC. We used version 10 of the table, the most recent table. This dataset provides information on real gross domestic product (GDP), population, employment, and a human capital index.

The data covers data for 183 countries over the extensive period from 1950 to 2019. To ensure consistency and relevance, we focused on countries for which data on average working hours were available for a significant portion of the period spanning from 1950 to 2019. Ultimately, our dataset incorporated 66 countries meeting this criterion for our analysis.

We mainly utilize these following variables:

Variable	Description
rgdpe	Expenditure-side real GDP at chained PPPs (in mil. 2017US$)
pop	Population (in millions)
emp	Number of persons engaged in the workforce(in millions)
avh	Average annual hours worked by persons engaged
hc	Human capital index, based on years of schooling and returns to education

Table 2: Variable description for the PWT data

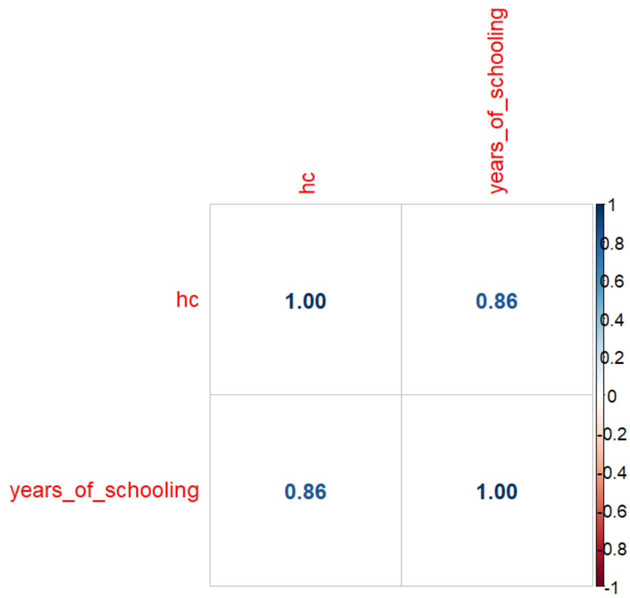
The human capital index is computed based on the average years of schooling and an estimated rate of return to education derived from the Mincer equation, which is:

$$hc = e^{\phi(s)} \text{, where}$$

$$\phi(s) = \begin{cases} 0.134s, & s \leq 4 \\ 0.134 * 4 + 0.101(s-4), & 4 < s \leq 8 \\ 0.134 * 4 + 0.101 * 4 + 0.068(s-8), & s > 8 \end{cases}$$

Two prominent sources provide the average number of years of education: Barro and Lee, which covers 146 nations at five-year intervals from 1950 to 2010, and Cohen and Leker, which provides data for 95 countries at ten-year intervals from 1960 to 2020 (Feenstra et al., 2015)

To comprehend the human capital index, we explore years of schooling data and assess its correlation with the human capital index. Our findings reveal a strong correlation between the human capital index and years of schooling, indicating that the formal is a suitable and practical means of examining the influence of education in the Penn World Table panel dataset.



From the PWT data, we also compute GDP per capita [denoted gdppc] for each country by dividing the expenditure-side real GDP by population, and employment rates [denoted emp_rate] by dividing number of workers by population. The formulas to calculate these two variables are provided below:

$$gdppc = \frac{rgdpe}{pop}$$

$$emp\_rate = \frac{emp}{pop}$$

With this dataset, we focused on exploring trends across time for average hours, and whether there are significant differences across continents and countries.

c. Data on gender equality and years of schooling

As we wanted to find if there is a significant relationship between average working hours and average years of schooling and between average working hours and gender equality, we included the gender equality index (GEI), which has been constructed by International Institute of Social Studies (ISD), and the average years of schooling taken from Our World in Data. Both datasets are available in five-year intervals, the gender equality index data spans from 1990 to 2020, while average years of schooling spans from 1870 to 2020.

The GEI is calculated by ISD using a wide range of complementary indicators, which span outcome measures such as access to jobs, educational placement, fair wage, as well as input measures which track the existence of discriminatory norms within society regarding a woman's right to equal treatment in the workplace, in access to education, and in the family. Because gender discrimination is multifaceted, attitudinal data also can form a useful proxy for the persistence of broader forms of discrimination, such as domestic violence, for which we have little or no comparative information. It has 4 levels, ranging from 1 to 4, 1 being the lowest level of gender equality and 4 being the highest.

Regarding the years of schooling data, Using the estimates on school enrollment and population structure, Lee and Lee (2016) have constructed projections of educational attainment for the population, disaggregated by gender and age group (15–24, 25–64, and 15–64) for 146 countries from 2015 to 2040 at five-year intervals. They use the 2010 data on educational attainment by age group as benchmark figures to project the educational attainment of the population by age group for the next three decades. They then estimate the distribution of educational attainment for the younger population, aged 15-24, at the five-year intervals from 2015 to 2040 and then forward-extrapolate the estimates to construct the distribution of educational attainment for the older population groups. For the population structure, they use existing U.N. projections.

For the purpose of our analysis, only the data in the year 2005 from both datasets are used.

2. Processing

We conduct our analysis entirely in R version 4.3. The two main datasets are first imported into R and converted to appropriate format. For both datasets, column “income_group” were added to categorise countries into their appropriate continents and income groups. We defined the three income groups as below:

Low-income: GDPPC <= 4095

Middle-income: 4095 < GDPPC <= 12695

High-income: GDPPC > 12695

The above thresholds were based on World Bank classifications (World Bank, 2022). However, the low and lower-middle income groups were merged into low-income group, while the higher-middle income group in World Bank categories become our middle-income group. It is also important to note that World Bank uses Gross National Income (GNI) per capita to classify countries into different income levels, while we used GDP per capita, as they were readily available in the data. As GNI is the sum of GDP and net income abroad,

$$\text{GNI} = \text{GDP} + \text{Net income abroad}$$

we expect minimal differences in how the countries in our analysis were classified.

In the Bick et al. data, a total of 34 countries were classified into high-income group, while 39 countries are middle-income and 17 are low-income. Concerning the Penn World Table, we do not have the fixed number of countries in each income groups, as countries can move from one income group to another over time. A full description of all the countries included in the analysis and their income group is available in the Appendix.

a. Bick et al. (2018) data

For the Bick et al. (2018) data, data on gender equality and average years of schooling were added as column "gender_equality" and "education" for later analysis. An initial EDA was performed on the datasets to explore any potential relationships between variables within the data. Then, relationships between average working hours and GDP per capita and levels of income are tested using linear regression. The general form of linear regression is provided below:

$$Y_i = \beta_0 + \beta_1 X_i$$

The specific form of econometric model used in the study is as given:

$$hwp\_a\_all_i = \beta_0 + \beta_1 \mathrm{ln\_gdppc\_e9ry}$$

$$hwp\_a\_all_i = \beta_0 + \beta_1 income\mathrm{e}\_group$$

b. The Pen World Table

For the Penn World Table data, we utilized both fixed effects modeling with the plm package and Bayesian multilevel modeling with the brm package to explore country-year trends and characteristics.

One problem is that only 22 out of 68 countries have data for the full period between 1950-2019. This can be a problem of unbalanced data where the effects of countries with more data available overcrowd the effects of countries with fewer years covered. If we set the starting year to 1995, 65 countries have data for the full period, however, we lose a substantial amount of data. To rectify this, we fit our model into both the full data and the data with the start year 1995 to account for any changes and differences over time. The average working hours reported in the PWT is per year, to be consistent with the Bick et al. data, we divide it by 52 to get average working hours per week.

$$avhpw = \frac{avh}{52}$$

We first fit a simple linear regression to see the general rate at which average working hours per week decreases over the years:

$$avhpw = \beta_0 + \beta_1\text{year}$$

We then use fixed-effects (FE) model to estimate the effects of GDP per capita, employment rates and human capital on average hours worked per week, controlling for time (year) specific effects. A second model is fitted to both the full dataset and data from 1995 onwards, with level of income as the additional variable. The model allows to eliminate bias from unobservables that change over time but are constant over countries. FE Model with robust standard errors has been applied to cope with the problem of heteroskedasticity. The models are specified below:

$avhpw_i = \beta_1 log(gdppc)_{it} + \beta_2 emp\_rate_{it} + \beta_3 hc_{it} + TimeFixedEffects + u_{it}$ (1)

$avhpw_i = \beta_1 log(gdppc)_{it} + \beta_2 emprate_{it} + \beta_3 hc_{it} + \beta_4 income_{it} + TimeFixedEffects + u_{it}$ (2)

With $i = 1, \ldots, n$ and $t = 1, \ldots, T$

We then use the Bayesian Linear model to quantify the variations in average working hours per week across countries. Bayesian regression provides a probabilistic framework for estimating model parameters and making inferences. It is based on Bayes' theorem, and is good at handling multi-level data such as panel data with varying intercepts and slopes. Bayesian Linear model differs from Ordinary Linear regression in a way that it explicitly quantifies uncertainty in parameter estimates by providing posterior distributions, while ordinary regression typically provides point estimates for parameters without quantifying the uncertainty around those estimates. One advantage of can get cross-country average working hours differences.

V. Results

1. Cross-country analysis using Bick et al. (2018) data

a. Relationship between working hours and GDP per capita

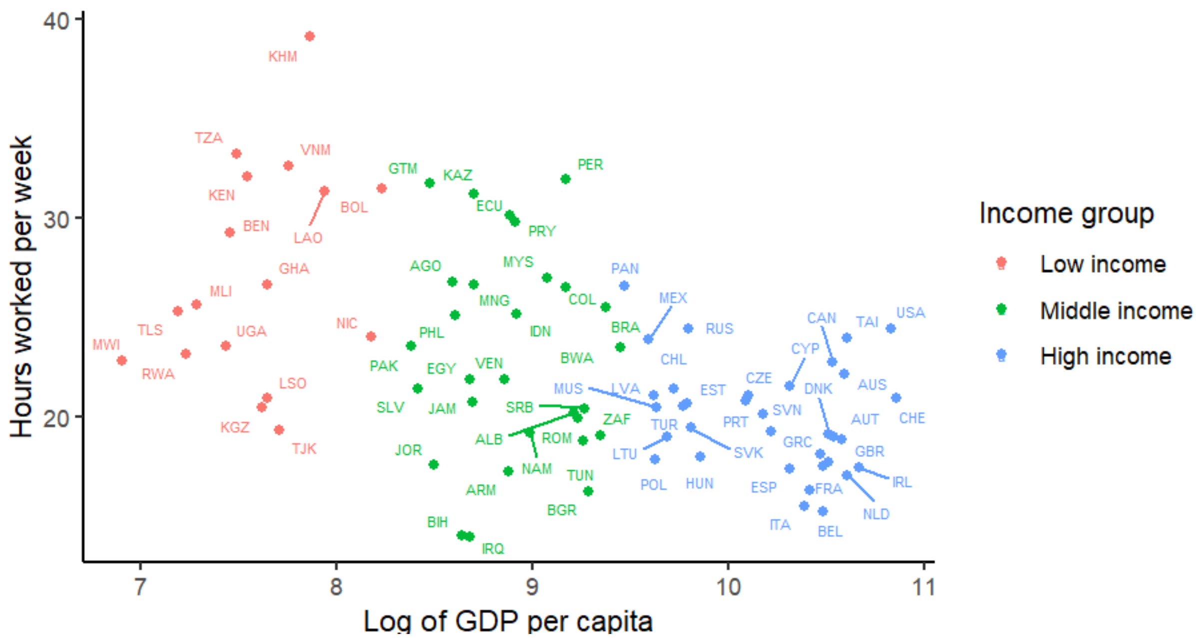


Figure 2: Average working hours against log of GDP per capita across countries

Figure 2 displays a scatterplot depicting the relationship between the average weekly hours worked by adults and the logarithm of GDP per capita for all countries in the Bick et al. dataset. The color coding represents the income group of each country. Logarithm is used for GDP per capita due to its skewed distribution. The scatterplot clearly illustrates the clustering of countries within the same income group. Low-income countries are concentrated in the top-left corner, signifying high average weekly hours worked and low GDP, while higher-income countries are situated in the bottom-right part of the graph, indicating lower average working hours and higher GDP. Moving from left to right, there is a noticeable downward trend in average hours as income per capita increases. Among the world's poorest countries, average weekly hours range from approximately 24 hours per week in Malawi, Rwanda, and Uganda to nearly 40 hours per week in Cambodia. In contrast, the wealthiest countries exhibit averages ranging from about 16 hours in Italy, Spain, Belgium, and France to 24.4 hours in the United States. Iraq has the lowest hours per adult in the sample, primarily due to women's participation.

Next, we regress hours worked per week on the log of GDP per capita to confirm that the differences we see in the scatter plot. Below is the result:

	Dependent variable:
	Average hours worked per week
Log of GDP per capital	-2.423^{***}
	(0.465)
Constant	44.843^{***}
	(4.299)
Observations	80
R^2	0.258
Adjusted R^2	0.248
Residual Std. Error	4.426 (df = 78)
F Statistic	27.099^{***} (df = 1; 78)
Note:	*p<0.1;* ***p<0.05;*** p<0.01

Table 3: Regression result for average working hours per week against log of GDP per capita

As expected, there is a significant and negative relationship between the logarithm of GDP per capita and average working hours. It is worth noting that the R-squared value is relatively low, suggesting that GDP per capita explains only a small portion of the variation in average working hours.

b. Differences in the means of three income groups

Next, we wanted to know if there are significant differences of average working hours between the three income groups. The box plot below shows the general distributions of working hours for low-income, middle-income, and high-income countries.

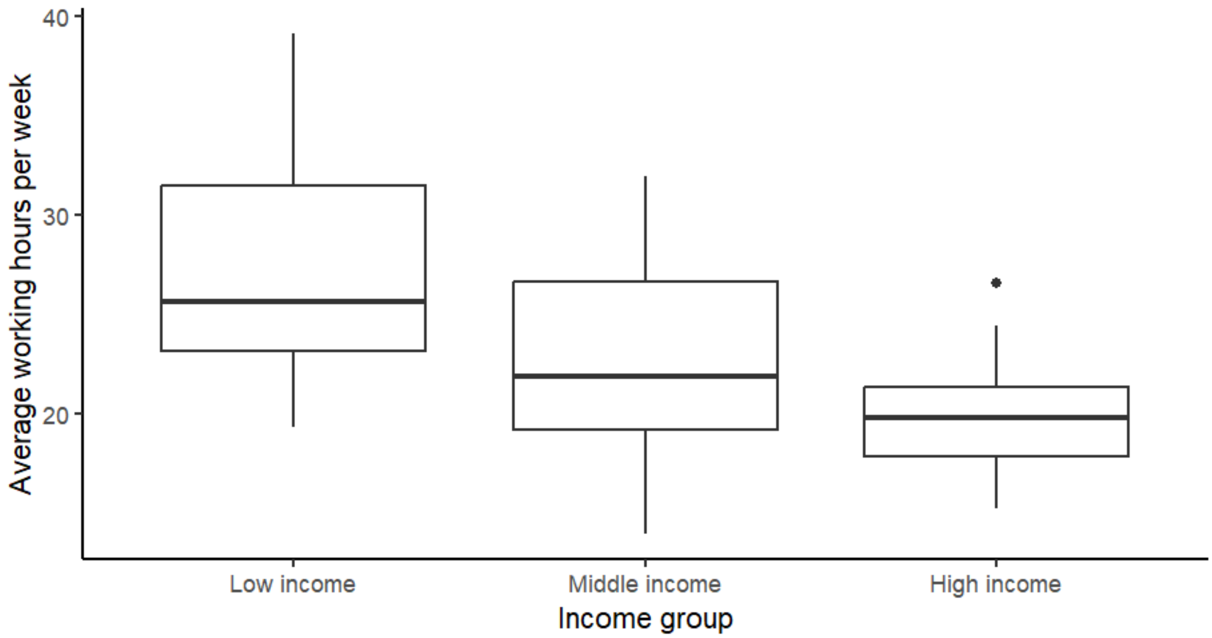


Figure 3: Average working hours by income groups

We can see the clear difference in the mean hours among the three groups. On average, an adult in a low-income country works around 27 hours a week, while in a middle-income country, he would work only 23 hours and around 20 hours in a high-income country. This is reported in the table below:

Income group	Average hours worked per week
High income	20.00
Low income	27.14
Middle income	23.02

Table 4: Average hour worked per week by income groups

To test if the means of three or more groups are different from one another, we used an analysis of variance (ANOVA) test. The result is shown below:

	Dependent variable:
	Average hours worked per week
Income group (High)	-4.117***
	(1.337)
Income group (Middle)	-7.137***
	(1.300)
Constant	27.136***
	(1.061)
Observations	80
R^2	0.284
Adjusted R^2	0.265
Residual Std. Error	4.375 (df = 77)
F Statistic	15.275*** (df = 2; 77)
Note:	*p<0.1;* ***p<0.05;*** p<0.01

Table 5: Results from ANOVA test *(The low-income group being the reference)*

The p-value is less than 0.05, we can conclude that there is evidence of at least one pair of income groups having different means. Specifically, observed difference in mean hours between the low- and high-income groups is 7.14 hours per week, between the low- and middle-income group 4.12 hours per week, and between the middle- and high-income group around 3 hours per week. All p-values are well under one percent. We conclude that the decreasing average hours over the income terciles are unlikely to be a coincidence and that average hours worked per adult are significantly higher in low-income countries than in high-income countries.

c. Average working hours by age group

In this section, we provide an account of the hours worked at various life stages within the three different country income groups. Figure 4 illustrates the average hours worked within five-year age intervals, commencing at ages 15-19 and concluding at ages 85-89. We interpret these findings primarily as age-related effects, though it's worth noting that we might also be capturing some influences related to the cohorts within these age groups.

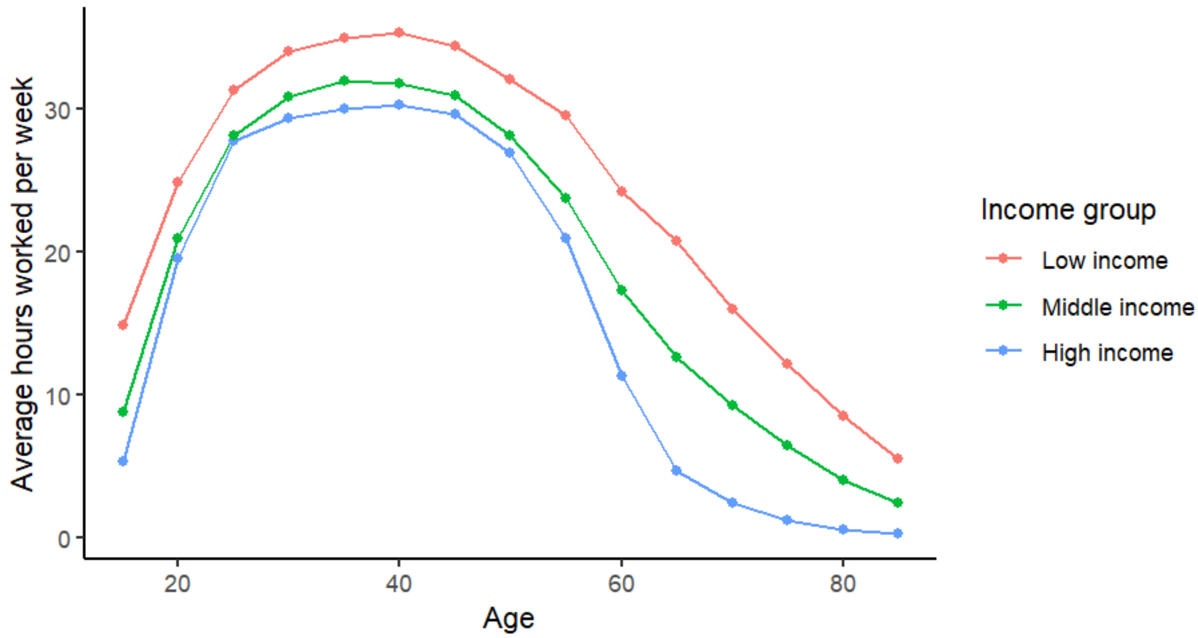


Figure 4: Average hours worked by age groups

The well-recognized trend of hours worked, characterized by a peak in mid-life, is evident in all three country income groups. More notably, the trend of declining hours worked as the country income level increases is consistent across all individual age groups. The most substantial disparities become apparent among older individuals. From the age group 55-59 onwards, the gaps in hours worked between low- and high-income countries increase until the age group 65-69, after which they begin to decrease again. This suggests that the presence or absence of social security programs plays a pivotal role in accounting for variations in hours worked, particularly around the retirement age.

group	High income	Middle income	Low income
Lower than 55 years old	24.38	26.13	30.13
$<$ 55 years old	3.43	8.67	14.50

Table 5: Average hour worked per week by age

On average, individuals aged 55 and above work 14.5 hours per week in low-income countries, while the corresponding figures are 8.67 and 3.43 hours for middle- and high-income countries, respectively. Among individuals below the age of 55, the average difference in hours worked between low- and middle-income countries stands at 4 hours, and between middle- and high-income countries, it amounts to 1.7 hours.

d. Average working hours by years of schooling

Bick et al. (2018) define three broad education groups and their respective average working hours: people who study (i) less than secondary school, (ii) secondary school completed (but not more), and (iii) more than secondary school. Using this data, we plot a barchart showing average working hours for each income group in each education level (Figure 5).

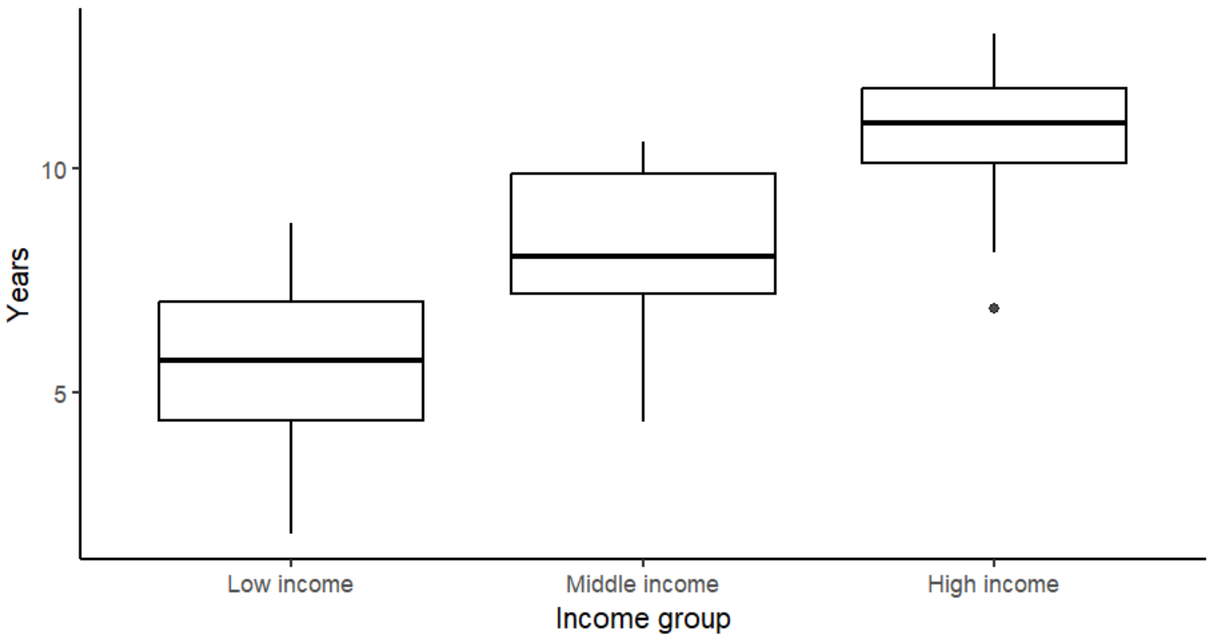


Figure 5: Box plot of differences in year of schooling

There is likely an inverse relationship between years of schooling and GDP per capita. In low-income countries, the average years of schooling typically range from just under 4 years to 7 years, while in middle-income countries, it falls between 7 to 10 years, and in high-income countries, it ranges from 10 to 12 years. This implies that a significant proportion of adults in low-income countries did not complete primary or secondary education, whereas the majority of workers in high-income countries have completed high school. How does this relate to working hours? We observe that there is a positive correlation between the level of education and the average hours worked, or the higher the level of education, the higher the average hours worked.

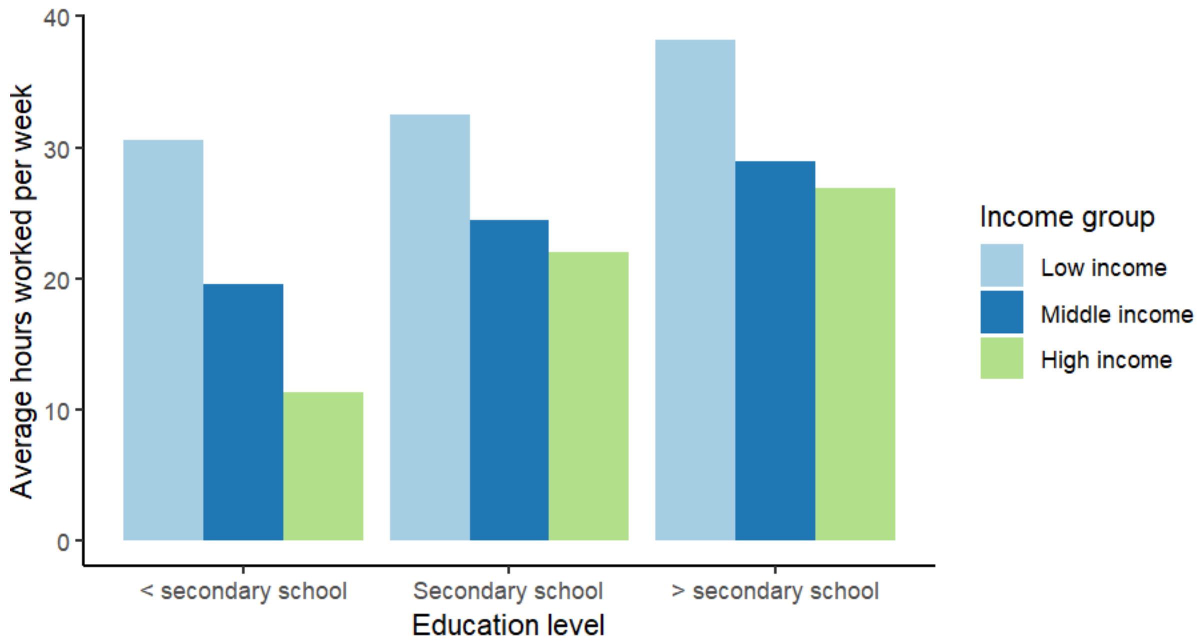


Figure 6: Bar chart showing average working hours by education levels across income groups

Figure 6 shows the mean years of schooling for each income group. We can see that people in lower-income countries consistently work more hours compared people in higher-income countries across education groups from less than secondary school to more than secondary school. The more educated group still work longer hours, consistent with what is found from Figure 5. Generally, a person who does not finish secondary school in a rich country works the least number of hours, while a high-school graduate from a low-income country works the most.

These two figures together show a consistent trend between education, income groups and working hours. It is worth noting however, in each education category, mean working hours are still the highest for low-income countries and the lowest for high-income countries.

Table 5 presents the average weekly working hours for different education groups. Notably, all three education categories show longer working hours in lower-income nations. For individuals with less than a secondary school education, the average weekly hours are 30.56 in low-income countries, while they are 19.56 in middle-income countries, and just 11.3 in high-income countries. In this lowest education group, there is a substantial 19.3-hour difference in weekly working hours between low- and high-income countries. For those with a completed secondary education in low-income countries, the average weekly working hours are approximately 10 hours more than their counterparts in high-income countries. In the case of individuals with more than a secondary education, the difference in average weekly working hours between low- and high-income countries increases to 11.3 hours. It's important to note that, within each country income group, average working hours tend to be higher for individuals with more education compared to those with less education, although this difference is less pronounced in low-income countries.

group	High income	Middle income	Low income
Lower than secondary school	11.30	19.56	30.56
Secondary school completed	22.06	24.49	32.56
More than secondary school	26.90	28.94	38.19

Table 6: Average hour worked per week by education levels

e. Average working hours by gender and gender equality

The next thing we are interested in is the potential differences in working hours by sex, and whether better gender equality warrants lower working hours. Due to history of being stay at home, we expect that women generally work fewer hours than men.

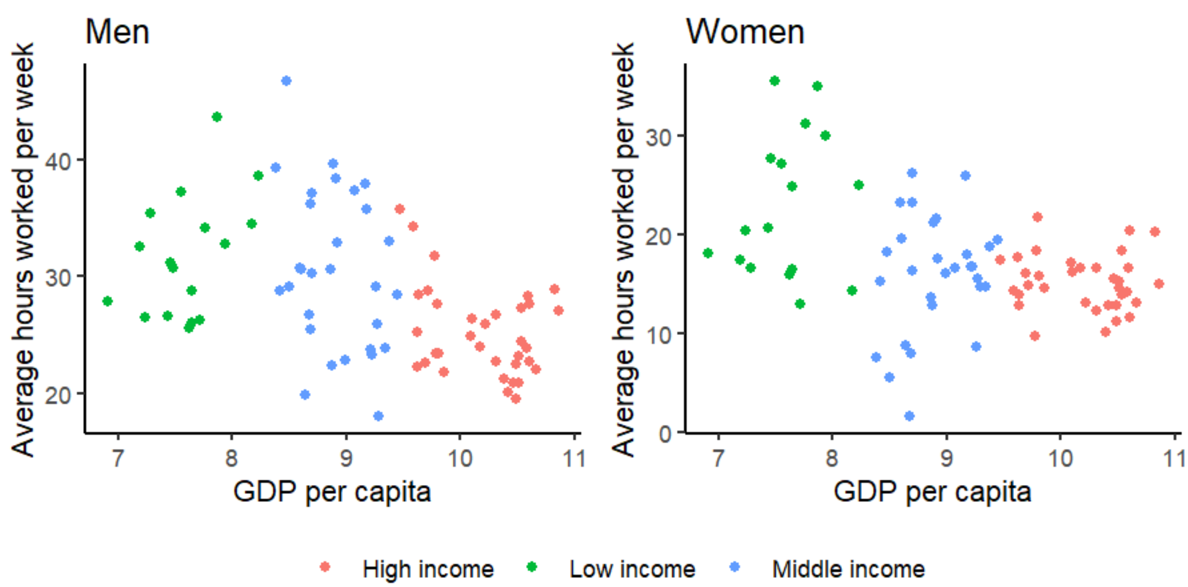


Figure 7: Average hours worked per week against GDP per capita by men and women

We first analyse average hours worked for both sexes across our set of countries. As Figure 7 shows, hours per adult are decreasing by development for both men and women. Interestingly, it seems that the gap in hours worked between woman in middle- and high-income countries are closer than that of low- and middle-income countries, while the opposite is true for men. We find that men work longer hours compared to women in every income group.

Next, we are interested in knowing if gender equality significantly affects average working hours. A scatterplot is plotted for gender equality and average working hours in Figure 9:

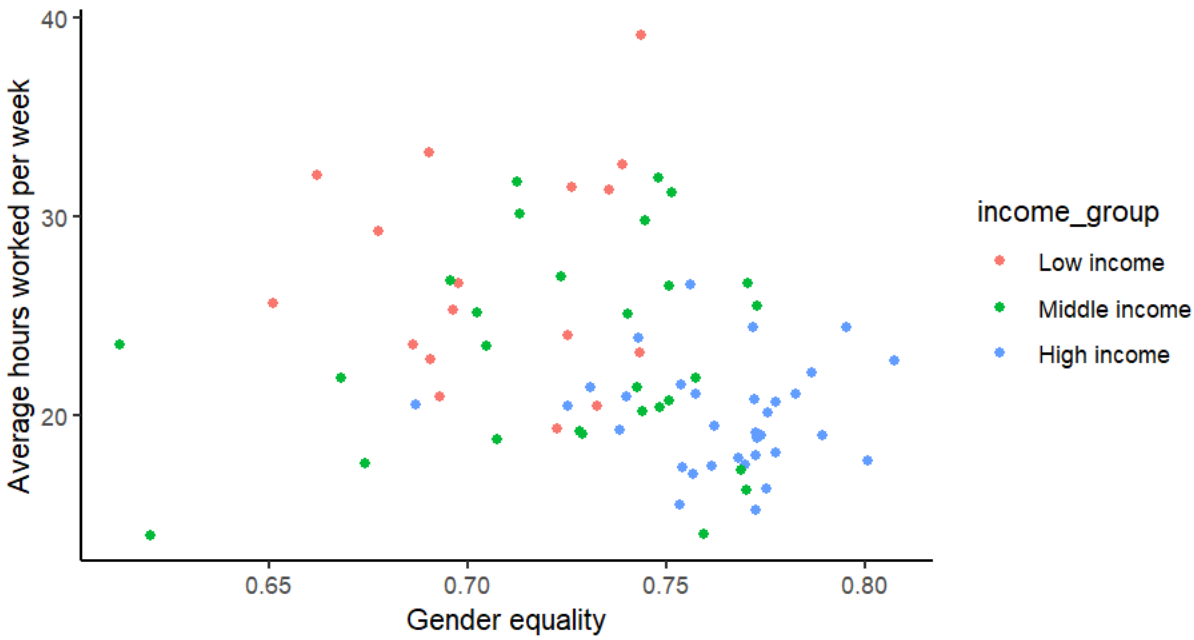


Figure 8: Average hours worked per week against gender equality

We can see a downward trend in average working hours as gender equality index gets higher, but not as clear cut as the relationship between hours of work per week and log GDP per capita. Furthermore, gender equality seems not to be correlated with There are some noticeable outliners, such as Iran, whose hours worked is very low but gender equality is low as well, or Cambodia, whose gender equality level is high compared to their average working hours. These outliners may be explained by other soci-cultural factors of each country, which are not accounted for in our analysis.

2. **Panel data analysis**

In this section, we attempt to study the trends of average working hours over time using the PWT panel data.

a. Global trends

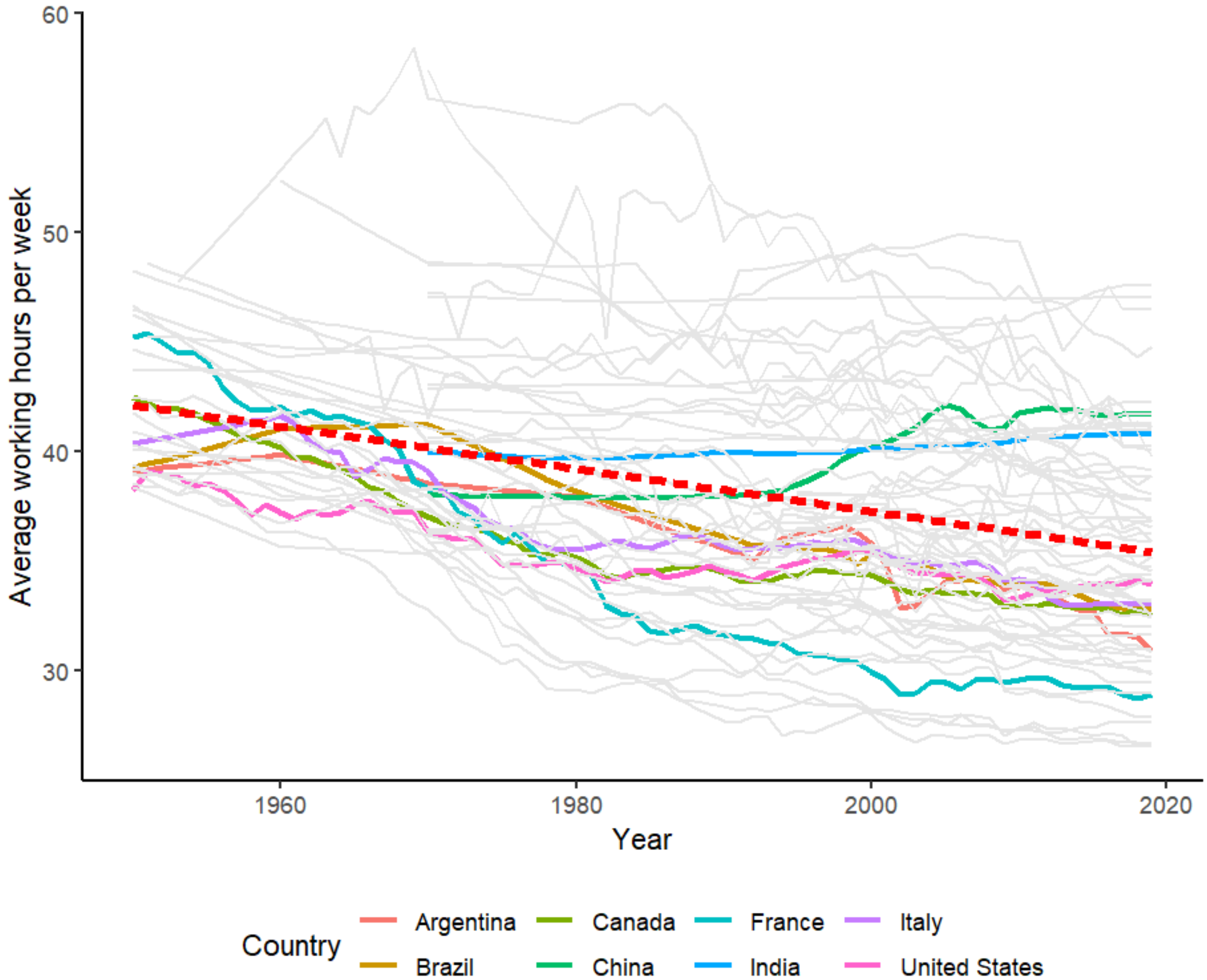


Figure 9: Cross-country average working hours throughout the years

We first look at the relationship between average working hours and time and how that relationship differs across continent and country. For each continent, we picked two representative countries (in bold lines). The global trend is that average working hours is decreasing overtime. However, countries each have their own trends over time. Interestingly, all highlighted countries show general decline in working hours, except for the two countries in Asia – India and China, where working hours are increasing over time.

Result from the simple regression model where we regress average working hours against year shows that on average, average working hours per week, the average working hours per week is 42.12 hours in the starting year, which is 1950, and it decreases by 0.097 hour each year after that. If we convert to year, average working hours per year decline by 5.04 hours. Based on p-value, this result is significant. Hence, we can conclude that the global average working hours per week are generally decreasing throughout the years, although some countries may have increasing average hours worked, such as China or India.

	Dependent variable:
	Average hours worked per week
Year	-0.097***
	(0.005)
Constant	42.124***
	(0.209)
Observations	3,388
R^2	0.113
Adjusted R^2	0.112
Residual Std. Error	5.191 (df = 3386)
F Statistic	429.262*** (df = 1; 3386)
Note:	*p<0.1;* ***p<0.05;*** p<0.01

Table 7: Regression result for average working hours per week against year

b. **Effect of GDP per capita, employment rates and human capital on average working hours across time.**

In this section, we want to ascertain whether the effects of GDP per capita, employment rates and human capital (can be considered as education) are significant for average working hours throughout the years. Treating country and year variables as fixed effects, we regress average working hours per week against log of GDP per capita (gdppc), employment rates (emp_rate), human capital (hc), and level of income (income_group) on the full dataset (1950-2019) and the data from 1995 to 2019, as already specified in section III.

The results of our estimations have been reported in Table:

	Dependent variable:			
	Average hours worked per week			
	(1)	(2)	(3)	(4)
Log of GDP per capita	-2.751***	-3.381***	-2.693***	-3.095***
	(0.118)	(0.204)	(0.169)	(0.290)
Employment rates	0.813	1.284*	4.026***	4.011***
	(0.782)	(0.780)	(0.914)	(0.915)
Human capital	-1.230***	-1.188***	-1.768***	-1.771***
	(0.173)	(0.173)	(0.251)	(0.250)
Income group (Low)		-2.053***		-0.635
		(0.502)		(0.794)
Income group (Middle)		0.050		-1.287***
		(0.284)		(0.445)
Observations	3,256	3,256	1,559	1,559
R^2	0.355	0.364	0.350	0.355
Adjusted R^2	0.340	0.349	0.339	0.343
F Statistic	583.543*** (df = 3; 3183)	364.311*** (df = 5; 3181)	274.866*** (df = 3; 1531)	168.370*** (df = 5; 1529)
Note:				*p<0.1; **p<0.05;** p<0.01

Table 8: Regression results for average working hours per week against GDP per capita, employment rate and human capital. *(Model (1) and (2) are fitted into the full dataset, while model (3) and (4) are fitted into the data from 1995 to 2019)*

Our results presented in Table 3 reveal that log of GDP per capita and human capital are negatively and significantly associated with average working hours. Employment rate is not significant in the first model where level of income is not factored; however, it is significant and positive in the 3 remaining models. It is worth noting that when we regress the model on the data from 1995 onwards, log of GDP per capita, human capita and employment rate all remain significant, which lessen our concerns about unbalanced data.

c. Variations in average working hours among countries

One of our concerns is that each country has different factors affected their average working hours that are not accounted for in our fix-effects model. As a result, we fit a Bayesian regression model that assumes that each country has a different offset. We can then obtain variance in country offsets, which shows us how much average working hours bounces around from country to country. We record a significant amount of cross-country variation: 3. 67 hours. This means that the cross-country difference in average working hours per week is on average, 3.67 hours.

If we look at country-level variance as a percentage of the total residual variance, we can see that country differences are really important. Country-level variation contributes 64% (3.67/ (3.67 + 2.05)) of the total variance in average working hours per week.

group	estimate	std.error	conf.low	conf.high
country	3.67	0.344	3.09	3.09
Residual	2.05	0.0257	2.00	2.10

Table 9: Variance of Bayesian regression model

We conclude that although the general trend for average working hours is decreasing, variations between countries are considerable and should be taken into consideration.

d. Implications for labour productivity

We have mentioned from the start that average working hours hold significant implication for labour productivity as it enters directly into the equation to calculate labour productivity. Labor productivity measures the efficiency and output of workers. It is typically expressed as the amount of output (goods or services) produced per hour worked.

We calculate labour productivity by dividing GDP per capita by the average working hour for each country, based on the formula provided by….

Labour productiviy = GDP per capita/Average working hours per week

Next, we visualize the evolution of labor productivity over the years, and the findings are intriguing. Firstly, it's evident that labor productivity has been on the rise for all countries in the dataset as the years have progressed. Secondly, there appears to be a distinct threshold in labor productivity that a country must surpass to enter a higher income bracket. As illustrated in the graph, low-income countries typically exhibit labor productivity ranging from approximately $0.4 to $2 per hour, middle-income countries fall within the range of $2 to around $6 per hour, and high-income countries show the broadest spectrum of labor productivity, spanning from over $6 per hour to nearly $50 per hour.

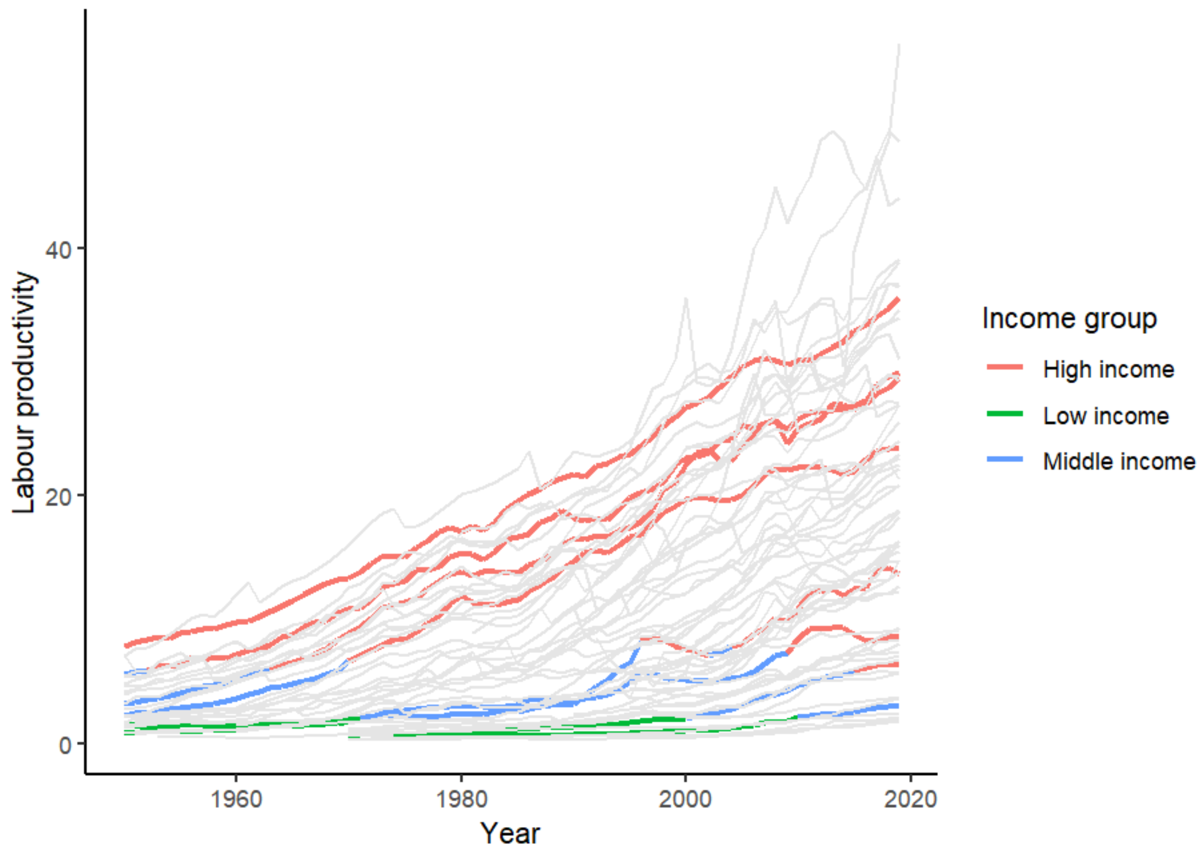


Figure 10: Countries' labour productivity evolution throughout the years

We plotted the labour productivity evolution for China seperately, as it stood out in our dataset for transitioning from a low-income status to a middle-income bracket, and finally, to a high-income category. We can see that as the labour productivity increases, the country changed into higher-income group. It's important to highlight that China, as one of the countries where we observed an increase in average working hours, demonstrated a continuous rise in labor productivity throughout the graph. This suggests that its GDP per capita is increasing at a faster pace than its average working hours.

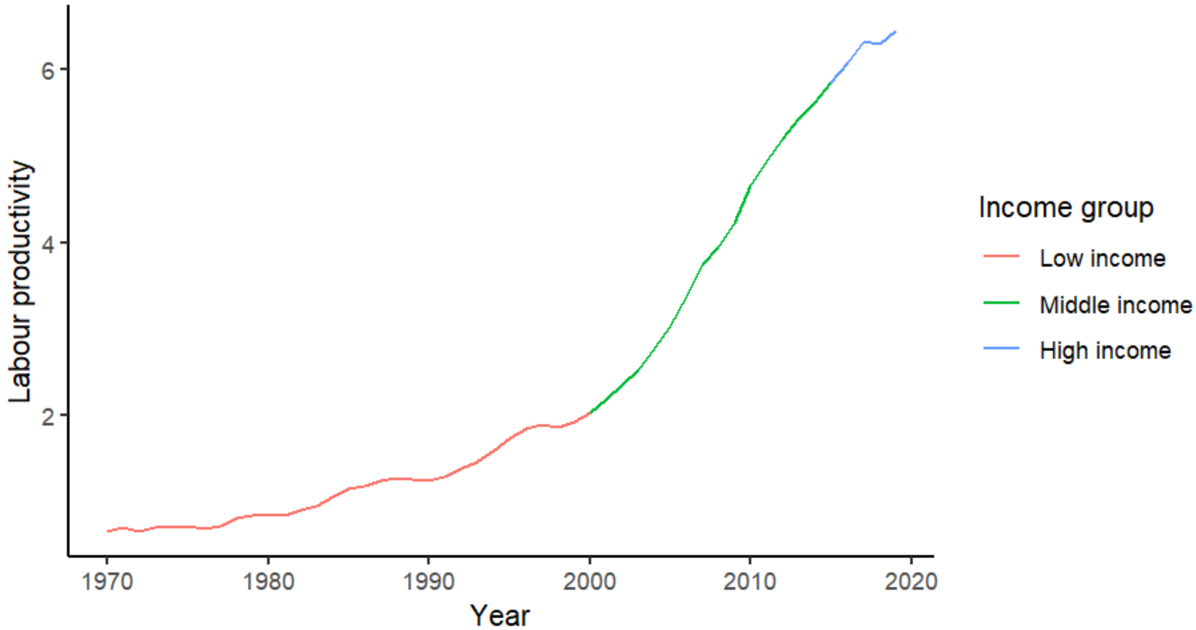
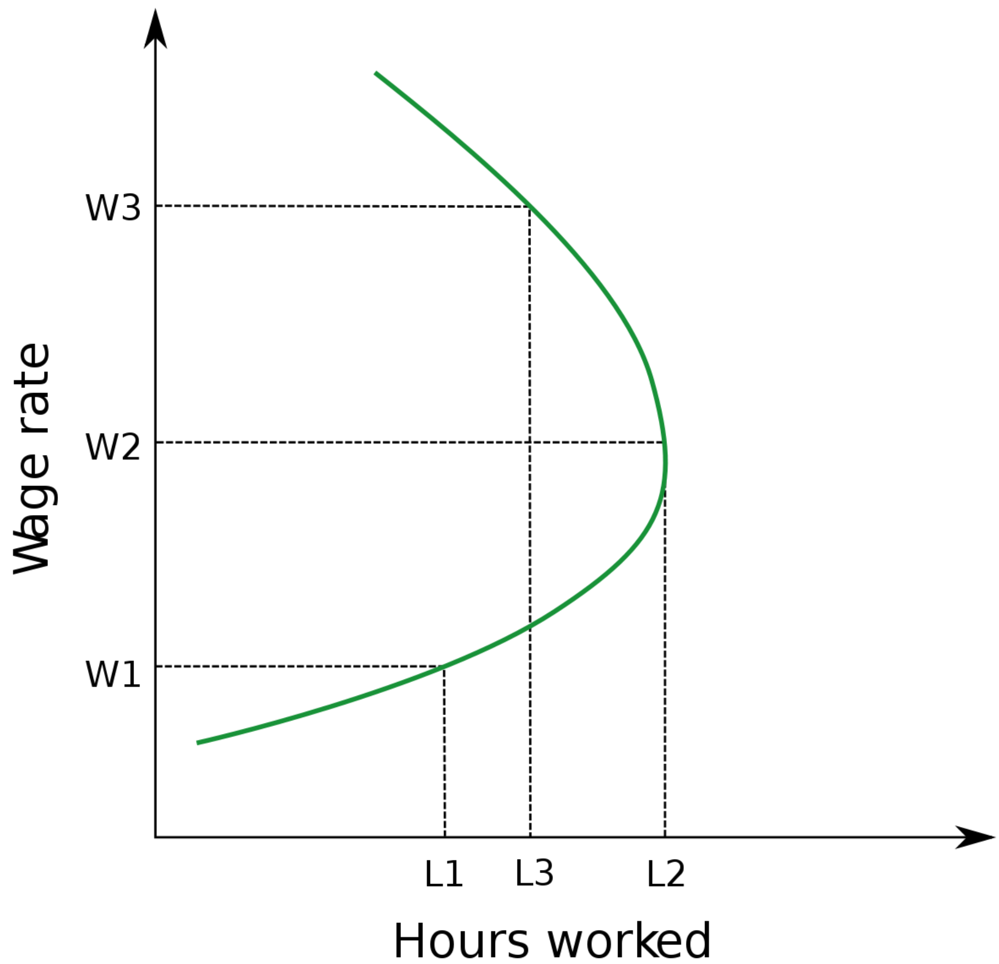


Figure 11: China’s labour productivity evolution throughout the years

Labour productivity is a key indicator of an economy's efficiency and growth potential. Higher labor productivity suggests that workers are producing more in less time, which can lead to economic growth. Our result confirms this: a country has to reach a certain point of labour productivity to drive its GDP and economic growth. Explanations for increasing labour productivity is beyond the scope of this project; however, many studies found that technological advancements are among the most important factor driving labour productivity. Other factors, such as capital investment, worker skills, and organization should also be taken into careful consideration.

VI. Discussion

1. Backward bending labour supply



Why is lower average working hours associated with higher GDP per capita? We have looked into average working hours by age group, by sex and by education to try to identify the driving forces. One other factor and economic theory that we think worth looking into is the backward-bending labour supply curve.

The backward-bending labor supply curve is a concept in labor economics that describes the relationship between the wage rate and the quantity of labor supplied by individuals. Unlike the typical upward-sloping labor supply curve, which suggests that individuals supply more labor as wages increase, the backward-bending labor supply curve shows that there is a point beyond which individuals may reduce their labor supply when wages continue to rise.

Traditionally, the labor supply curve is upward-sloping, indicating that as the wage rate increases, people are generally willing to work more hours. This is because higher wages provide a stronger financial incentive to work, and individuals seek to maximize their income. The backward-bending labor supply curve suggests that, at some point, individuals may reach a level of income at which they become "satiated" or content with their earnings. Beyond this point, they may value leisure time more than additional income. Therefore, as wages continue to rise, they might choose to work fewer hours or reduce their labor force participation.

This phenomenon is often explained by two main effects: income and substitution effects. Income effect says that as wages increase, individuals can earn more income for the same amount of work. However, some people may decide that they already have enough income to meet their needs and preferences. Consequently, they may opt to work fewer hours to enjoy more leisure time. On the other hand, when wages rise, the opportunity cost of leisure time also increases. This might encourage people to work more hours to take advantage of the higher wage rate. Backward bending labour supply shows that when the substitution effect is higher than the income effect, labour supply increases when wage increases, however, when a person's wage reaches a high enough point, the income effect may become dominant, and labour decrease as wage goes higher. The decision to work more or less as wages increase depends on individual preferences and circumstances. Some individuals may prioritize income and work more hours even at high wage rates, while others may value leisure and choose to reduce their working hours.

This may be an appealing explanation for both the generally reverse relationship between GDP per capita/income and average working hours and the reason why some countries such as China have increasing working hours although their GDP per capita is high. It is probable that the wage in China has not reached the satiation point for the majority of its workers, and the income effect is still larger than the substitution effect. The reasons for the higher satiation may be contributed to a variety of factors such as culture, traditions, welfare system and regulation frameworks, which are interesting topics that warrant further investigation beyond our analysis.

2. The US vs. European countries

Generally, higher income means lower average working hours. However, there are some countries that have both higher income and higher working hours, namely the United States, as shown in section. This may be due to culture or other factors not accounted for in the analysis. Several research have also acknowledged that working hours in the US is generally higher than their European counterparts. According to Bick et al. (2019), the working hours of Europeans are 19% lower than those of individuals in the United States.

One potential explanation for this phenomenon is variations in labor taxes (Prescott (2004), McDaniel, 2011), although the inconsistent effects of taxes on labor inputs between microeconometric studies (Alesina et al. 2005) and cross-country studies (Nickell, 2003) suggest that taxation may not provide the complete explanation. Another consideration is the social security system, which includes elements such as early retirement benefits, sickness and disability benefits, and unemployment benefits. While these factors explain changes in certain aspects of labor input like inactivity among different demographic groups, they do not directly account for the disparity in working hours. Additionally, the presence of strong labor unions, leading to more generous welfare benefits and reduced working hours, is another hypothesis proposed by Alesina et al. (2005). Bick et al. (2019) conducted a decomposition of average hours worked differences across OECD countries and the US, revealing that approximately one third to one half of the 14 percent lower hours in Europe compared to the US can be attributed to fewer weeks worked in Europe, and a similar portion can be attributed to lower average education levels in Europe.

3. Limitations of the data

It should be noted that the data we use have some limitations. Particularly, our dataset has significantly higher number of high-income countries compared to middle- and low-income countries, which may lead to inaccurate assessment. Efforts to balance the data more and include more lower-income countries should be made in future research.

VII. Conclusion

In this study, we examine the relationship between income and working hours both within and across countries of varying income levels. To conduct our analysis, we utilized data from Bick et al. (2021), which offers a comprehensive dataset suitable for international comparisons, as well as the Penn World Table, which provides longitudinal data for countries spanning nearly seven decades. Our findings reveal that, on average, adults in developing nations work approximately 7 more hours per week compared to their counterparts in wealthier countries. This pattern holds true across gender and all age and education groups, with individuals in developing countries consistently working more hours. Furthermore, we observe a gradual decline in average working hours, amounting to a decrease of 5.04 hours annually (equivalent to 0.09 hours per week). This decline is a prevailing trend in most countries worldwide, although there are noteworthy exceptions, particularly in Asian countries such as China and India. Variations in average working hours across countries are found to be significant. Understanding the underlying factors contributing to these variations warrants further investigation.

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APPENDIX

List of countries in Bick et al. data and their income group category

country	income_group
ALB	Middle income
AUT	High income
BEL	High income
BGR	Middle income
BWA	Middle income
CHE	High income
COL	Middle income
CYP	High income
CZE	High income
DEU	High income
DNK	High income
ECU	Middle income
ESP	High income
EST	High income
FIN	High income
FRA	High income
GBR	High income
GHA	Low income
GRC	High income
HUN	High income

country	income_group
IRL	High income
IRQ	Middle income
ITA	High income
KEN	Low income
KHM	Low income
LTU	High income
LVA	High income
MNG	Middle income
MUS	High income
MWI	Low income
NLD	High income
PAK	Middle income
PER	Middle income
POL	High income
PRT	High income
ROM	Middle income
RWA	Low income
SVK	High income
SVN	High income
SWE	High income
TLS	Low income
TUR	High income
TZA	Low income
UGA	Low income
USA	High income
VNM	Low income
AGO	Middle income
ARM	Middle income
AUS	High income
BEN	Low income
BIH	Middle income
BOL	Low income
BRA	Middle income
CAN	High income

country	income_group
CHL	High income
EGY	Middle income
GTM	Middle income
IDN	Middle income
JAM	Middle income
JOR	Middle income
KAZ	Middle income
KGZ	Low income
LAO	Low income
LSO	Low income
MEX	High income
MLI	Low income
MYS	Middle income
NAM	Middle income
NIC	Low income
PAN	High income
PHL	Middle income
PRY	Middle income
RUS	High income
SLV	Middle income
SRB	Middle income
TAI	High income
TJK	Low income
TUN	Middle income
VEN	Middle income
ZAF	Middle income