An Analysis on the Impact of Hourly Wage on Labour Productivity: A Multi-Country Study from 2013 to 2022*

A Linear Regression Approach Using OECD Data on GDP per Hour Worked and Hourly Wage

Hyuk Jang

November 11, 2024

Labour productivity is a crucial economical measure as increased labour productivity leads to more output for the same cost which leads to economic growth. Since wage is a significant factor in motivation in working this stimulated a question on how minimum wage may affect labour productivity in the more economical developed countries. Data from OCED for the years 2013 ~ 2022 is used to produce our analysis. In general we observe that a $1 increase in minimum wage is corrleated to an increase in labour productivity by $11.87. It is difficult to conclude the exact effects of miminum wage on labour productivity overall, but we are able to analyze the effects on all selected countries individually.

Table of contents

*Code and data are available at: https://github.com/anggimude/OECD.

1 Introduction

Labour productivity(GDP per hour worked) is defined as the amount of goods and services that an individual worker produces in a given amount of time(Wikipedia (2006)). OECD defines it by how efficiently labour input is combined with other factors of production and used in the production process(OECD (2024a)). Factors that affect worker productivity include technological factors, motivational and behavioral factors, flexibility in internal labour markets, individual rewards, and so forth. This paper intends to look into the correlation between labour productivity and a measurable factor; minimum wage of OECD countries. Maximizing labour productivity is crucial for many countries and its economies because it leads to direct economic growth. Growth in productivity, an economy is able to produce and consume more in other words, produces more goods and services given the same input, allowing consumers to consume more goods and services at a reasonable price. These importance of labour productivity leads us to researching deeper into how hourly minimum wage may affect labour productivity as wage is a large motivating factor for all employees within a capitalist society. For accuracy of data, we use relevant data from the OECD for only the OECD countries as the member countries stimulate economic progress and world trade. In addition, the majority of OECD countries are high-income economies by the world bank income group, and very high in the human development index. In order to create a precise regression result, we look into the data of GDP per person employed, GDP per head of population, GDP per person employed, and Hourly Wage over the years 2013 to 2022 of all OECD countries other than 9 countries due to the availability to the data.

This paper will produce a multiple linear regression to analyze the regression coefficients of each factor. The results of the model will be checked by doing a 95% confident interval on the regression coefficients. The results will allow us to analyze the correlation between average minimum hourly wage and average labour productivity, as well as each countrys' hourly minimum wage and labour productivity. The interaction terms represent how the effect of hourly wage on GDP per hour worked changes across different countries compared to the reference country. The data was obtained from the OECD database(OECD (2024b)) and (OECD (2024c)). R Core Team (2023) was used to clean the raw data to what we use for modelling in other to write an analysis of the intended study. The estimand of this paper are the intercept and coefficients of each predictors which correspond to hourly minimum wage and the countries.

This paper has 4 sections in total not including the introduction. In Section 2 we look at the data that used to carry out the reports including tables and graphs of cleaned data that will be used for the models and the summary statistics. In the next section, we discuss about the models that will be used to analyze our cleaned data, how it is set up and the justifications of it. Next we display and examine the results obtained from the models including tables of the model summaries which helps us make predictions. Lastly, we make final discussions of our results and research based on each cause and dive into some weaknesses that our paper has. In addition, we explore some next steps we or anyone else interested is willing to take after reading this paper.

2 Data

2.1 Raw Data

The data used in this paper is derived from OECD data explorer for GDP(OECD (2024b)), and hourly wage(OECD (2024c)). OECD database provides data of GDP per person employed, GDP per head of population, and GDP per person employed in terms of USD current purchasing power parities as of 2022 for all OECD countries. Minimum wage data provides the minimum hourly wages of all OECD countries in current(2022) USD purchasing power parity for the selected years. For a valid analysis of the trends, we use the data available of the most recent 10 years which is 2013 to 2022. The GDP per hour worked(labour productivity) is used as the dependent variable for our model as we are interested in the correlation between the independent variables which is minimum hourly wage.

The cleaning and modelling of the data for this paper was done through R (R Core Team 2023) with the aid of the following packages: tidyverse (Wickham et al. 2019), dplyr (Wickham et al. 2023), rstanarm (Goodrich et al. 2020), ggplot2 (Wickham 2016), modelsummary (Arel-Bundock 2022), kableExtra (Zhu 2021), arrow(Richardson et al. 2024), tidyr(Wickham, Vaughan, and Girlich 2024), purrr(Wickham and Henry 2023), here(Müller 2020), gt(Iannone et al. 2024), patchwork(Pedersen 2024), broom.mixed(Bolker and Robinson 2022), and broom(Robinson, Hayes, and Couch 2023).

2.2 Cleaned Data

The goal of the cleaning process of this paper is to create a table including GDP per person employed, GDP per head of population, GDP per person employed, Hourly Wage, Year as the columns for each OECD country as the row. To do this we merge the two raw data tables we have downloaded. After merging and doing some minor cleaning like removing repeated columns and rounding to two decimal points. To produce the correlation between average minimum hourly wage and GDP per head of population we must calculate the average hourly wage of all OECD countries for the 10 years. The cleaned table with all relevant data is available in Section A as the table is too large.

As mentioned, Table 5 is the table that consists of all the data that will be relevant in the analysis in this paper. Below Table 1 is the table that shows us all 29 countries that are selected for analysis. There are 38 OECD member countries, but we only use 29 due to the availability of data. An accurate regression result will not be feasible if we fill in missing points from different sources as the sources will not be from the same place creating discrepancies in methods of obtaining the data. Thus, instead of doing so, countries with missing data were removed.

Figure 1[1] displays Table 5 as a scatter plot. Each scatter plot is a representation of each country's economic metrics. The economic metrics values are changed into logarithmic form as the graphs become too difficult to interpret and the logarithmic representation shows the trend in a satisfactory manner; it is easier to interpret the trends. We can observe that certain countries have a much higher growth rate compared to the change in hourly wage over time. In general, we are not able to clearly see the trends in hourly wage and GDP per hour worked. This is likely because values of GDP per person employed, GDP per head of population are much larger than GDP per hour worked and hourly wage making the logarithmic values too small to be able to see a trend in the graph. Ireland and Luxembourg exhibit extreme growth in GDP per person employed and GDP per head of population. It is also observable all countries show a growing trend in all categories over time even if the rate is slow.

Figure 2 presents a scatter plot of the GDP per hour worked against hourly wage over time. It is noticeable by looking at the average of the data that there has been an increasing trend in both hourly wage and GDP per hour worked over time. Some significant trends to mention include Spain, Ireland, and the US. Ireland has had a relatively small change in hourly wages while GDP per hour worked has increased remarkably. Spain has had a steep increase in hourly wages from 2018 to 2019 then slowly decreased while GDP per hour worked has increased at a regular rate. The US has decreased their hourly wages from 2013 on but has had an increase in GDP per hour worked the entire time which has converse from what we expected or the average shows.

[1] Clearer screenshots of all graphs are available at https://github.com/anggimude/OECD

Table 1: Countries Selected for Analysis

Australia	Belgium	Canada	Chile	Colombia	Costa Rica
Czechia	Estonia	France	Greece	Hungary	Ireland
Israel	Japan	Korea	Latvia	Lithuania	Luxembourg
Mexico	Netherlands	New Zealand	Poland	Portugal	Slovak Republic
Slovenia	Spain	Türkiye	United Kingdom	United States	

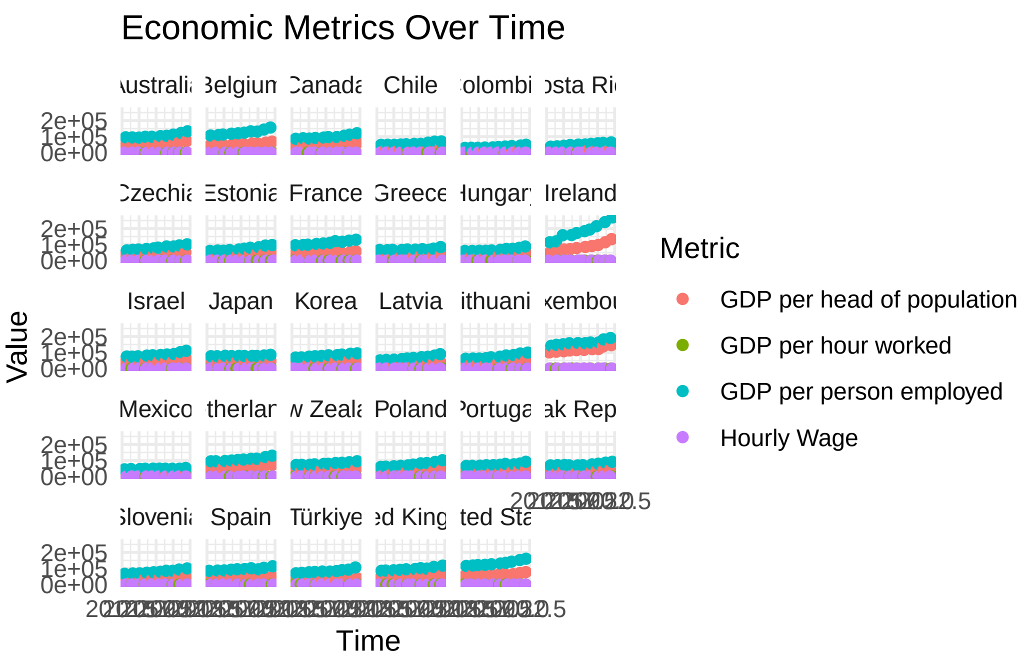

Figure 1: Economic Metrics by Time and Country

2.3 Basic Summary Statistics

Table 2 is a representation of a summary of the economic metrics data. The summary includes the minimum, maximum, mean, standard deviation, variance, and number of observations of the four different economic metrics we are using in this paper. We have a total of 290 observations because we have data of 29 countries for a 10 year period. It is shown that the mean hourly wage is 8 with a minimum of 1 and a maximum of 14, and the similar works for the other metrics as well. It is crucial to mention the notable variances which come from the large range of GDP per person employed and GDP per head of population. For instance,

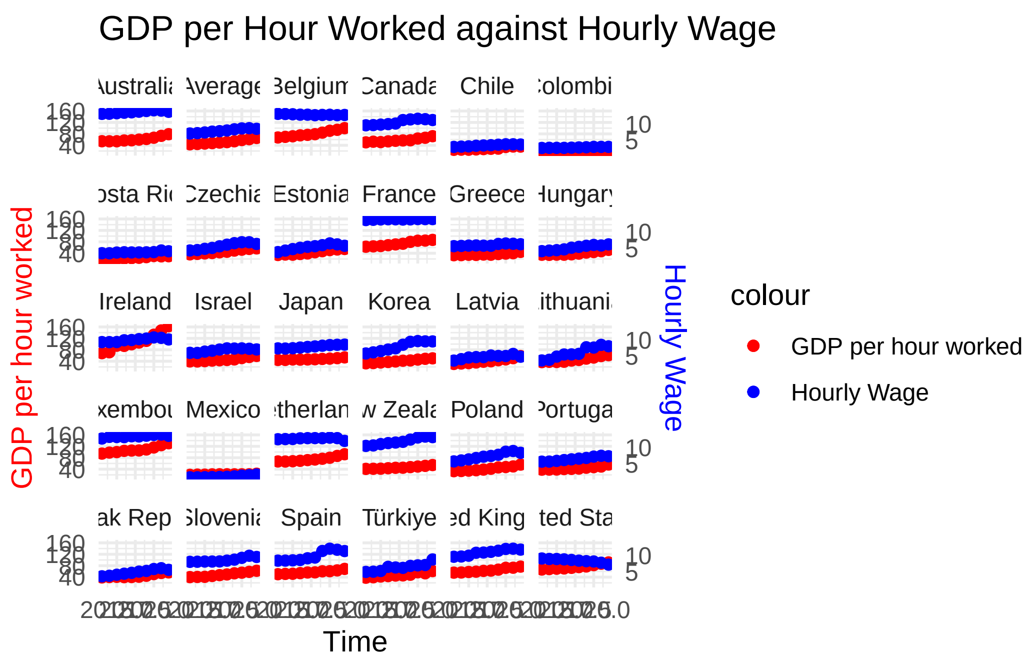

Figure 2: GDP per Hour Worked and Hourly Wage by Time and Country

GDP per person employed has a minimum of 29,380 and a maximum of 269,404 which is a significantly large range. GDP per hour worked is less variant as the mean stays at 52 with a minimum of 12 and maximum of 163.

3 Model

The goal of the Bayesian model is to incorporate prior knowledge, such as insights from previous studies or analyses, into the selection of the model. In this paper, we use linear regression because this model is commonly applied when predicting a continuous outcome variable based

Table 2: Summary statistics of Worker Productivity, GDP per head of population, GDP per person employed, and Hourly Wage

	Min	Mean	Max	SD	Var	N
GDP per person employed	29 380	88 212	269 404	33 989	1 155 235 149	290
GDP per head of population	13 266	42 462	145 971	21 288	453 190 542	290
GDP per hour worked	12	52	163	24	555	290
Hourly Wage	1	8	14	4	12	290

on a predictor variables. The normal (Gaussian) distribution is effective when used for modeling scenarios where the residuals of the data are assumed to be independent and normally distributed around the regression line. Given that our response variable, labour productivity is continuous and random as we have seen from Figure 1 the Gaussian family model from the Bayesian framework allows a flexible approach to understanding the relationships between the continuous outcome (labour productivity) and predictors (country, time, hourly wage) with the benefits of integrating prior knowledge and quantifying uncertainty around estimates.

3.1 Model set-up

The linear regression models utilized in this paper is run on R (R Core Team 2023) using the `rstanarm` package of Goodrich et al. (2020). We use the default priors from `rstanarm`. The response variable y_i is defined as an individual observation of 'GDP per hour worked' for each combination of hourly wage and its corresponding country. The intercept α represents the intercept of our linear model. It is the expected value of y_i when all predictors are held at reference level. Each β_j is the coefficient associated with each predictor in our model. This would correspond to the different countries and years. β_j tells us the change in the expected GDP per hour worked to per unit change in the predictor assuming all else is held constant. We have specified that both α and β_j will have normal priors with a mean of 0 and a standard deviation of 2.5. With this, the `rstanarm` model will internally adjust the priors based on the scale of the predictors to help with the convergence and effectiveness. The error term σ is the standard deviation of the residual errors in our model. By default, the `rstanarm` uses the student-t distribution with 3 degrees of freedom for the standard deviation.

$$
\begin{aligned}
y_i \mid \mu_i, \sigma &\sim \text{Normal}(\mu_i, \sigma^2) && (1)\\
\mu_i &= \alpha + \beta_1 x_{i1} + \beta_2 x_{i2} + ... + \beta_p x_{ip} && (2)\\
\alpha &\sim \text{Normal}(0, 2.5) && (3)\\
\beta_j &\sim \text{Normal}(0, 2.5) \quad \text{for } j = 1, 2, \dots, p && (4)\\
\sigma &\sim \text{Exponential}(1) && (5)
\end{aligned}
$$

3.1.1 Model justification

Based on our inference from Figure 2 and Table 5, we create a new column including the hourly wage centered values of the hourly wage in other words we will use the data of hourly wage centered around the average hourly wages of the whole data set to each countries hourly wage dependent on year. This implies that the entire set of data will be clustered around a mean which allows us to use the normal distribution to produce an analysis. The intercept will represent the predicted value of GDP per hour worked when hourly wage is at average. Each country coefficients represent the difference in the intercept for each country compared to the reference country. In our case, the reference country is the average hourly wages; the process is specified in the data_cleaning code script. The hourly wage and country coefficient shows the effect of hourly wage on how GDP per hour worked changes for each country depending on the reference country.

4 Results

4.1 Overview of model results

Our results are summarized in Table 3 and Table 4. We are primarily interested how labour productivity changes from its predictors. The normal distribution model provides us with the estimates for the intercept and coefficients for the predictors which the 29 countries and its hourly wage correlation as well. The model results will display the estimates - posterior means or medians for each coefficient including the intercept, and uncertainty measures - credible intervals. The output values of each predictor is the regression coefficient, meaning how much the outcome is expected to increase or decrease with a unit increase in hourly wage of that country, holding all else constant. The value in the brackets represent the Median Absolute Deviation of the posterior distributions of the coefficients. It conveys the dispersion around the median of each coefficient's posterior distribution, exhibiting how spread the distributions are. Num.Obs represents the number of observations made in the model. R2 is the R-squared value which is the proportion of variance in the dependent variable that can be explained by the independent variable. The R2 adj is the adjusted R squared which accounts for the number of predictors used. Log.lik is the log-likelihood which gives us an idea of the likelihood of the data, higher is better, but this is typically used for comparison between models. ELPD and ELPD s.e. explains the log predictive density and its standard error. The ELPD measures the sum of the log predictive densities for each observation, used for model comparison. LOOIC is an acronym for leave-one-out information criterion in which a lower value indicates a model with better out-of-sample predictive performance. WAIC stands for Watanabe-Akaike information criterion which is another measure of good fit; lower values are better fit. RMSE is the room mean squared error measuring the model's predictive performance where the lower values mean more accurate predicts.

4.2 Normal regression results

Table 3, Table 4 are both tables of the results from our model. The intercept is the baseline value which in our case is 52.15 implying the expected GDP per hour worked when hourly wage centered is at its mean \$0. Hourly wage centered 11.24 conveys that for each unit(dollar 2022 PPPs) increase in hourly wage is expected to lead to an increase in GDP per hour worked by 11.24(dollar 2022 PPPs). Some notable trends in the results include Belgium, France, Australia, and Columbia. Belgium has a correlation coefficient of 301.27 and a standard deviation of 62.93. This describes that Belgium has a higher GDP per hour worked than the average by around 301.27 units when the hourly wage centered is at zero. Similarly, France is expected to have a labour productivity 327.19 units lower than the average at average centered wage, Australia 77.42 units lower, and Columbia 71.37 units higher. The interaction effects Hourly_Wage_Centered*Country captures how the relationship between hourly wage centered and GDP per hour worked by country are compared to the averages. For instance, Belgium has a interaction effect of -67.43 implying the effect of an increase in hourly wage centered on GDP per hour worked is 67.43 units lower than the reference country. The adjusted R-squared value is at 0.934, which is lower than the R-squared value of 0.942 indicates strong results as 94.2% of the variance on GDP per hour worked is justified by the model. The RMSE is at 5.06 telling us the average magnitude of the model's prediction errors and the value indicates better predictive accuracy. Lower values imply better fit so we can assume that GDP per hour worked is predicted accurately. Thus, by ignoring values like LOOIC and WAIC as we don't have another model to compare it to and analyzing other results, we can conclude that the model is performing well on the data set we have cleaned. Further evaluation of the model results will be done in Section B.

Table 3: Model Summary - Part 1

Term	Coefficient	Standard Error
(Intercept)	52.15	1.70
Hourly_Wage_Centered	11.24	3.19
CountryAustralia	-77.42	28.16
CountryBelgium	301.27	62.93
CountryCanada	-12.13	6.71
CountryChile	37.27	28.72
CountryColombia	71.37	71.85
CountryCosta Rica	35.64	30.95
CountryCzechia	9.39	4.94
CountryEstonia	12.13	5.96
CountryFrance	-327.19	98.36
CountryGreece	1.88	12.56
CountryHungary	7.61	6.93
CountryIreland	-35.80	7.69
CountryIsrael	2.36	4.36
CountryJapan	-4.68	2.44
CountryKorea	-11.65	2.50
CountryLatvia	22.34	10.82
CountryLithuania	2.27	3.12
CountryLuxembourg	-86.62	29.85
CountryMexico	-11.66	40.36
CountryNetherlands	63.58	32.42
CountryNew Zealand	-22.89	7.74
CountryPoland	-7.23	2.51
CountryPortugal	1.72	4.29
CountrySlovak Republic	11.93	6.98

Table 3: Model Summary - Part 1 *(continued)*

Term	Coefficient	Standard Error
CountrySlovenia	-11.76	3.44
CountrySpain	-1.84	3.65
CountryTürkiye	4.16	3.45
CountryUnited Kingdom	-11.22	6.57

Table 4: Model Summary - Part 2

Term	Coefficient	Standard Error
CountryUnited States	31.93	3.20
Hourly_Wage_Centered:CountryAustralia	4.35	5.92
Hourly_Wage_Centered:CountryBelgium	-67.43	13.27
Hourly_Wage_Centered:CountryCanada	-4.39	3.96
Hourly_Wage_Centered:CountryChile	2.26	7.00
Hourly_Wage_Centered:CountryColombia	10.17	14.36
Hourly_Wage_Centered:CountryCosta Rica	4.34	8.02
Hourly_Wage_Centered:CountryCzechia	-4.13	3.70
Hourly_Wage_Centered:CountryEstonia	-2.98	3.81
Hourly_Wage_Centered:CountryFrance	48.34	17.10
Hourly_Wage_Centered:CountryGreece	-2.25	7.02
Hourly_Wage_Centered:CountryHungary	-3.91	3.93
Hourly_Wage_Centered:CountryIreland	33.92	4.79
Hourly_Wage_Centered:CountryIsrael	-2.99	4.53
Hourly_Wage_Centered:CountryJapan	-5.62	5.16
Hourly_Wage_Centered:CountryKorea	-7.24	3.34
Hourly_Wage_Centered:CountryLatvia	-0.47	4.62
Hourly_Wage_Centered:CountryLithuania	-6.39	3.31
Hourly_Wage_Centered:CountryLuxembourg	14.67	6.36
Hourly_Wage_Centered:CountryMexico	-8.42	6.95
Hourly_Wage_Centered:CountryNetherlands	-19.63	7.61
Hourly_Wage_Centered:CountryNew Zealand	-7.08	3.62
Hourly_Wage_Centered:CountryPoland	-4.77	3.57
Hourly_Wage_Centered:CountryPortugal	-3.59	4.32
Hourly_Wage_Centered:CountrySlovak Republic	-4.73	3.90
Hourly_Wage_Centered:CountrySlovenia	-0.43	4.27
Hourly_Wage_Centered:CountrySpain	-7.83	3.41
Hourly_Wage_Centered:CountryTürkiye	-4.96	3.50
Hourly_Wage_Centered:CountryUnited Kingdom	-3.65	3.67
Hourly_Wage_Centered:CountryUnited States	-25.53	4.61

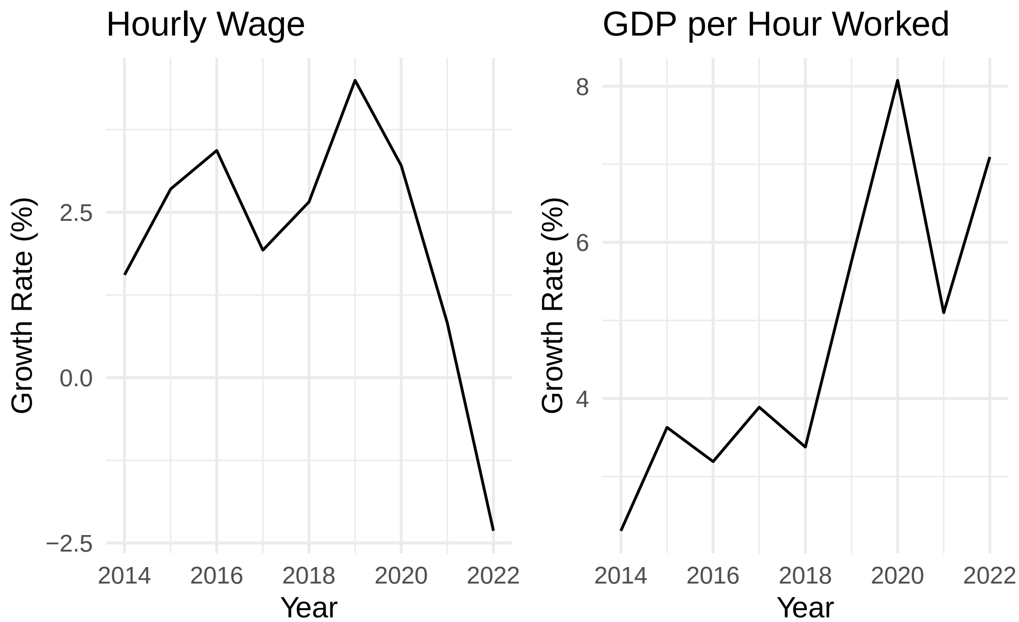

Figure 3: Growth Rate of Hourly Wage and Labour Productivity

5 Discussion

5.1 Further analysis of model results

To look into the general trend of the growth rate, we further analyze Figure 2 to create Figure 3. This graph shows that on average, countries have been experiencing an increase in its labour productivity growth rate for the past decade while the rate of growth of hourly wages have been decreasing. This exhibits some discrepancies from what people generally assume and the actual results because we tend to expect that a higher salary will improve labour productivity. A noticeable trend from the average growth rate of hourly wage is that since 2020, there has been a steep decline. From 2020, the COVID-19 pandemic occurred which had led to the COVID-19 recession. From this inference, due to the global economic recession, we had a spike in inflation decreasing the real wage growth rate. This is correlated to our analysis and graph because we have standardized all values to US dollar purchasing power parities as of 2022, we are able to observe the real effects of these events on the economy. This partially explains the decrease in labour productivity from 2020 to 2021 as this must also be from the lockdown and the recession decreasing consumer confidence. The reason behind the growth in labour productivity may be from various reasons such as technological improvements, investments in human capital, investments in physical capital, and improved management practices(Investopedia (2024)). For the past few decades, technology has been improving at a significant rate each year which could be the underlying reason to labour productivity growth.

From Figure 2, most countries, when scaled like our graph, have similar values in GDP per hour worked and hourly wage while some countries are able to reach the same level of labour productivity with lower minimum wages and some can't reach that level with even higher minimum wages implying that there may not be a strong correlation between minimum wage and labour productivity. One reasoning to such tendencies can be from the different costs of living and purchasing power. More developed countries with higher cost of living set the minimum wage high so that citizens are able to afford basic needs. For example, countries like the US, Australia, Canada, Luxembourg, UK, and Netherlands have a high price level index leading to higher minimum wages (Statista (2022)). Some countries may even intentionally increase their minimum wage to fight income inequalities. For example, Australia has used such methods and has seen positive results with a tight labour market and an increase in minimum wages led to the unemployment averaging at 3.8%; lowest in 50 years (ACOSS (2024)). Others may be supplementing lower minimum wages by providing generous social benefits.

Belgium has an interaction term coefficient of -67.43, suggesting an increase in the minimum wage has substantially lower effect on labour productivity than the average. A possible motive behind this could be related to Belgium's labour market structure and wage policies. Belgium uses the automatic wage indexation system which is the annual adjustment of minimum wages and pay levels in line with the cost of living(Evertys (2023), Eurofound (2021)). This policy helps maintain stable real incomes whilst creating a disconnection in between wages and labour productivity as the policy is aimed to fight inflation instead of optimizing productivity(OECD (2023)). In addition, Belgium is a high income country with a generous social welfare system thus additional increases in minimum wages may not necessarily be a strong driving factor for labour productivity. France has a positive interaction effect indicating an increase in minimum wage will increase labour productivity by 48.34. High value sectors such as manufacturing and services in France receive significant investments in technology and innovation in emphasis of the productivity driven economic policies. This emphasis on capital investment allows workers to be more productive, especially as wage rises(Eurostat (2023)). Furthermore, French labour laws and work culture favors efficient work methods which may be the underlying reason to such results. The educational and vocational training systems can also be policies that link minimum wage and productivity closer as the labour force is trained enough and the quality is relatively high. As mentioned in the previous sections, Luxembourg and the United States exhibit odd trends compared to the average. Luxembourg has a interaction effect coefficient of 14.67 which is slightly above the average. This could be related to Luxembourg's highly skilled workforce and high cost of living, where higher minimum wages are common to fight inflation(LISER (2022)). The coefficient of US -25.53 might be a representation of the wide range of productivity across different sectors. In the US, wage changes tend to reflect inflation as it is usually driven by cost of living changes for lower wage and less skilled sectors(Labor Statistics (2022)). Since COVID-19 pandemic, there has been a start-up boom and start-ups drive up productivity as they adopt new technologies, advance innovation, and make the market more competitive. Such trends may have allowed the US to lower minimum wages but have improvements in labour productivity over the years. Thus, these results highlight the complexity of the wage to labour productivity correlations as many factors such as country, policy, economic structure, and so forth must be taken into account for an accurate analysis.

5.2 Weaknesses and next steps

In this paper, within the processes of analysis of data, there may exist a plethora of weaknesses. One weakness of our analysis is that we have not considered and analyzed all the possible different economic policies or economic fluctuations for each country. For an accurate research, one may expect a detailed explanation on how each country uses different policies to improve labour productivity however since the data is so big, and it is very difficult to conclude the effects on the average country we extract this for later. Another weakness is that we lack predictors. In order to accurate calculate the effect of we must add all the other factors that may influence labour productivity. Without adding other factors and only looking into the correlation between labour productivity and minimum wages can lead to fallacies in properly understanding the results. Our results currently display the correlation between labour productivity and minimum wage but these results include potential effects of other factors inclusive, thus making our results not as accurate as we desire. This helps us know what we can take and improve in the next steps. For future studies, this paper can provide generally analyzed data for labour productivity and minimum wage, so one can further gather data of other predictors or study deeper into a country's economic policies and its correlation to labour productivity. This is not done in this paper as we intend to look at OECD countries for 10 years and data for other significant predictors is very difficult due to its ambiguity.

Appendix

A Cleaned data details

Table 5: GDP per head of population, GDP per hour worked, GDP per person employed, Hourly wage by Country and Time

Country	Year	GDP per head of population	GDP per hour worked	GDP per person employed	Hourly Wage
Australia	2013	47796.02	54.21	95680.59	12.98
Australia	2014	47648.63	53.92	94944.67	13.02
Australia	2015	47266.59	54.15	93808.82	13.18
Australia	2016	50152.48	56.89	98985.87	13.33
Australia	2017	50758.58	57.55	99299.92	13.45
Australia	2018	53118.79	59.85	103083.19	13.64
Australia	2019	53670.04	62.15	105193.92	13.86
Australia	2020	56892.08	66.47	112304.60	14.07
Australia	2021	64113.76	73.10	122700.50	13.97
Australia	2022	71804.15	78.85	133333.21	13.61
Belgium	2013	43672.71	67.42	106894.74	12.98
Belgium	2014	44929.93	69.57	110027.88	12.94
Belgium	2015	46201.69	71.60	112807.60	12.86
Belgium	2016	48599.20	74.83	117784.43	12.74
Belgium	2017	50442.95	76.57	120835.74	12.73
Belgium	2018	52530.84	78.86	124583.85	12.59
Belgium	2019	56621.43	84.26	132887.38	12.66
Belgium	2020	55754.74	90.84	131336.93	12.70
Belgium	2021	62108.15	94.19	144136.10	12.60
Belgium	2022	68287.33	99.98	156511.06	12.65
Canada	2013	44298.51	50.36	86301.03	9.52
Canada	2014	45753.78	52.53	89797.15	9.58
Canada	2015	44670.05	51.23	87624.18	9.73
Canada	2016	46472.37	53.73	91427.81	9.88
Canada	2017	48317.19	55.74	94141.40	10.05
Canada	2018	49992.81	56.99	97022.96	11.11
Canada	2019	50522.15	57.59	97389.84	11.30
Canada	2020	48618.17	63.67	105235.09	11.50
Canada	2021	55801.21	66.38	111872.32	11.38
Canada	2022	62056.15	71.86	121167.24	11.12
Czechia	2013	30828.53	36.15	63773.75	4.31
Czechia	2014	32504.22	37.75	66960.67	4.43

Table 5: GDP per head of population, GDP per hour worked, GDP per person employed, Hourly wage by Country and Time

Country	Year	GDP per head of population	GDP per hour worked	GDP per person employed	Hourly Wage
Czechia	2015	33909.31	39.39	68990.71	4.80
Czechia	2016	36101.29	40.84	72454.13	5.08
Czechia	2017	38842.90	43.31	76943.92	5.58
Czechia	2018	41157.37	45.24	80736.02	6.06
Czechia	2019	44870.50	49.36	88159.78	6.52
Czechia	2020	43913.10	52.50	88038.06	6.81
Czechia	2021	47551.16	55.13	94941.96	6.80
Czechia	2022	51625.60	57.18	101471.84	6.29
France	2013	39528.47	62.86	95936.87	13.52
France	2014	40144.06	64.15	97389.07	13.60
France	2015	40829.89	65.32	99247.75	13.71
France	2016	42855.94	68.26	103896.17	13.77
France	2017	44444.93	70.97	106990.81	13.75
France	2018	46336.93	73.29	110994.38	13.67
France	2019	50961.75	79.82	121173.65	13.73
France	2020	49180.70	83.86	117383.93	13.82
France	2021	53462.66	84.44	124537.53	13.81
France	2022	57179.61	86.75	130196.38	13.82
Greece	2013	25986.64	33.18	66256.96	5.61
Greece	2014	26625.16	33.40	65116.50	5.68
Greece	2015	26760.28	34.62	66990.34	5.78
Greece	2016	27511.80	34.14	66330.84	5.83
Greece	2017	28604.83	35.53	69184.13	5.76
Greece	2018	29617.52	34.86	68356.55	5.73
Greece	2019	31611.26	37.19	71322.67	6.29
Greece	2020	29088.26	38.81	67217.54	6.42
Greece	2021	32797.28	40.15	74452.79	6.34
Greece	2022	38396.50	44.78	84459.72	6.20
Hungary	2013	24547.98	34.72	60188.77	4.11
Hungary	2014	25691.53	34.36	60082.70	4.27
Hungary	2015	26798.85	35.03	61162.22	4.40
Hungary	2016	27941.93	34.83	61302.72	4.64
Hungary	2017	29496.16	36.24	63323.58	5.14
Hungary	2018	31908.86	38.67	66889.46	5.40
Hungary	2019	35152.60	42.30	72847.61	5.72
Hungary	2020	35016.14	44.23	73297.51	5.98
Hungary	2021	38643.76	47.14	79555.34	5.82

Table 5: GDP per head of population, GDP per hour worked, GDP per person employed, Hourly wage by Country and Time

Country	Year	GDP per head of population	GDP per hour worked	GDP per person employed	Hourly Wage
Hungary	2022	43475.99	51.79	87964.49	6.16
Ireland	2013	47836.19	68.16	114319.14	9.26
Ireland	2014	51296.93	71.24	120290.36	9.25
Ireland	2015	69305.54	94.22	158483.15	9.27
Ireland	2016	71505.75	93.54	159417.59	9.81
Ireland	2017	78252.21	99.35	171595.01	9.88
Ireland	2018	85034.73	105.39	183575.19	10.15
Ireland	2019	91072.87	111.11	193566.96	10.32
Ireland	2020	97165.19	132.64	214822.59	10.67
Ireland	2021	114451.03	147.75	240458.43	10.53
Ireland	2022	134148.79	162.54	269404.44	10.06
Japan	2013	39436.68	44.44	77063.18	7.35
Japan	2014	39559.76	44.50	76946.48	7.30
Japan	2015	40908.78	46.17	79366.21	7.40
Japan	2016	40642.70	45.51	78002.06	7.60
Japan	2017	41531.22	46.07	78738.55	7.79
Japan	2018	42264.59	46.78	78582.20	7.95
Japan	2019	42835.82	47.91	78765.03	8.16
Japan	2020	42567.69	49.08	78387.40	8.35
Japan	2021	44355.37	50.77	81614.60	8.44
Japan	2022	46916.83	53.40	85815.97	8.49
Korea	2013	34244.24	32.50	68258.64	5.81
Korea	2014	35324.26	33.43	69219.85	6.15
Korea	2015	37902.36	35.56	73863.97	6.54
Korea	2016	39575.30	37.22	76752.63	7.00
Korea	2017	40957.35	39.11	78715.32	7.37
Korea	2018	43044.34	41.65	82784.06	8.46
Korea	2019	43864.89	42.68	83718.29	9.34
Korea	2020	45142.97	45.71	86976.10	9.56
Korea	2021	48594.47	48.40	92198.84	9.47
Korea	2022	51666.49	50.09	94963.45	9.46
Luxembourg	2013	100561.37	94.43	142239.23	12.74
Luxembourg	2014	104917.95	98.05	148254.48	13.24
Luxembourg	2015	107898.30	99.78	151607.56	13.20
Luxembourg	2016	112955.47	104.11	158028.63	13.16
Luxembourg	2017	114862.53	105.20	158659.31	13.43
Luxembourg	2018	116334.72	105.56	158191.36	13.37

Table 5: GDP per head of population, GDP per hour worked, GDP per person employed, Hourly wage by Country and Time

Country	Year	GDP per head of population	GDP per hour worked	GDP per person employed	Hourly Wage
Luxembourg	2019	121111.05	108.79	162457.27	13.60
Luxembourg	2020	121984.65	115.92	163242.86	13.83
Luxembourg	2021	137737.71	124.03	182002.24	13.95
Luxembourg	2022	145971.49	130.74	190753.95	13.56
Mexico	2013	18481.03	20.03	44679.80	1.00
Mexico	2014	19153.92	20.92	46639.68	1.00
Mexico	2015	19395.33	20.86	46607.55	1.02
Mexico	2016	20410.42	21.71	48583.39	1.06
Mexico	2017	20756.35	21.99	49212.00	1.09
Mexico	2018	21131.37	22.04	49314.59	1.15
Mexico	2019	21116.85	21.81	48592.18	1.29
Mexico	2020	19413.76	21.94	48435.97	1.50
Mexico	2021	20981.22	22.04	48837.21	1.63
Mexico	2022	23659.10	23.99	53402.20	1.84
Netherlands	2013	49242.79	66.98	94752.75	12.53
Netherlands	2014	49233.23	66.75	95165.44	12.58
Netherlands	2015	50288.35	67.83	96717.15	12.60
Netherlands	2016	52289.40	69.28	99573.81	12.81
Netherlands	2017	55089.58	71.73	103062.10	12.86
Netherlands	2018	57825.40	73.75	105914.89	12.87
Netherlands	2019	61089.14	76.41	110110.27	12.85
Netherlands	2020	61066.65	80.03	111135.70	13.01
Netherlands	2021	67693.50	86.31	121443.79	12.87
Netherlands	2022	74533.26	92.32	129906.70	12.03
New Zealand	2013	36084.87	41.01	72006.72	10.51
New Zealand	2014	37084.79	41.35	72695.48	10.66
New Zealand	2015	37246.95	41.62	72964.82	11.06
New Zealand	2016	39696.95	43.27	75892.30	11.36
New Zealand	2017	41994.49	44.81	78681.93	11.53
New Zealand	2018	42320.91	45.12	79362.99	11.75

Table 5: GDP per head of population, GDP per hour worked, GDP per person employed, Hourly wage by Country and Time

Country	Year	GDP per head of population	GDP per hour worked	GDP per person employed	Hourly Wage
New Zealand	2019	44886.22	47.24	84233.70	12.43
New Zealand	2020	45159.14	49.18	85521.34	13.06
New Zealand	2021	48092.31	51.53	89146.94	13.33
New Zealand	2022	52029.50	54.43	95141.88	13.17
Poland	2013	24028.19	32.94	59825.74	5.82
Poland	2014	25005.66	33.57	61173.33	6.11
Poland	2015	26495.81	34.88	63800.66	6.42
Poland	2016	27830.93	36.27	66427.27	6.84
Poland	2017	29609.45	38.49	69730.56	7.24
Poland	2018	31662.21	41.48	74144.28	7.47
Poland	2019	35099.14	46.09	82163.91	7.82
Poland	2020	35891.21	47.46	83949.56	8.75
Poland	2021	40022.79	49.69	90832.58	8.97
Poland	2022	45370.97	56.02	101656.58	8.42
Portugal	2013	27936.01	38.22	65645.90	5.74
Portugal	2014	28742.31	38.41	66242.53	5.76
Portugal	2015	29660.85	38.77	67142.02	5.97
Portugal	2016	31607.61	40.40	70188.02	6.22
Portugal	2017	33044.70	41.03	70872.05	6.45
Portugal	2018	34928.62	42.07	73096.71	6.65
Portugal	2019	37845.06	45.07	78599.10	6.86
Portugal	2020	35874.74	47.13	75935.60	7.26
Portugal	2021	39036.30	49.14	81023.39	7.51
Portugal	2022	44962.90	56.24	91950.63	7.38
Slovak Republic	2013	28021.09	39.05	69188.36	3.71
Slovak Republic	2014	29029.59	40.21	70754.83	3.87
Slovak Republic	2015	30062.18	40.99	71901.40	4.19
Slovak Republic	2016	29737.53	39.99	69580.05	4.50

Table 5: GDP per head of population, GDP per hour worked, GDP per person employed, Hourly wage by Country and Time

Country	Year	GDP per head of population	GDP per hour worked	GDP per person employed	Hourly Wage
Slovak Republic	2017	30147.02	40.33	69111.93	4.76
Slovak Republic	2018	31374.19	41.44	70607.89	5.13
Slovak Republic	2019	33949.00	44.75	75712.80	5.34
Slovak Republic	2020	34988.90	50.66	79638.03	5.92
Slovak Republic	2021	37840.73	54.52	86318.00	6.17
Slovak Republic	2022	40586.47	56.58	91778.84	5.67
Spain	2013	32463.12	50.28	84962.03	8.45
Spain	2014	33558.98	51.27	86669.58	8.47
Spain	2015	34945.48	51.77	87709.83	8.56
Spain	2016	37333.06	53.97	91823.11	8.66
Spain	2017	39601.48	56.18	95075.89	9.17
Spain	2018	40776.77	56.66	96190.64	9.38
Spain	2019	43767.03	60.45	101399.35	11.39
Spain	2020	38975.56	60.81	94736.56	12.07
Spain	2021	43698.22	63.56	103791.46	11.76
Spain	2022	48852.44	68.80	113681.75	11.36
Türkiye	2013	22373.14	37.95	69520.99	5.04
Türkiye	2014	24104.98	39.47	72209.70	5.11
Türkiye	2015	25855.91	42.09	76220.30	5.33
Türkiye	2016	26695.91	43.60	78012.64	6.58
Türkiye	2017	28193.06	45.45	80696.00	6.39
Türkiye	2018	28299.47	46.04	80343.69	6.27
Türkiye	2019	28461.33	48.39	83807.62	6.86
Türkiye	2020	28680.09	56.94	89527.80	7.03
Türkiye	2021	31637.65	53.42	92527.38	7.14
Türkiye	2022	38355.11	61.27	106131.06	8.81
United Kingdom	2013	39968.10	55.62	85287.76	9.63
United Kingdom	2014	41281.54	56.23	86713.68	9.71

Table 5: GDP per head of population, GDP per hour worked, GDP per person employed, Hourly wage by Country and Time

Country	Year	GDP per head of population	GDP per hour worked	GDP per person employed	Hourly Wage
United Kingdom	2015	42500.91	58.00	88452.33	9.96
United Kingdom	2016	44057.69	59.11	91109.45	10.84
United Kingdom	2017	46061.35	61.78	94880.71	10.91
United Kingdom	2018	47107.71	62.80	96466.14	11.12
United Kingdom	2019	49940.54	66.18	101720.40	11.46
United Kingdom	2020	48006.08	72.60	99059.63	12.00
United Kingdom	2021	52841.89	72.95	109290.04	12.07
United Kingdom	2022	56765.79	76.73	117526.68	11.80
United States	2013	53234.74	66.65	115473.22	9.11
United States	2014	55094.13	68.19	118567.73	8.96
United States	2015	56796.90	69.46	121154.25	8.95
United States	2016	57930.97	70.37	122437.38	8.84
United States	2017	60001.54	72.43	126128.52	8.66
United States	2018	62825.10	75.05	130806.99	8.45
United States	2019	65115.12	77.34	134744.52	8.30
United States	2020	64266.79	81.94	142173.85	8.20
United States	2021	70991.30	86.87	152451.67	7.83
United States	2022	77171.74	91.50	160484.42	7.25
Chile	2013	22295.74	24.16	48841.84	2.97

Table 5: GDP per head of population, GDP per hour worked, GDP per person employed, Hourly wage by Country and Time

Country	Year	GDP per head of population	GDP per hour worked	GDP per person employed	Hourly Wage
Chile	2014	22650.71	24.78	49416.90	3.06
Chile	2015	22563.58	24.53	48896.30	3.14
Chile	2016	23384.61	25.61	50635.90	3.32
Chile	2017	24479.46	26.73	52476.92	3.42
Chile	2018	25496.43	27.83	54430.27	3.50
Chile	2019	25762.12	28.42	54840.40	3.64
Chile	2020	25258.08	34.12	62282.10	3.77
Chile	2021	28873.95	35.79	68568.31	3.77
Chile	2022	31080.13	35.51	69700.54	3.70
Estonia	2013	27418.69	33.90	60239.90	3.82
Estonia	2014	28917.83	35.49	62840.77	4.28
Estonia	2015	29222.75	34.94	61612.19	4.73
Estonia	2016	31310.15	37.33	65953.30	5.12
Estonia	2017	33867.80	39.28	69456.71	5.42
Estonia	2018	36488.64	43.55	74348.73	5.60
Estonia	2019	39640.13	47.28	80103.78	5.92
Estonia	2020	40115.55	51.05	83569.70	6.45
Estonia	2021	45076.58	53.11	93855.54	6.16
Estonia	2022	48784.81	54.93	97248.03	5.72
Israel	2013	34744.04	39.27	74871.31	6.00
Israel	2014	34729.39	39.11	74048.05	5.97
Israel	2015	35795.51	40.25	76245.94	6.37
Israel	2016	38084.53	42.11	80775.27	6.65
Israel	2017	39352.29	43.26	82973.05	7.00
Israel	2018	40082.47	44.34	84707.87	7.36
Israel	2019	41236.22	46.23	87584.96	7.30
Israel	2020	41054.68	51.02	90757.27	7.35
Israel	2021	46258.37	54.64	102593.82	7.23
Israel	2022	52169.36	58.51	110696.88	7.03
Slovenia	2013	29979.62	40.04	66555.68	8.09
Slovenia	2014	30872.73	40.63	68321.82	8.12
Slovenia	2015	31631.84	40.98	69147.72	8.19
Slovenia	2016	33942.77	44.12	72908.88	8.19
Slovenia	2017	36517.58	47.02	76265.27	8.22
Slovenia	2018	39008.30	49.39	79173.96	8.46
Slovenia	2019	42735.11	53.31	85365.85	8.76
Slovenia	2020	42033.26	55.54	85108.48	9.30

Table 5: GDP per head of population, GDP per hour worked, GDP per person employed, Hourly wage by Country and Time

Country	Year	GDP per head of population	GDP per hour worked	GDP per person employed	Hourly Wage
Slovenia	2021	46509.76	58.48	93185.31	9.93
Slovenia	2022	51344.91	62.15	100071.42	9.57
Colombia	2013	13266.00	12.17	29379.64	2.66
Colombia	2014	13777.24	12.63	30372.60	2.70
Colombia	2015	13762.75	12.49	29919.46	2.69
Colombia	2016	14514.22	13.29	31790.30	2.68
Colombia	2017	14930.87	13.80	32805.69	2.75
Colombia	2018	15814.70	14.72	35121.94	2.82
Colombia	2019	16712.41	15.91	37897.59	2.88
Colombia	2020	15938.86	19.92	41217.84	2.98
Colombia	2021	18141.22	18.47	44429.62	2.98
Colombia	2022	21523.65	20.51	49329.68	2.98
Latvia	2013	22637.27	30.41	51275.28	3.65
Latvia	2014	23810.01	31.95	54165.38	4.09
Latvia	2015	24975.54	33.40	55550.57	4.59
Latvia	2016	26724.54	35.51	59079.91	4.71
Latvia	2017	28689.65	38.10	62857.70	4.70
Latvia	2018	30891.88	39.85	66199.45	5.19
Latvia	2019	33305.57	43.50	70952.41	5.05
Latvia	2020	33725.72	46.35	73092.17	5.04
Latvia	2021	36806.73	50.65	81105.38	5.67
Latvia	2022	41473.66	57.93	89983.70	4.83
Lithuania	2013	26721.69	36.79	60970.62	3.69
Lithuania	2014	28184.26	37.87	62479.18	3.89
Lithuania	2015	28834.53	37.32	62446.58	4.86
Lithuania	2016	30925.26	38.16	64661.69	5.50
Lithuania	2017	33761.99	42.32	70117.63	5.53
Lithuania	2018	36376.54	44.36	73815.94	5.69
Lithuania	2019	40577.85	49.03	81654.04	7.69
Lithuania	2020	41168.18	52.78	84182.82	7.60
Lithuania	2021	46285.42	58.02	93998.57	8.42
Lithuania	2022	50968.93	61.17	99344.40	8.00
Costa Rica	2013	15542.37	17.16	37014.43	3.48
Costa Rica	2014	16615.97	18.40	39303.96	3.46
Costa Rica	2015	17649.31	19.71	42507.84	3.67
Costa Rica	2016	19119.34	21.64	47885.71	3.77
Costa Rica	2017	20368.23	22.92	50093.14	3.71

Table 5: GDP per head of population, GDP per hour worked, GDP per person employed, Hourly wage by Country and Time

Country	Year	GDP per head of population	GDP per hour worked	GDP per person employed	Hourly Wage
Costa Rica	2018	21312.71	24.08	51235.69	3.72
Costa Rica	2019	23082.52	26.45	54728.01	3.74
Costa Rica	2020	21778.79	30.36	58570.83	3.81
Costa Rica	2021	23667.72	29.25	60858.41	4.31
Costa Rica	2022	26027.85	29.63	63884.17	4.07

B Model details

B.1 Posterior predictive check

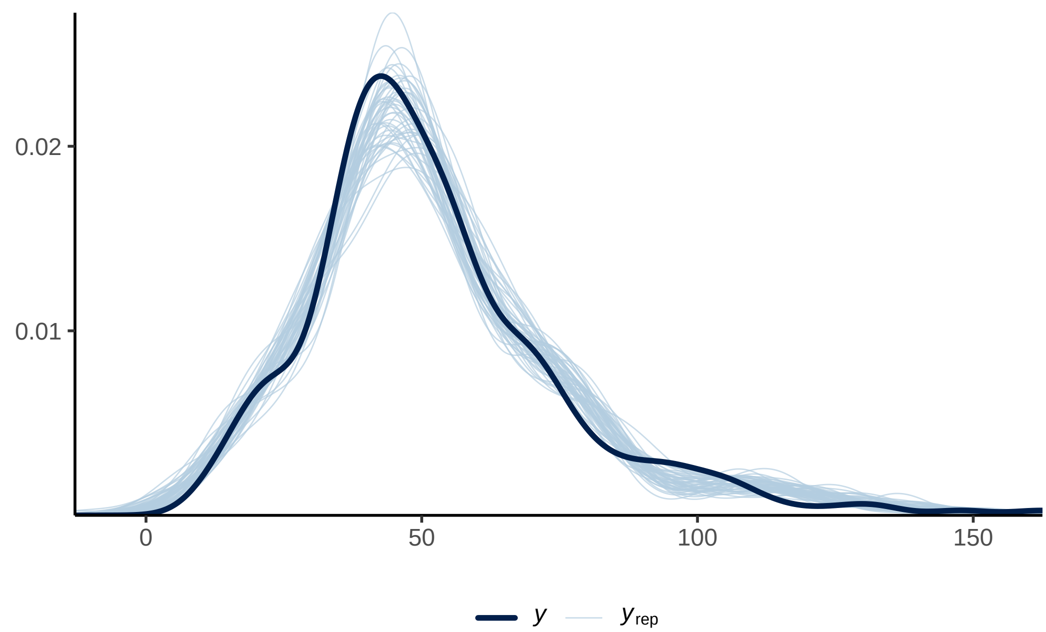

Figure 4: Examining how the model fits, and is affected by, the data

In Figure 4 we implement a posterior predictive check. This show the comparison between the simulated data to the actual observed data to assess whether the model is adequate. This shows the comparison for the poisson model and we can assess how well each model fits the observed data. Based on the check we can conclude that the multiple linear model fits the observed data as the trace of the Y plot follows the trends of Yrep.

B.2 Credibility interval

Figure 5 is a visualization of the estimated effect of each predictor on the outcome variable. The credibility interval we have created is the range in which we can say the true value of the coefficient lies with 95% credibility.

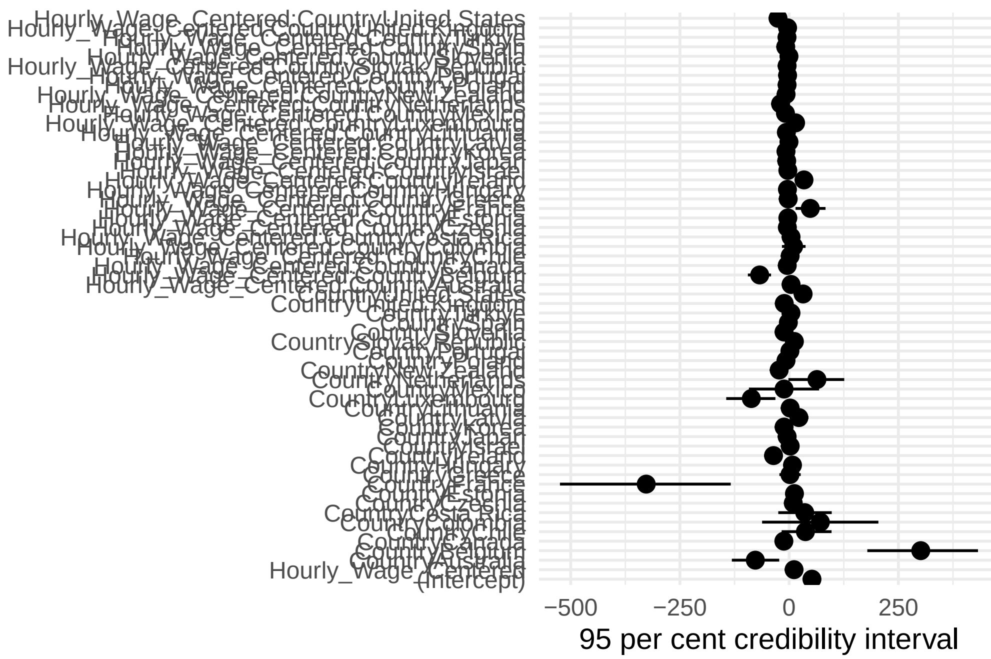

Figure 5: Credibility intervals of the predictors

References

ACOSS. 2024. "Submission to the Fair Work Commission on the Minimum Wage." Australian Council of Social Service (ACOSS). https://www.fwc.gov.au/documents/wage-reviews/2023-24/c2024-1-subs-acoss-2024-03-28.pdf.

Arel-Bundock, Vincent. 2022. "modelsummary: Data and Model Summaries in R." *Journal of Statistical Software* 103 (1): 1–23. https://doi.org/10.18637/jss.v103.i01.

Bolker, Ben, and David Robinson. 2022. *Broom.mixed: Tidying Methods for Mixed Models*. https://CRAN.R-project.org/package=broom.mixed.

Eurofound. 2021. "Wage Indexation in Belgium: Background and Main Trends." Eurofound.

Eurostat. 2023. "Labour Productivity and Compensation Per Hour Worked." Statistical Office of the European Union.

Evertys. 2023. "Understanding Automatic Wage Indexation in Belgium." Evertys. https://www.evertys.be/insights/understanding-automatic-wage-indexation-belgium#:~:text=Automatic%20wage%20indexation%20refers%20to,with%20the%20cost%20of%20living.

Goodrich, Ben, Jonah Gabry, Imad Ali, and Sam Brilleman. 2020. "Rstanarm: Bayesian Applied Regression Modeling via Stan." https://mc-stan.org/rstanarm.

Iannone, Richard, Joe Cheng, Barret Schloerke, Ellis Hughes, Alexandra Lauer, and JooYoung Seo. 2024. *Gt: Easily Create Presentation-Ready Display Tables*. https://CRAN.R-project.org/package=gt.

Investopedia. 2024. "Labor Productivity: What It Is, Calculation, and How to Improve It." Investopedia. https://www.investopedia.com/terms/l/labor-productivity.asp.

Labor Statistics, Bureau of. 2022. "Labor Productivity and Costs." U.S. Department of Labor.

LISER. 2022. "Annual Report on Economic and Social Trends in Luxembourg." Luxembourg Institute of Socio-Economic Research.

Müller, Kirill. 2020. *Here: A Simpler Way to Find Your Files*. https://CRAN.R-project.org/package=here.

OECD. 2023. "Statistical Databases on Labor Markets." Organisation for Economic Co-operation and Development.

———. 2024a. "GDP Per Hour Worked." OECD. https://www.oecd.org/en/data/indicators/gdp-per-hour-worked.html.

———. 2024b. "OECD Data Explorer." Oecd.org. https://data-explorer.oecd.org/vis?df%5Bds%5D=DisseminateFinalDMZ&df%5Bid%5D=DSD_PDB%40DF_PDB_LV&df%5Bag%5D=OECD.SDD.TPS&dq=.A.GDPPOP%2BGDPEMP%2BGDPHRS..USD_PPP....&pd=2013%2C2022&to%5BTIME_PERIOD%5D=false&vw=tb.

———. 2024c. "OECD Data Explorer - Labor Markets." Oecd.org. https://data-explorer.oecd.org/vis?lc=en&df%5Bds%5D=DisseminateArchiveDMZ&df%5Bid%5D=DF_DP_LIVE&df%5Bag%5D=OECD&av=true&pd=2013%2C2022&dq=ITA%2BAUS%2BAUT%2BBEL%2BCAN%2BCHL%2BCOL%2BCRI%2BCZE%2BDNK%2BEST%2BFIN%2BFRA%2BDEU%2BGRC%2BHUN%2BISL%2BIRL%2BISR%2BJPN%2BKOR%2BLVA%2BLTU%2BLUX%2BMEX%2BNLD%2BNZL%2BNOR%

2BPOL%2BPRT%2BSVK%2BSVN%2BESP%2BSWE%2BCHE%2BTUR%2BGBR%2BUSA%2BOAVG%2BOECD...USD%2BHR_MINWAGE.A&to%5BTIME_PERIOD%5D=false&vw=tb&lb=bt.

Pedersen, Thomas Lin. 2024. *Patchwork: The Composer of Plots*. https://CRAN.R-project.org/package=patchwork.

R Core Team. 2023. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/.

Richardson, Neal, Ian Cook, Nic Crane, Dewey Dunnington, Romain François, Jonathan Keane, Dragoș Moldovan-Grünfeld, Jeroen Ooms, Jacob Wujciak-Jens, and Apache Arrow. 2024. *Arrow: Integration to 'Apache' 'Arrow'*. https://CRAN.R-project.org/package=arrow.

Robinson, David, Alex Hayes, and Simon Couch. 2023. *Broom: Convert Statistical Objects into Tidy Tibbles*. https://CRAN.R-project.org/package=broom.

Statista. 2022. "Price Level Index by Country 2022." Statista. https://www.statista.com/statistics/426431/price-level-index-comparison-imf-and-world-bank-by-country/.

Wickham, Hadley. 2016. *Ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag New York. https://ggplot2.tidyverse.org.

Wickham, Hadley, Mara Averick, Jennifer Bryan, Winston Chang, Lucy D'Agostino McGowan, Romain François, Garrett Grolemund, et al. 2019. "Welcome to the tidyverse." *Journal of Open Source Software* 4 (43): 1686. https://doi.org/10.21105/joss.01686.

Wickham, Hadley, Romain François, Lionel Henry, Kirill Müller, and Davis Vaughan. 2023. *Dplyr: A Grammar of Data Manipulation*. https://dplyr.tidyverse.org.

Wickham, Hadley, and Lionel Henry. 2023. *Purrr: Functional Programming Tools*. https://purrr.tidyverse.org/.

Wickham, Hadley, Davis Vaughan, and Maximilian Girlich. 2024. *Tidyr: Tidy Messy Data*. https://tidyr.tidyverse.org.

Wikipedia, Contributors to. 2006. "Amount of Goods and Services That a Group of Workers Produce in a Given Period of Time." Wikipedia.org. https://en.wikipedia.org/wiki/Workforce_productivity.

Zhu, Hao. 2021. *kableExtra: Construct Complex Table with 'Kable' and Pipe Syntax*. https://CRAN.R-project.org/package=kableExtra.