An Analysis of 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

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*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(citation). OECD defines it by how efficiently labour input is combined with other factors of production and used in the production process. 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 importances 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(citation) 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 Germany as its data from 2013 to 2015 is not available from the source.

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 countries 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(citation). 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(citataion), and hourly wage(citation). OECD database(citation) 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 of all OECD countries. Minimum wage OECD data provides the minimum hourly wages of all OECD countries in current USD purchasing power parity for the selected years. For a valid anlaysis 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 (**citetidyverse?**), dplyr (**citedplyr?**), rstanarm (**citerstanarm?**), ggplot2 (**citeggplot2?**), modelsummary (**citemodelsummary?**), kableExtra (**citekableExtra?**), arrow(**citearrow?**), tidyr(**citetidyr?**), purrr(**citepurrr?**), and broom(**citebroom?**).

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 4 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. We won't be provided with an accurate regression result 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 was removed; only the intersected data of all countries for the columns we have selected were kept and the rest were not considered.

Figure 1 displays Table 4 as a scatter plot. Each scatter plot is a representation of each country's economic metrics. The economic metrics values are changed into log form as the graphs become too messy and the log representation shows the trend in a satisfactory manner; it is easier to interpret the trends. We can observe that the older age groups, Age 85+ and Age 75-84 have the highest suicide rates. Especially the 85+ age group is an outlier in every region/income/sex group. We can also notice that the younger the age, the lower suicide rates tends to be. Some notable exceptions are Oceania's high suicide rate among the ages 15-44. Unlike the other region/income/sex groups, Oceania's younger generation and 85+ has the highest suicide rates. In addition, the older the age group, we notice more extreme suicide rates that goes above 100 per 100,000 population. This occurs three times all of which are in 85+ of age, and male, lower income, and Africa displays such results. The x-axis variables other than Africa, male, and lower income, the data points tend to be gathered up around the average of each variable, meaning that the standard deviation of each region/income group/sex is small.

Table 1: Countries Selected for Analysis

Country
Australia
Belgium
Canada
Czechia
France
Greece
Hungary
Ireland
Japan
Korea
Luxembourg
Mexico
Netherlands

Table 1: Countries Selected for Analysis

Country
New Zealand
Poland
Portugal
Slovak Republic
Spain
Türkiye
United Kingdom
United States
Chile
Estonia
Israel
Slovenia
Colombia
Latvia
Lithuania
Costa Rica

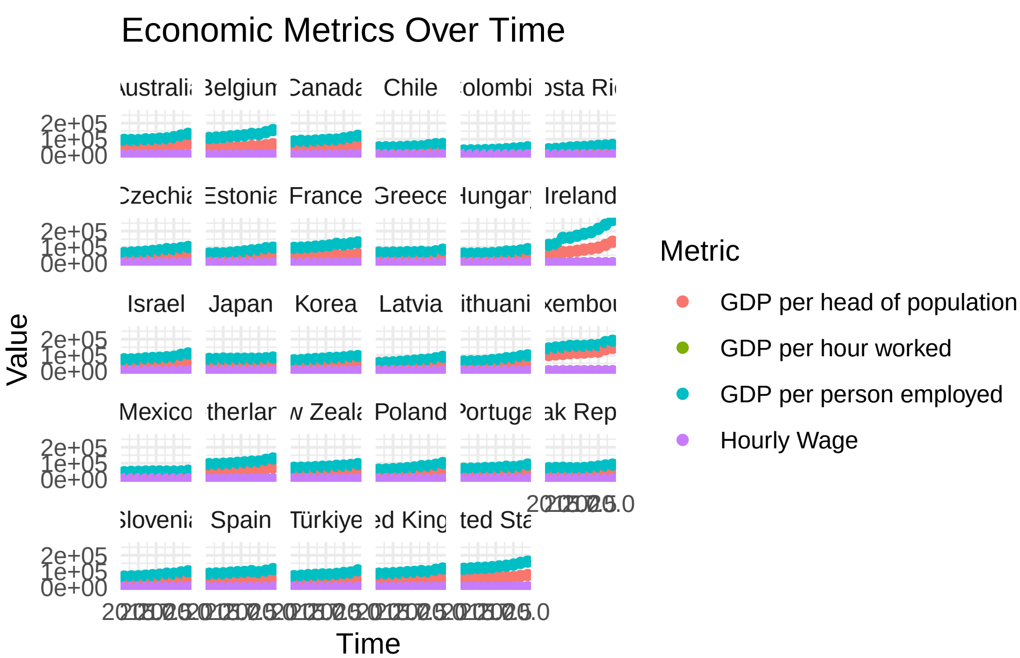

Figure 1: Economic Metrics by Time and Country

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 person employed	29 380	88 212	269 404	33 989	1 155 235 149	290
Hourly Wage	1	8	14	4	12	290

2.3 Basic Summary Statistics

Table 2 is a representation of an summary of the suicide rates of the different age groups. The summary includes the minimum, maximum, mean, standard deviation, variance, and number of observations. The observations is 13 as the summary is created from Table 2, and we have 13 rows representing region/income group/sex. It is shown that the age-standardized suicide rate has a mean of 10, with a minimum of 5, and a maximum of 16. Again it is noticeable that the older the age, suicide rate is higher. Moreover, the variance also gets larger, the older the age group. For example, because age 85+ group has a range of 14 to 132, and a mean of 59 which leads to a extreme variance of 1806 as the data is skewed off the global averages. As the younger the age group, the summary becomes more similar to the global average. The age groups from 15-74 are clustered around a mean of 15, and the ages 75~ consists of means higher than the previous group.

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 multiple linear regression because this model is commonly applied when predicting a continuous outcome variable based on multiple 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. Table 2 captures how suicide rate changes depending on various demographic segments. Given that our response variable, suicide rate is continuous and follows a normal distribution as we have seen from Figure 1 and, each region/income group/sex demographic consists of data points clustered around its mean. Thus, the Gaussian family model from the Bayesian framework allows a flexible approach to understanding the relationships between the continuous outcome (age-standardized suicide rates(per 100,000 population)) and predictors (region/income/sex, age categories) with the benefits of integrating prior knowledge and quantifying uncertainty around estimates.

3.1 Model set-up

The multiple linear regression models utilized in this paper is run on R (R Core Team 2023) using the `rstanarm` package of (**citerstanarm?**). We use the default priors from `rstanarm`. The response variable y_i is defined as an individual observation of 'Age-standardized suicide rates (per 100 000 population)' for each combination of the explanatory variables. 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 'Region/Income/Sex', 'Age 85+', 'Age 75-84', … , 'Age 15-24'. β_j tells us the change in the expected suicide rate 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.

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

3.1.1 Model justification

Based on our inference from Section 2, we expect a stronger positive coefficient in male, and the relatively lower income groups. Because there is a higher suicide rate among males and lower income and lower-middle income groups, we can expect that when there is an increase in the suicide rates of these predictors, age-standardized suicide rate is likely to increase as well. Female and the higher income countries have lower suicide rates than the global average in which helps us conclude that an increase in suicide rates of these predictors isn't likely to increase the global average rate leading us to expect a negative coefficient. The results of the model will let us verify whether our expectations are true or false.

4 Results

4.1 Overview of model results

Our results are summarized in Table 3. We are primarily interested how global age standardized suicide rate depends on each of its predictors. The multiple linear model provides us with the estimates for the intercept and coefficients for the predictors which are male, female, global, lower income, lower-middle, upper-middle, high income, Asia, Europe, North America, South America, Africa, Oceania, age 85+, age 75-84, age 65-74, age 55-64, age 45-54, age 35-44, age 25-34, age 15-24. The intercept represents the estimate of age-standardized suicide rate when the predictors are zero. The coefficients represent the additional suicide rates per 100,000 population associated with each predictor. The model results will display the estimates - posterior means or medians for each coefficient including the intercept, 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 one unit increase in the suicide rate of that predictor, 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 Multiple linear regression results

Table 3 is a table of the results from our model. The intercept is the baseline value which in our case is 3.07. Asia shows a negative coefficient of -1.45, suggesting lower values compared to the baseline, with a large standard error of 12.58. This can be interpreted as the predictor increases, the outcome tends to increase. Conversely, a negative coefficient indicates a decrease. Europe has a negligible negative effect of -0.11 on the outcome with a large standard error of 11.24. Female has a more substantial negative impact of -2.07 and the standard error of 16.91 defines considerable variability in the estimate. Global, high income, and lower income groups show minimal negative coefficients suggesting slight decreases from the baseline. Lower middle income presents almost a neutral effect of 0.01 which is surprising. Male shows a positive relation of 0.91 compared to the baseline. North American and Oceania have more notable negative and positive coefficients respectively in which we can observe significant regional variations. In general, age category shows an increasing trend in coefficients as age decreases. Age groups of 55~ has a very small coefficient, stipulating minor increases compared to the baseline, all with small standard errors. The younger age groups from 15-54 suggesting that younger ages are associated with increasing values of the age standardized suicide rate. With the model having a R-squared value of 0.791 is a good level of explanatory power supporting the accuracy of the results. The adjusted R-squared value is at 0.596, which is lower than the R-squared value which may be because the number of observations is only 13 not the whole dataset before getting the averages. The RMSE is at 0.64 telling us the average magnitude of the model's prediction errors and the value indicates better predictive accuracy. 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 dataset we have cleaned. Further evaluation of the model results will be done in **?@sec-model_details**.

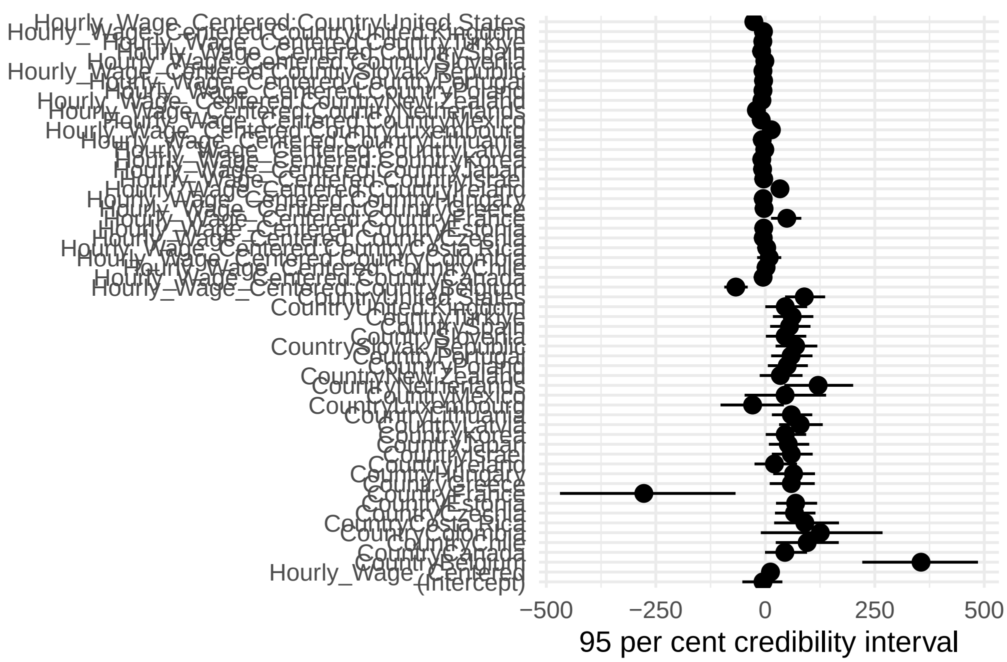

Figure 2: Credibility intervals of the predictors

Table 3: Multiiple linear model summary

	Gaussian(Normal)
(Intercept)	-5.20
	(24.05)
Hourly_Wage_Centered	11.87
	(4.27)
CountryBelgium	355.64
	(68.88)
CountryCanada	44.73
	(24.89)
CountryChile	95.67
	(37.54)
CountryColombia	125.68
	(70.38)
CountryCosta Rica	90.36
	(39.67)
CountryCzechia	66.70
	(24.82)
CountryEstonia	69.23
	(24.74)
CountryFrance	-277.31
	(102.94)
CountryGreece	59.46
	(28.10)
CountryHungary	64.55
	(25.46)
CountryIreland	20.91
	(25.70)
CountryIsrael	59.37
	(24.51)
CountryJapan	52.48
	(24.21)
CountryKorea	45.55
	(23.90)
CountryLatvia	79.70
	(26.71)
CountryLithuania	59.59
	(24.04)
CountryLuxembourg	-28.97
	(37.40)
CountryMexico	45.24
	(47.38)
CountryNetherlands	120.70
	(40.81)
CountryNew Zealand	34.36
	(25.70)
CountryPoland	50.15
	(24.06)
CountryPortugal	58.91
	(24.79)
CountrySlovak Republic	69.31
	(24.87)
CountrySlovenia	45.36
	(24.47)
CountrySpain	55.35
	(24.39)
CountryTürkiye	61.43
	(24.30)
CountryUnited Kingdom	45.61
	(25.18)
CountryUnited States	89.09
	(24.21)
Hourly_Wage_Centered × CountryBelgium	-67.35
	(13.83)
Hourly_Wage_Centered × CountryCanada	-4.99
	(4.84)
Hourly_Wage_Centered × CountryChile	1.82

5 Discussion

5.1 First discussion point

If my paper were 10 pages, then should be be at least 2.5 pages. The discussion is a chance to show off what you know and what you learnt from all this.

5.2 Second discussion point

5.3 Third discussion point

5.4 Weaknesses and next steps

Weaknesses and next steps should also be included.

Appendix

A Cleaned data details

Table 4: 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 4: 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 4: 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 4: 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 4: 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 4: 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 4: 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 4: 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 4: 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 4: 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

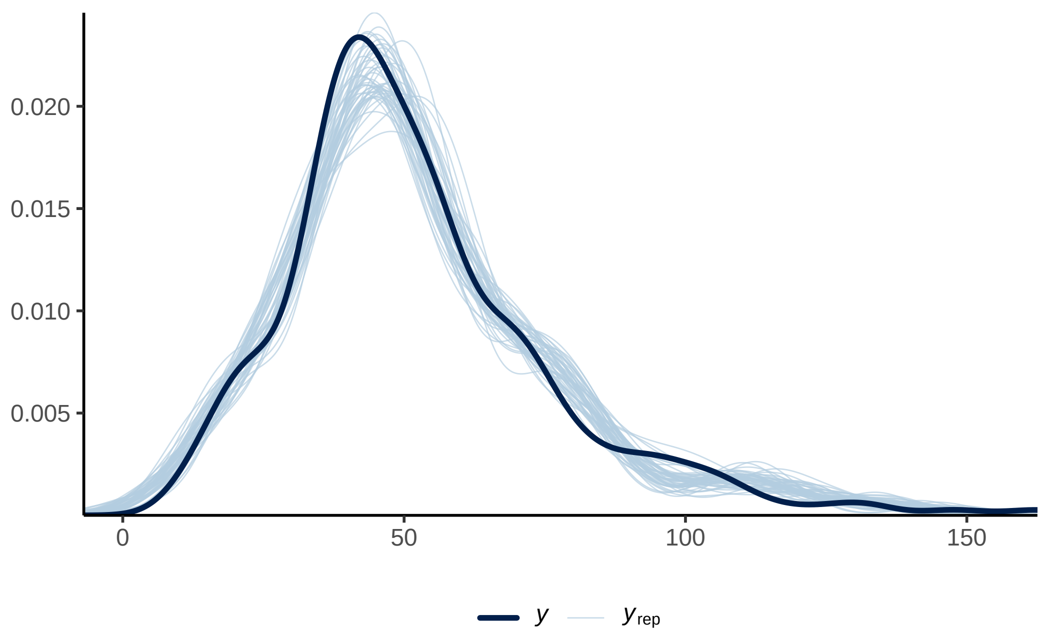

Figure 3: Examining how the model fits, and is affected by, the data

References

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