Phase3

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Link to our github project

Our Github Project

I. Research question

How are changes in health and social protection expenditures associated with avoidable mortality across OECD countries over time?

Population health differs significantly across countries. One key factor explaining these differences is the strength of social and health protection systems. In particular, public investment in healthcare and social protection is expected to reduce mortality from causes that are considered preventable or treatable through effective public policies.

This report seeks to understand the relationship between social and health protection spending and avoidable mortality, used as an indicator of the effectiveness of a country's health system. Avoidable mortality captures premature deaths (under age 75) that could be prevented through healthcare, making it a relevant proxy for population health.

There are two goals in our analysis. First, using panel data for 41 OECD countries between 2000 and 2023, this report aims to describe and analyse the global evolution of avoidable mortality across OECD countries and assess if high levels of social and health spending are correlated with lower avoidable mortality rates. Second, it focuses on the Covid-19 crisis, to understand if countries with a stronger health protection pre-Covid experienced lower avoidable mortality rates from 2019 to 2021.

Method

To conduct our study we will be using a **linear mixed model (LMM)**. Lagged variables will be used as investments in both the social and health systems likely impact the population's general health with a delay. Such a model will allow us to properly study the OECD countries taking into account their differences.

For explanatory variables, in order to estimate the strength and quality of a country's health protection scheme, we will use the following variables:

- Health expenditure
- Social expenditure aggregates
- Number of hospitals beds

We also have more general variables such as :

- GDP per capita
- Unemployment rate
- Human development index
- Life expectancy

They will be used as control variables, since richer countries tend to have better living conditions which may lead to a generally healthier population, without the need for a strong health protection.

Finally, the explained variable will be :

- Avoidable mortality

II. Description of the datasets

This report relies on 8 datasets. Here is a short description of each of them. More details on the datasets and their descriptive statistics can be found in Phase 2.

Health expenditure - OECD (2025)

This dataset details the annual health expenditure and financing as a percentage of GDP for 52 countries. The data is available for a period ranging from 2000 to 2024. It was computed using financial flows related to the consumption of healthcare goods and services from different health providers such as Hospitals or Residential long-term care facilities.

Avoidable mortality - OECD (2025)

This dataset describes the number of "avoidable deaths" per 100,000 inhabitants annually for the period 2000-2024 for 46 countries. It contains contains both "preventable mortality" and "treatable (or amenable) mortality". The first refers to deaths that can be avoided through effective public health and primary prevention interventions. The second refers to timely and effective health care interventions, including prevention and treatment.Both indicators refer to premature mortality (under age 75).

GDP per Capita - World Bank (2024)

The GDP per Capita dataset presents the GDP per capita (constant 2015 US$) from 1960 to 2024 for 70 countries. This indicator is expressed in constant prices, meaning the series has been adjusted to account for price changes over time. The reference year for this adjustment is 2015. This indicator is expressed in United States dollars.

Hospital beds - OECD (2025)

This dataset provides data on the number of total hospitals beds by function of healthcare and by type of care (ie. somatic or psychiatric care) for the period 2000-2024 for 48 different countries. Total hospital beds are the sum of the following categories: Curative care (acute care) beds in hospitals, Rehabilitative care beds in hospitals, Long-term care beds in hospitals, All other beds in hospitals not elsewhere classified.

Life expectancy - World Bank (2023)

This dataset provides the life expectancy in years for women and men for a period ranging from 1960 to 2023, for 69 different countries or economies.

Social Expenditure Aggregate - OECD (2025)

This dataset includes statistics on public and private social expenditure at program level (e.g. Old age, Survivors, Incapacity-related benefits, Health, etc) as a percentage of GDP. It covers 38 OECD countries for the period 1980-2021/23 and estimates for aggregates for 2022-24.

Unemployement Rate - IMF (2025)

This IMF dataset describes the percentage of the labor force that is unemployed and actively seeking employment. It is available from 1980 to 2025 and features 120 geographic regions.

HDI (Human Development Index) - UNDP (2025)

This dataset describes the human development index, per country (195), annually (1990-2023). It is a summary measure of average achievement in key dimensions of human development: a long and healthy life, being knowledgeable and having a decent standard of living. The HDI is between 0 (low human development) and 1 (very high human development).

Table 1: Brief summary of the datasets used in this report

Dataset	Observations	Variables
Health Expenditure	1246	46
Avoidable Mortality	997	44
GDP per Capita	266	70
Number of Hospital Beds	1034	38
Life Expectancy	266	70
Social Expenditure	1046	34
Unemployement	122	32
HDI	4484	10

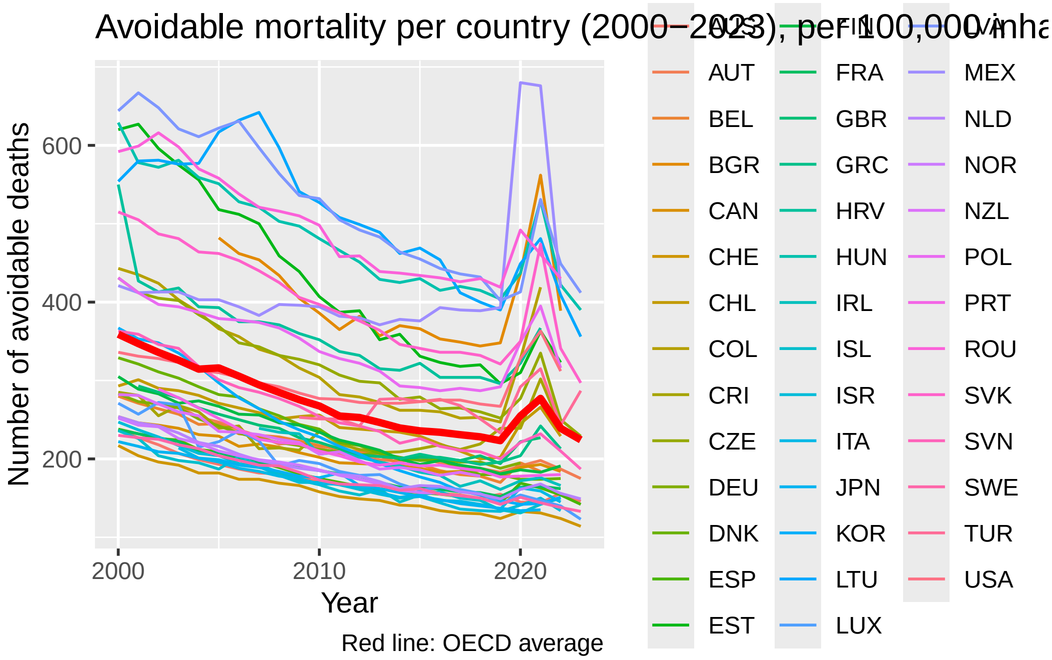
Description of the merged and cleaned dataset

Number of rows	Number of columns	Percentage of NA	Number of countries studied	Time period
888	10	1.05%	41	2000-2023

3. Data Analysis

We first start by a visual exploration of our main variable : avoidable mortality (*OBS_VALUE_mortality*) and its link to explanatory variables.

Evolution of avoidable mortality per country

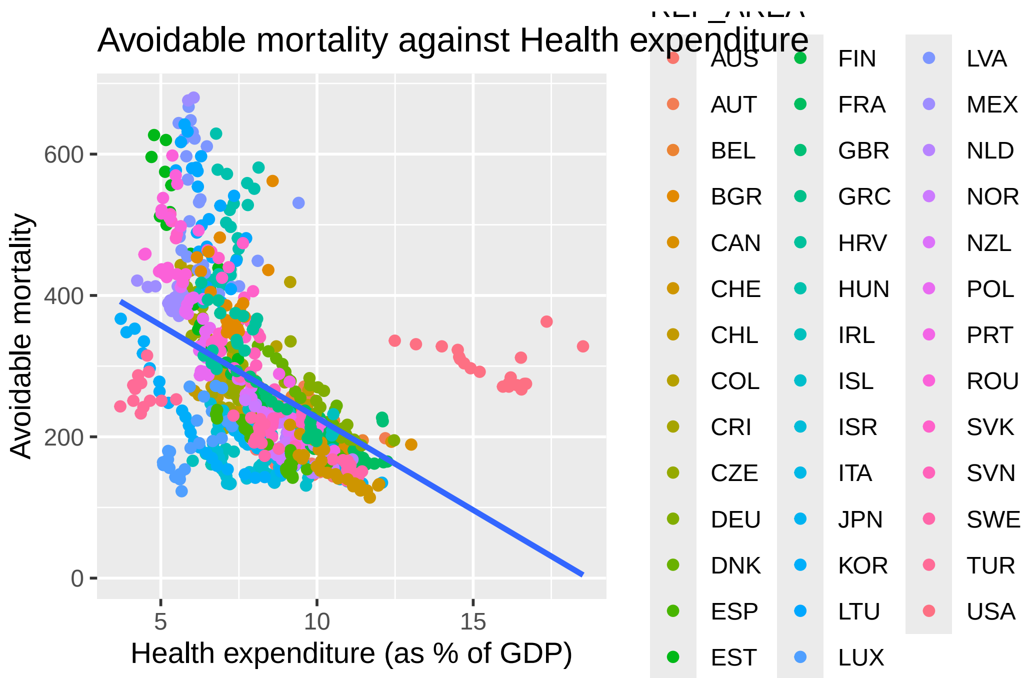


Most countries share the same downward sloping trend in avoidable mortality. A distinct increase appears in 2019, with a peak in 2020 and a decrease to previous trend values from 2021 in all countries. The country with the lowest avoidable death rate is Switzerland (CHE) and the highest is Latvia at the beginning of the 2000s, then surpassed by Lithuania (LTU) around 2007. Additionally, there is a strong increase in avoidable deaths from around 400 to almost 650 per 100,000 inhabitants in Mexico in 2019.

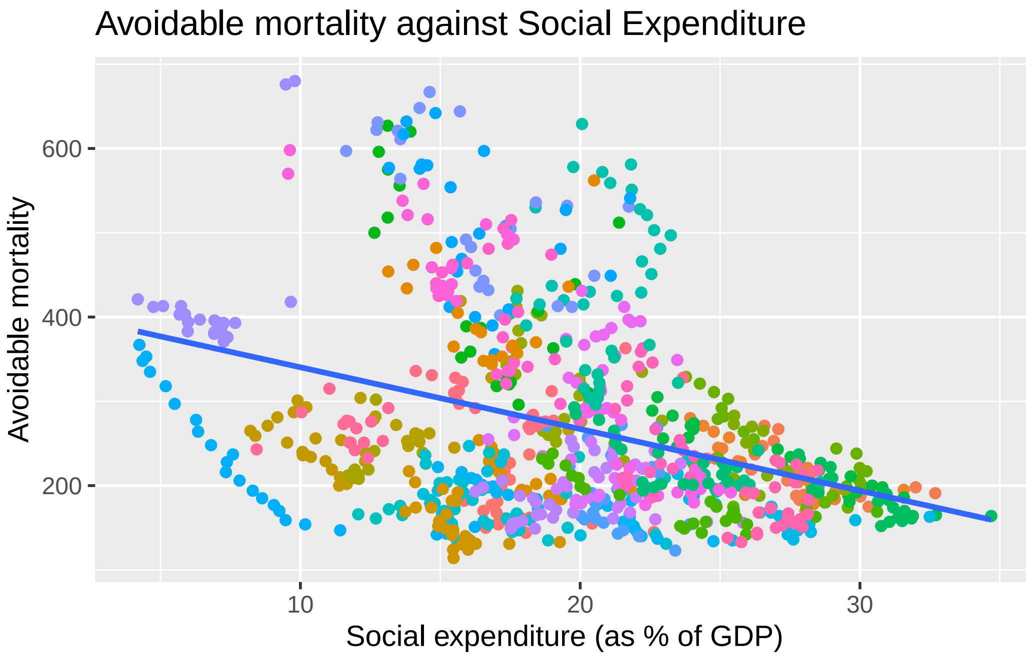
It is important to note that this report primarily studies developed countries with the most available data from 2000 to 2023. We chose to exclude the following countries : South Africa (ZAF), Argentina (ARG), Peru (PER), Thailand (THA) and Brazil (BRA) as the data was not sufficient to proceed with proper data analysis. Thus, our conclusions will be biased due to the fact that we study more developed countries with, perhaps, more similar institutional structures and resistance to global health crises such as Covid-19.

Visualising ***avoidable_mortality*** against independent variables

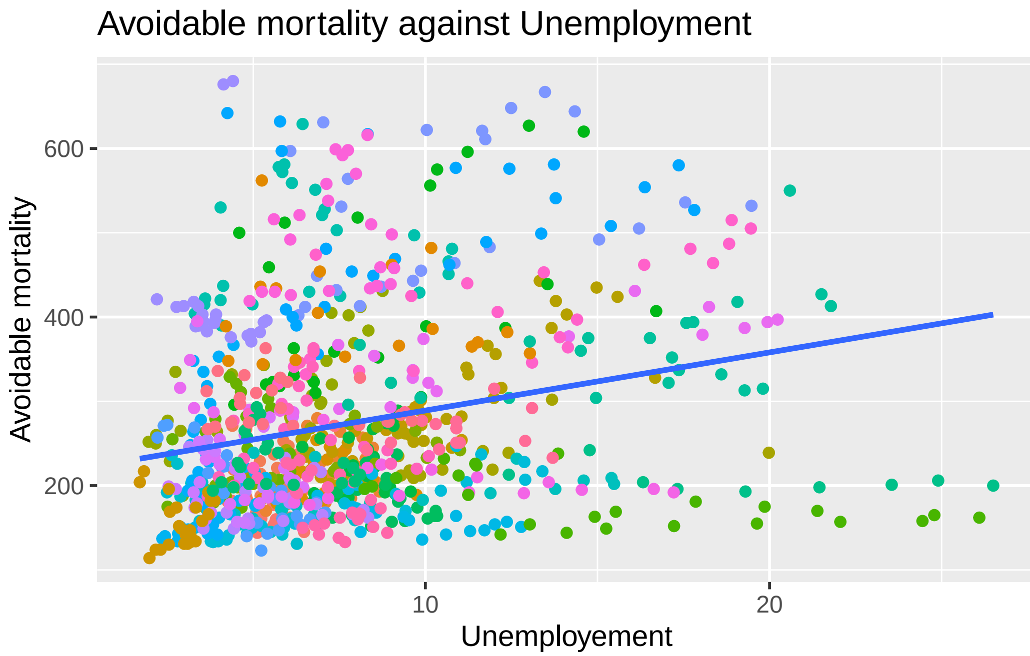
The goal of our analysis is to determine if the evolution of health and social expenditures are correlated with the evolution of avoidable mortality. We can start the data analysis by simply plotting some independent variables against *avoidable_mortality* and observe the general trend.



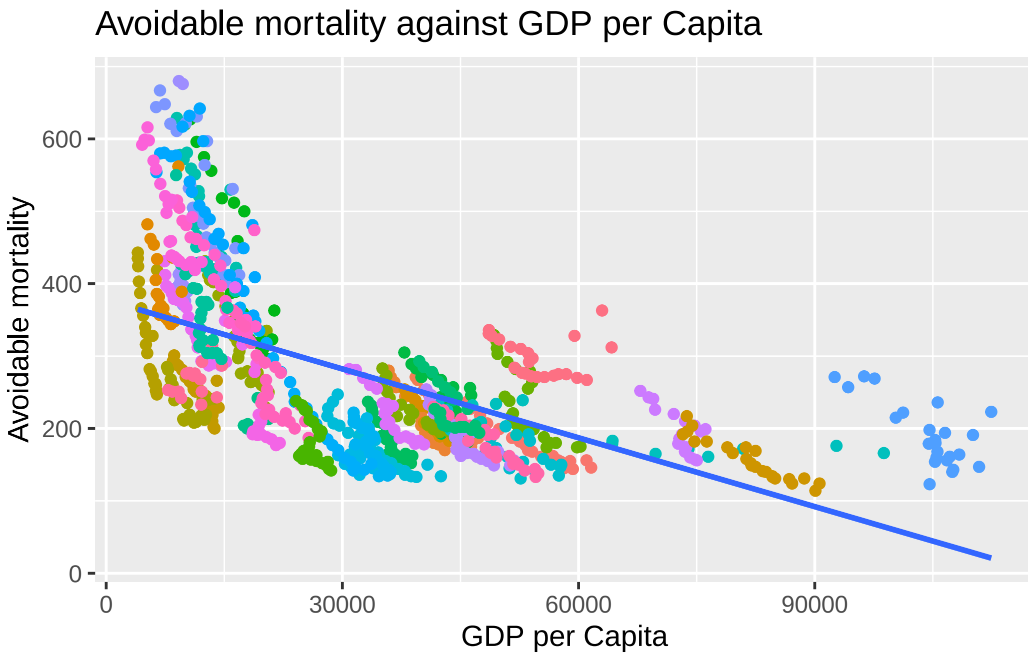
As expected, as the level of health expenditure increases, avoidable mortality tends to decrease. Australia (AUS) detaches itself from other countries by having a particularly high level of health expenditure, but still a moderately high level of avoidable mortality. Most countries are situated on the left side of the graph (with low health expenditure) showcasing countries with high and low rates of avoidable mortality for the same level of health expenditure.



As social expenditure increases, the avoidable mortality rate decreases. Most countries' social expenditure is within 10% and 25% of their GDP. However, for these countries similar in social expenditure levels, avoidable mortality goes from 100 to almost 700 per 100,000 deaths, suggesting an important variability. This observation is consistent with the trend observed using the health expenditure variable. Fro similar levels of health or social expenditure, avoidable mortality seems to vary significantly between countries.



Here, the trend indicates that as unemployment increases, avoidable mortality does too. Most countries have low levels of unemployment and low rates of avoidable mortality. In the bottom right, Spain (ESP) and Greece (GRC) display very high rates of unemployment while keeping their avoidable mortality rates among the lowest of all countries. On the contrary, countries such as Mexico (MEX) in purple showcase high levels of avoidable mortality with very low rates of unemployment.



This graph suggests that as GDP per capita increases, the rate of avoidable mortality decreases. The avoidable mortality rate doesn't seem to go below 100 deaths per 100,000 inhabitants. Thus, as GDP per capita increases, avoidable mortality remains between 100 and 300 deaths per 100,000 inhabitants suggesting marginal change in mortality as a country's population becomes richer.

4. Econometric Analysis : Linear Mixed Model (LMM)

Correlation matrix for control variables

	OBS_VALUE_mortality	OBS_VALUE_gdp	OBS_VALUE_hdi	OBS_VALUE_life_exp	OBS_VALUE_unemp
OBS_VALUE_mortality	1.0000000	-0.6047638	-0.6593684	-0.9559693	0.2393598
OBS_VALUE_gdp	-0.6047638	1.0000000	0.7179984	0.6348101	-0.4273404
OBS_VALUE_hdi	-0.6593684	0.7179984	1.0000000	0.7670182	-0.3755789
OBS_VALUE_life_exp	-0.9559693	0.6348101	0.7670182	1.0000000	-0.2437086
OBS_VALUE_unemp	0.2393598	-0.4273404	-0.3755789	-0.2437086	1.0000000

The correlation matrix reveals strong linear relationships among several control variables.

- Avoidable mortality is highly negatively correlated with life expectancy (-0.96), reflecting the fact that both variables capture very similar aspects of general population health.
- Life expectancy is also strongly correlated with HDI (0.76) and GDP per capita (0.65), meaning there is an overlap between these variables.

In order to avoid multicollinearity issues in our regression, we choose to exclude HDI and life expectancy from our control variables. We retain GDP per capita and unemployment, which can adjust for differences in economic development between countries and remain sufficiently distinct from avoidable mortality.

Creating pandemic dummies

To account for the Covid-19 shock, we introduce a pandemic dummy variable equal to 1 for the years 2019 to 2021 and 0 otherwise. We also add 2 interaction terms with Health expenditure and Social expenditure to assess the impact of these factors on avoidable mortality during this period.

Creating lag operators/ lagged variables

Before making any regression, we created lagged version of our variables. We believe that past investments in health sector and social protection have an impact on mortality and we want this to appear in our model.

We will be creating lagged versions of 4 variables : mortality, health expenditure, social expenditure and hospital beds.

Consequently we have :

- `mortality_lag1` : first lag of the mortality variable (at time t-1)
- `mortality_lag2` : second lag of the mortality variable (at time t-2)
- `healthExp_lag1` : first lag of the health expenditure variable (at time t-1)
- `healthExp_lag2` : second lag of the health expenditure variable (at time t-2)
- `hospBeds_lag1` : first lag of the hospital Beds variable (at time t-1)
- `hospBeds_lag2` : second lag of the hospital Beds variable (at time t-2)
- `socialExp_lag1` : first lag of the social expenditure variable (at time t-1)
- `socialExp_lag2` : second lag of the social expenditure variable (at time t-2)

Model testing

First test

The model we first want to test is :

$$
\begin{aligned}
Mortality_{i,t} = \gamma_{0,i} &+ \beta_1\, mortality_{i,t-1} + \beta_2\, mortality_{i,t-2} + \beta_3\, health.expenditure_{i,t-1} \\
&+ \beta_4\, health.expenditure_{i,t-2} + \beta_5\, Hospital.Beds_{i,t-1} + \beta_6\, Hospital.Beds_{i,t-2} \\
&+ \gamma_7\, GDP.per.capita_{i,t} + \gamma_8\, Unemployment_{i,t} + \gamma_9\, HDI_{i,t} \\
&+ \gamma_{10}\, Life.expectancy_{i,t}
\end{aligned}
$$

With

- i = index for country i
- t = index for period t (here our periods are years)

We also assume that mortality (at time t-1), social expenditure and hospital beds, our explanatory variables, are fixed effects. GDP per capita, Unemployment, Life expectancy and HDI, our control variables, are random effects (meaning that we take into account in this model the fact that they will be different for each country).

- Fixed effects have their coefficient represented by the symbol beta
- Random effects have their coefficient represented by the symbol gamma

```
Linear mixed model fit by maximum likelihood  ['lmerMod']
Formula:
OBS_VALUE_mortality ~ mortality_lag1 + mortality_lag2 + healthExp_lag1 +
    healthExp_lag2 + hospBeds_lag1 + hospBeds_lag2 + OBS_VALUE_gdp +
    OBS_VALUE_unemp + OBS_VALUE_hdi + OBS_VALUE_life_exp + (OBS_VALUE_gdp +
    OBS_VALUE_unemp + OBS_VALUE_hdi + OBS_VALUE_life_exp | REF_AREA)
   Data: data_lagged

      AIC       BIC    logLik -2*log(L)  df.resid
   6304.6    6429.2   -3125.3    6250.6       719

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.0405 -0.4830 -0.0190  0.4847 11.8870

Random effects:
 Groups   Name               Variance  Std.Dev.  Corr
 REF_AREA (Intercept)        9.020e+01  9.497517
          OBS_VALUE_gdp      3.569e-05  0.005974 -0.99
          OBS_VALUE_unemp    1.507e+01  3.882621  0.38 -0.38
          OBS_VALUE_hdi      1.965e+02 14.018316  0.23 -0.24  0.01
          OBS_VALUE_life_exp 5.730e+00  2.393691  0.67 -0.68 -0.03  0.83
```

```
 Residual                    1.301e+02 11.407150
Number of obs: 746, groups:  REF_AREA, 41

Fixed effects:
                     Estimate Std. Error t value
(Intercept)         2.750e+03  6.920e+01  39.734
mortality_lag1      1.864e-01  2.688e-02   6.936
mortality_lag2     -1.441e-01  2.678e-02  -5.382
healthExp_lag1     -3.610e-01  1.322e+00  -0.273
healthExp_lag2      3.708e-01  1.340e+00   0.277
hospBeds_lag1      -2.252e-04  1.266e-04  -1.779
hospBeds_lag2       1.830e-04  1.264e-04   1.447
OBS_VALUE_gdp      -1.396e-03  1.104e-03  -1.265
OBS_VALUE_unemp     8.273e-01  7.596e-01   1.089
OBS_VALUE_hdi       7.160e+02  7.383e+01   9.698
OBS_VALUE_life_exp -3.939e+01  1.093e+00 -36.049

Correlation of Fixed Effects:
            (Intr) mrtl_1 mrtl_2 hltE_1 hltE_2 hspB_1 hspB_2 OBS_VALUE_g
mortlty_lg1 -0.431
mortlty_lg2 -0.181 -0.664
hlthExp_lg1 -0.098 -0.210  0.282
hlthExp_lg2  0.229  0.103 -0.228 -0.719
hospBds_lg1  0.028 -0.035  0.023  0.036  0.028
hospBds_lg2 -0.051  0.028 -0.030 -0.003 -0.008 -0.972
OBS_VALUE_g  0.105 -0.026  0.064 -0.050 -0.039 -0.005 -0.016
OBS_VALUE_n  0.050  0.006  0.027 -0.116  0.010  0.011 -0.033 -0.072
OBS_VALUE_h -0.203 -0.108  0.171 -0.102 -0.056 -0.048  0.049 -0.254
OBS_VALUE__ -0.639  0.420 -0.038  0.132 -0.150  0.003  0.003 -0.193
            OBS_VALUE_n OBS_VALUE_h
mortlty_lg1
mortlty_lg2
hlthExp_lg1
hlthExp_lg2
hospBds_lg1
hospBds_lg2
OBS_VALUE_g
OBS_VALUE_n
OBS_VALUE_h -0.046
OBS_VALUE__ -0.079      -0.502
fit warnings:
Some predictor variables are on very different scales: consider rescaling.
You may also use (g)lmerControl(autoscale = TRUE) to improve numerical stability.
```

```
optimizer (nloptwrap) convergence code: 0 (OK)
boundary (singular) fit: see help('isSingular')
```

After the first test, respecting our first model, we can see two things :

- Firstly, having a second lag for each of the explanatory variables is not as useful to our model as we could have thought. Their coefficient are not coherent compared to variables lagged only once (`healthExp_lag1` compared to `healthExp_lag2` for example). This can be explained by the fact that there is not really a direct effect of the second lag on the explained variable and that they only affect the explained variable through their relation with the first lag. Moreover the coefficients between explanatory variables lagged twice and lagged once are too high, having both is unnecessary. Therefore we can remove second lags from our regressions.
- Secondly, when assuming this many variables have random effects (here, gdp, hdi, unemployment and life expectancy), we notice there is a lot of correlation between the variables with random effects. Especially, there is a lot of correlation between each of these variables and the intercept which is random too (to take in account structural differences between countries). We can conclude it is probably not relevant to have these variables as random effects.

Second test

After this first test, what we are going to try is to largely reduce the number of random effects, and only use one lag. The model we will use for our regression is now :

$$
\begin{aligned}
Mortality_{i,t} = {} & \gamma_{0,i} + \beta_1\, mortality_{i,t-1} + \beta_2\, health.expenditure_{i,t-1} \\
& + \beta_3\, Hospital.Beds_{i,t-1} + \beta_4\, GDP.per.capita_{i,t} + \beta_5\, Unemployment_{i,t} \\
& + \beta_6\, HDI_{i,t} + \beta_7\, Life.expectancy_{i,t}
\end{aligned}
$$

```
Linear mixed model fit by maximum likelihood  ['lmerMod']
Formula:
OBS_VALUE_mortality ~ mortality_lag1 + healthExp_lag1 + hospBeds_lag1 +
    OBS_VALUE_gdp + OBS_VALUE_unemp + OBS_VALUE_hdi + OBS_VALUE_life_exp +
    (1 | REF_AREA)
   Data: data_lagged

      AIC       BIC    logLik -2*log(L)  df.resid
   6657.8    6704.5   -3318.9    6637.8       780
```

```
Scaled residuals:
    Min      1Q  Median      3Q     Max
-4.1635 -0.4504 -0.0189  0.4252 11.4544

Random effects:
 Groups   Name        Variance Std.Dev.
 REF_AREA (Intercept) 453.0    21.28
 Residual             215.4    14.68
Number of obs: 790, groups:  REF_AREA, 41

Fixed effects:
                     Estimate Std. Error t value
(Intercept)         2.266e+03  7.018e+01  32.291
mortality_lag1      2.449e-01  2.189e-02  11.188
healthExp_lag1      9.080e-01  7.087e-01   1.281
hospBeds_lag1       6.237e-06  9.063e-06   0.688
OBS_VALUE_gdp       1.689e-04  1.422e-04   1.188
OBS_VALUE_unemp     1.351e+00  2.335e-01   5.788
OBS_VALUE_hdi       4.119e+02  5.048e+01   8.159
OBS_VALUE_life_exp -3.108e+01  1.013e+00 -30.691

Correlation of Fixed Effects:
            (Intr) mrtl_1 hltE_1 hspB_1 OBS_VALUE_g OBS_VALUE_n OBS_VALUE_h
mortlty_lg1 -0.858
hlthExp_lg1  0.174 -0.004
hospBds_lg1  0.013 -0.003 -0.043
OBS_VALUE_g  0.166  0.000  0.011 -0.010
OBS_VALUE_n  0.043 -0.107 -0.179  0.002  0.258
OBS_VALUE_h  0.017 -0.031 -0.293  0.021 -0.304       0.237
OBS_VALUE__ -0.845  0.699 -0.058 -0.038 -0.042      -0.187      -0.536
fit warnings:
Some predictor variables are on very different scales: consider rescaling.
You may also use (g)lmerControl(autoscale = TRUE) to improve numerical stability.
```

The results seem better and more coherent than in the first model. However we do notice that the AIC - Akaike information criterion, which is a measure for how well fitted a model is - is higher than it was in the previous model (6657.8 versus 6325.4). The AIC checks both if explanatory variables explain the observed variable correctly and for whether or not the number of parameters in the model is too high. Generally the lower the AIC is, the better the model is. The AIC is not absolute, for example here we do see that our second model is more coherent but it encourages us to make more tests.

Third test

For our third test model we add non lagged explanatory variables (variables at lag = 0). We will also add social expenditures which was not in the previous regression to see if it is relevant in our model (OBS_VALUE_social_expenditure and socialExp_lag1)

Our model becomes :

$$
\begin{aligned}
Mortality_{i,t} = \gamma_{0,i} &+ \beta_1\, mortality_{i,t-1} + \beta_2\, social.expenditure_{i,t} + \beta_3\, social.expenditure_{i,t-1} \\
&+ \beta_4\, health.expenditure_{i,t} + \beta_5\, health.expenditure_{i,t-1} + \beta_6\, Hospital.Beds_{i,t} \\
&+ \beta_7\, Hospital.Beds_{i,t-1} + \beta_8\, GDP.per.capita_{i,t} + \beta_9\, Unemployment_{i,t} \\
&+ \beta_{10}\, HDI_{i,t} + \beta_{11}\, Life.expectancy_{i,t}
\end{aligned}
$$

```
Linear mixed model fit by maximum likelihood  ['lmerMod']
Formula: OBS_VALUE_mortality ~ mortality_lag1 + OBS_VALUE_social_expenditure +
    socialExp_lag1 + OBS_VALUE_health_exp + healthExp_lag1 +
    OBS_VALUE_hosp_beds + hospBeds_lag1 + OBS_VALUE_gdp + OBS_VALUE_unemp +
    OBS_VALUE_hdi + OBS_VALUE_life_exp + (1 | REF_AREA)
   Data: data_lagged

      AIC       BIC    logLik -2*log(L)  df.resid
   6495.0    6560.0   -3233.5    6467.0       758

Scaled residuals:
    Min      1Q  Median      3Q     Max
-5.0433 -0.4683 -0.0107  0.4330 11.7165

Random effects:
 Groups   Name        Variance Std.Dev.
 REF_AREA (Intercept) 438.2    20.93
 Residual             209.4    14.47
Number of obs: 772, groups:  REF_AREA, 41

Fixed effects:
                               Estimate Std. Error t value
(Intercept)                   2.140e+03  7.276e+01  29.407
mortality_lag1                2.948e-01  2.335e-02  12.627
OBS_VALUE_social_expenditure -7.100e-02  5.858e-01  -0.121
socialExp_lag1                1.248e-01  5.755e-01   0.217
OBS_VALUE_health_exp          6.857e+00  1.903e+00   3.603
```

```
healthExp_lag1             -4.987e+00  1.880e+00  -2.652
OBS_VALUE_hosp_beds         1.278e-04  1.499e-04   0.853
hospBeds_lag1              -1.226e-04  1.486e-04  -0.825
OBS_VALUE_gdp               2.072e-04  1.426e-04   1.453
OBS_VALUE_unemp             1.231e+00  2.517e-01   4.890
OBS_VALUE_hdi               3.860e+02  5.472e+01   7.053
OBS_VALUE_life_exp         -2.948e+01  1.057e+00 -27.890

Correlation of Fixed Effects:
              (Intr) mrtl_1 OBS_VALUE_s_ sclE_1 OBS_VALUE_hl_ hltE_1
mortlty_lg1   -0.868
OBS_VALUE_s_   0.003  0.049
soclExp_lg1   -0.004  0.008 -0.750
OBS_VALUE_hl_ -0.156  0.164 -0.649        0.542
hlthExp_lg1    0.195 -0.161  0.536       -0.645 -0.878
OBS_VALUE_hs_ -0.019  0.035  0.053        0.031 -0.013        -0.017
hospBds_lg1    0.020 -0.036 -0.051       -0.029  0.010         0.017
OBS_VALUE_g    0.145  0.030  0.085        0.020  0.013        -0.047
OBS_VALUE_n    0.057 -0.143 -0.120       -0.102  0.016         0.006
OBS_VALUE_h    0.031 -0.075 -0.071       -0.106 -0.081         0.035
OBS_VALUE_l_  -0.839  0.717  0.019        0.051  0.160        -0.181
              OBS_VALUE_hs_ hspB_1 OBS_VALUE_g OBS_VALUE_n OBS_VALUE_h
mortlty_lg1
OBS_VALUE_s_
soclExp_lg1
OBS_VALUE_hl_
hlthExp_lg1
OBS_VALUE_hs_
hospBds_lg1   -0.998
OBS_VALUE_g    0.038        -0.038
OBS_VALUE_n    0.005        -0.006  0.186
OBS_VALUE_h   -0.066         0.066 -0.325       0.340
OBS_VALUE_l_   0.042        -0.044 -0.010      -0.244      -0.557
fit warnings:
Some predictor variables are on very different scales: consider rescaling.
You may also use (g)lmerControl(autoscale = TRUE) to improve numerical stability.
```

The AIC is lower in this model than it was in the second test (6495.0 vs 6657.8). However, contrary to what we could believe theoretically, social expenditures at time t and time t-1 do not have a significant impact on mortality at time t (we see that their t-value are close to 0 and not 1 in absolute value)

Fourth test

Fourth test with an additional random effect : GDP per capita (in order to try taking into account countries' richness level)

$$
\begin{aligned}
Mortality_{i,t} = \gamma_{0,i} &+ \beta_1\, mortality_{i,t-1} + \beta_2\, social.expenditure_{i,t} + \beta_3\, social.expenditure_{i,t-1} \\
&+ \beta_4\, health.expenditure_{i,t} + \beta_5\, health.expenditure_{i,t-1} + \beta_6\, Hospital.Beds_{i,t} \\
&+ \beta_7\, Hospital.Beds_{i,t-1} + \gamma_8\, GDP.per.capita_{i,t} + \beta_9\, Unemployment_{i,t} \\
&+ \beta_{10}\, HDI_{i,t} + \beta_{11}\, Life.expectancy_{i,t}
\end{aligned}
$$

```
Linear mixed model fit by maximum likelihood  ['lmerMod']
Formula: OBS_VALUE_mortality ~ mortality_lag1 + OBS_VALUE_social_expenditure +
    socialExp_lag1 + OBS_VALUE_health_exp + healthExp_lag1 +
    OBS_VALUE_hosp_beds + hospBeds_lag1 + OBS_VALUE_gdp + OBS_VALUE_unemp +
    OBS_VALUE_hdi + OBS_VALUE_life_exp + (1 + OBS_VALUE_gdp |      REF_AREA)
   Data: data_lagged

      AIC       BIC    logLik -2*log(L)  df.resid
   6391.7    6466.1   -3179.9    6359.7       756

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.8550 -0.4896  0.0076  0.4040 11.8947

Random effects:
 Groups   Name          Variance  Std.Dev.  Corr
 REF_AREA (Intercept)   1.679e+03 40.974794
          OBS_VALUE_gdp 4.113e-06  0.002028 -0.88
 Residual               1.632e+02 12.776543
Number of obs: 772, groups:  REF_AREA, 41

Fixed effects:
                               Estimate Std. Error t value
(Intercept)                   2.337e+03  6.846e+01  34.139
mortality_lag1                1.875e-01  2.259e-02   8.300
OBS_VALUE_social_expenditure  1.436e-01  5.318e-01   0.270
socialExp_lag1                1.012e-01  5.272e-01   0.192
OBS_VALUE_health_exp          4.985e+00  1.721e+00   2.897
healthExp_lag1               -2.873e+00  1.740e+00  -1.651
OBS_VALUE_hosp_beds           1.292e-04  1.344e-04   0.962
```

```
hospBeds_lag1             -1.288e-04  1.328e-04  -0.970
OBS_VALUE_gdp             -9.085e-04  4.469e-04  -2.033
OBS_VALUE_unemp            6.838e-01  2.692e-01   2.540
OBS_VALUE_hdi              5.759e+02  5.797e+01   9.935
OBS_VALUE_life_exp        -3.350e+01  1.009e+00 -33.188

Correlation of Fixed Effects:
              (Intr) mrtl_1 OBS_VALUE_s_ sclE_1 OBS_VALUE_hl_ hltE_1
mortlty_lg1   -0.817
OBS_VALUE_s_   0.014  0.041
soclExp_lg1   -0.029  0.005 -0.678
OBS_VALUE_hl_ -0.172  0.183 -0.648        0.514
hlthExp_lg1    0.204 -0.174  0.485       -0.636 -0.824
OBS_VALUE_hs_ -0.010  0.039  0.057        0.036 -0.004        -0.006
hospBds_lg1    0.005 -0.040 -0.054       -0.031  0.004         0.011
OBS_VALUE_g    0.065  0.088  0.041       -0.058 -0.009        -0.048
OBS_VALUE_n    0.081 -0.010 -0.129       -0.144  0.036        -0.028
OBS_VALUE_h   -0.010 -0.098 -0.094       -0.105 -0.065         0.038
OBS_VALUE_l_  -0.804  0.670  0.026        0.082  0.164        -0.189
              OBS_VALUE_hs_ hspB_1 OBS_VALUE_g OBS_VALUE_n OBS_VALUE_h
mortlty_lg1
OBS_VALUE_s_
soclExp_lg1
OBS_VALUE_hl_
hlthExp_lg1
OBS_VALUE_hs_
hospBds_lg1   -0.996
OBS_VALUE_g    0.016        -0.033
OBS_VALUE_n    0.004        -0.018  0.311
OBS_VALUE_h   -0.079         0.078 -0.288       0.184
OBS_VALUE_l_   0.041        -0.037  0.015      -0.218      -0.565
fit warnings:
Some predictor variables are on very different scales: consider rescaling.
You may also use (g)lmerControl(autoscale = TRUE) to improve numerical stability.
optimizer (nloptwrap) convergence code: 0 (OK)
boundary (singular) fit: see help('isSingular')
```

Fifth test

Fifth test using HDI as the additional random effect (and no longer GDP per capita) :

$$
\begin{aligned}
Mortality_{i,t} = {} & \gamma_{0,i} + \beta_1\, mortality_{i,t-1} + \beta_2\, social.expenditure_{i,t} + \beta_3\, social.expenditure_{i,t-1} \\
& + \beta_4\, health.expenditure_{i,t} + \beta_5\, health.expenditure_{i,t-1} + \beta_6\, Hospital.Beds_{i,t} \\
& + \beta_7\, Hospital.Beds_{i,t-1} + \beta_8\, GDP.per.capita_{i,t} + \beta_9\, Unemployment_{i,t} \\
& + \gamma_{10}\, HDI_{i,t} + \beta_{11}\, Life.expectancy_{i,t}
\end{aligned}
$$

```
Linear mixed model fit by maximum likelihood  ['lmerMod']
Formula: OBS_VALUE_mortality ~ mortality_lag1 + OBS_VALUE_social_expenditure +
    socialExp_lag1 + OBS_VALUE_health_exp + healthExp_lag1 +
    OBS_VALUE_hosp_beds + hospBeds_lag1 + OBS_VALUE_gdp + OBS_VALUE_unemp +
    OBS_VALUE_hdi + OBS_VALUE_life_exp + (1 + OBS_VALUE_hdi |      REF_AREA)
   Data: data_lagged

      AIC       BIC    logLik -2*log(L)  df.resid
   6209.1    6283.5   -3088.5    6177.1       756

Scaled residuals:
    Min      1Q  Median      3Q     Max
-2.5379 -0.4702 -0.0087  0.3922 12.8280

Random effects:
 Groups   Name          Variance Std.Dev. Corr
 REF_AREA (Intercept)   153841.5 392.23
          OBS_VALUE_hdi 188467.1 434.13   -1.00
 Residual                  121.1  11.01
Number of obs: 772, groups:  REF_AREA, 41

Fixed effects:
                               Estimate Std. Error t value
(Intercept)                   2.585e+03  8.870e+01  29.140
mortality_lag1                9.396e-02  2.092e-02   4.490
OBS_VALUE_social_expenditure  6.424e-01  4.737e-01   1.356
socialExp_lag1                6.618e-02  4.764e-01   0.139
OBS_VALUE_health_exp          2.431e+00  1.518e+00   1.601
healthExp_lag1               -2.430e+00  1.566e+00  -1.552
OBS_VALUE_hosp_beds           8.580e-05  1.172e-04   0.732
hospBeds_lag1                -7.008e-05  1.159e-04  -0.605
OBS_VALUE_gdp                 2.010e-05  1.676e-04   0.120
OBS_VALUE_unemp               5.812e-01  2.372e-01   2.450
OBS_VALUE_hdi                 6.253e+02  9.299e+01   6.725
```

```
OBS_VALUE_life_exp          -3.705e+01  9.379e-01 -39.506

Correlation of Fixed Effects:
             (Intr) mrtl_1 OBS_VALUE_s_ sclE_1 OBS_VALUE_hl_ hltE_1
mortlty_lg1   -0.584
OBS_VALUE_s_   0.014  0.025
soclExp_lg1   -0.019  0.002 -0.571
OBS_VALUE_hl_ -0.113  0.199 -0.649        0.453
hlthExp_lg1    0.158 -0.177  0.423       -0.646 -0.757
OBS_VALUE_hs_ -0.012  0.034  0.060        0.048 -0.009        -0.023
hospBds_lg1    0.008 -0.035 -0.054       -0.041  0.005         0.019
OBS_VALUE_g    0.132  0.062  0.093       -0.030  0.013        -0.069
OBS_VALUE_n   -0.037  0.021 -0.176       -0.147  0.057        -0.019
OBS_VALUE_h   -0.578  0.019 -0.069       -0.069 -0.053        -0.034
OBS_VALUE_l_  -0.512  0.590  0.035        0.082  0.166        -0.145
             OBS_VALUE_hs_ hspB_1 OBS_VALUE_g OBS_VALUE_n OBS_VALUE_h
mortlty_lg1
OBS_VALUE_s_
soclExp_lg1
OBS_VALUE_hl_
hlthExp_lg1
OBS_VALUE_hs_
hospBds_lg1   -0.995
OBS_VALUE_g    0.032        -0.032
OBS_VALUE_n    0.004        -0.006  0.228
OBS_VALUE_h   -0.047         0.051 -0.219       0.256
OBS_VALUE_l_   0.051        -0.053  0.006      -0.250      -0.396
fit warnings:
Some predictor variables are on very different scales: consider rescaling.
You may also use (g)lmerControl(autoscale = TRUE) to improve numerical stability.
```

Sixth

Sixth test using both GDP and HDI as additional random effects :

$$
\begin{aligned}
Mortality_{i,t} = \gamma_{0,i} &+ \beta_1\, mortality_{i,t-1} + \beta_2\, social.expenditure_{i,t} + \beta_3\, social.expenditure_{i,t-1} \\
&+ \beta_4\, health.expenditure_{i,t} + \beta_5\, health.expenditure_{i,t-1} + \beta_6\, Hospital.Beds_{i,t} \\
&+ \beta_7\, Hospital.Beds_{i,t-1} + \gamma_8\, GDP.per.capita_{i,t} + \beta_9\, Unemployment_{i,t} \\
&+ \gamma_{10}\, HDI_{i,t} + \beta_{11}\, Life.expectancy_{i,t}
\end{aligned}
$$

```
Linear mixed model fit by maximum likelihood  ['lmerMod']
Formula: OBS_VALUE_mortality ~ mortality_lag1 + OBS_VALUE_social_expenditure +
    socialExp_lag1 + OBS_VALUE_health_exp + healthExp_lag1 +
    OBS_VALUE_hosp_beds + hospBeds_lag1 + OBS_VALUE_gdp + OBS_VALUE_unemp +
    OBS_VALUE_hdi + OBS_VALUE_life_exp + (1 + OBS_VALUE_hdi +
    OBS_VALUE_gdp | REF_AREA)
   Data: data_lagged

      AIC       BIC    logLik -2*log(L)  df.resid
   6407.7    6496.1   -3184.9    6369.7       753

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.8545 -0.4861 -0.0056  0.4184 11.7795

Random effects:
 Groups   Name          Variance  Std.Dev.  Corr
 REF_AREA (Intercept)   1.012e+03 31.807070
          OBS_VALUE_hdi 1.225e+03 35.000608  0.72
          OBS_VALUE_gdp 9.937e-06  0.003152 -0.74 -0.95
 Residual               1.575e+02 12.548771
Number of obs: 772, groups:  REF_AREA, 41

Fixed effects:
                               Estimate Std. Error t value
(Intercept)                   2.360e+03  6.785e+01  34.788
mortality_lag1                1.779e-01  2.246e-02   7.921
OBS_VALUE_social_expenditure  1.660e-01  5.281e-01   0.314
socialExp_lag1                1.358e-01  5.221e-01   0.260
OBS_VALUE_health_exp          4.869e+00  1.702e+00   2.861
healthExp_lag1               -2.827e+00  1.723e+00  -1.641
OBS_VALUE_hosp_beds           1.102e-04  1.329e-04   0.829
hospBeds_lag1                -1.149e-04  1.312e-04  -0.876
OBS_VALUE_gdp                -1.156e-03  6.216e-04  -1.859
OBS_VALUE_unemp               6.019e-01  2.803e-01   2.147
OBS_VALUE_hdi                 6.167e+02  6.133e+01  10.055
OBS_VALUE_life_exp           -3.417e+01  1.013e+00 -33.716

Correlation of Fixed Effects:
              (Intr) mrtl_1 OBS_VALUE_s_ sclE_1 OBS_VALUE_hl_ hltE_1
mortlty_lg1   -0.808
OBS_VALUE_s_   0.020  0.041
soclExp_lg1   -0.030  0.001 -0.656
```

```
OBS_VALUE_hl_ -0.174  0.182 -0.647        0.505
hlthExp_lg1    0.201 -0.175  0.472       -0.632 -0.815
OBS_VALUE_hs_ -0.012  0.040  0.056        0.036 -0.003        -0.005
hospBds_lg1    0.004 -0.040 -0.053       -0.029  0.005         0.013
OBS_VALUE_g    0.064  0.083  0.046       -0.056 -0.010        -0.040
OBS_VALUE_n    0.086  0.015 -0.122       -0.156  0.038        -0.035
OBS_VALUE_h   -0.019 -0.100 -0.104       -0.098 -0.064         0.035
OBS_VALUE_l_  -0.791  0.657  0.026        0.082  0.166        -0.182
              OBS_VALUE_hs_ hspB_1 OBS_VALUE_g OBS_VALUE_n OBS_VALUE_h
mortlty_lg1
OBS_VALUE_s_
soclExp_lg1
OBS_VALUE_hl_
hlthExp_lg1
OBS_VALUE_hs_
hospBds_lg1   -0.995
OBS_VALUE_g    0.016        -0.031
OBS_VALUE_n    0.005        -0.024  0.290
OBS_VALUE_h   -0.083         0.079 -0.344       0.126
OBS_VALUE_l_   0.046        -0.040  0.031      -0.202      -0.571
fit warnings:
Some predictor variables are on very different scales: consider rescaling.
You may also use (g)lmerControl(autoscale = TRUE) to improve numerical stability.
optimizer (nloptwrap) convergence code: 0 (OK)
boundary (singular) fit: see help('isSingular')
```

Tests four to six helped us notice that :

- GDP and HDI were not varying enough to be random effects. Since we already have a moving intercept and there is not much of a difference between having a moving intercept from one country to another and having a random effect for GDP and HDI per country) Particularly having a random effect for HDI is not great since it has a perfect correlation (-1) with the intercept, meaning that having HDI as a random effect would be useless. We see the same thing with GDP but at a lower level since the correlation is slightly less high.

- Health expenditure at present time and t-1 are relevant in the regression
- Social expenditure not so much (they still have a t value closer to 0 than 1 in absolute value). However it is interesting to keep this variable in our model since it is different from what we were expecting
- The Hospital beds variable is barely relevant (0.8)
- Control variables are really relevant (especially life expectancy)

We also notice that the fifth test (which is not that great since it has correlation problems) has the lowest AIC. We were able to find a lower AIC but it ended up not being a coherent model. Consequently we will have to compromise by choosing a more coherent model with a slightly higher AIC.

Chosen model

The best model we were able to find ended up being our third test.

So our chosen model is :

$$
\begin{aligned}
Mortality_{i,t} = \gamma_{0,i} &+ \beta_1\, mortality_{i,t-1} + \beta_2\, social.expenditure_{i,t} + \beta_3\, social.expenditure_{i,t-1} \\
&+ \beta_4\, health.expenditure_{i,t} + \beta_5\, health.expenditure_{i,t-1} + \beta_6\, Hospital.Beds_{i,t} \\
&+ \beta_7\, Hospital.Beds_{i,t-1} + \beta_8\, GDP.per.capita_{i,t} + \beta_9\, Unemployment_{i,t} \\
&+ \beta_{10}\, HDI_{i,t} + \beta_{11}\, Life.expectancy_{i,t}
\end{aligned}
$$

```
Linear mixed model fit by maximum likelihood  ['lmerMod']
Formula: OBS_VALUE_mortality ~ mortality_lag1 + OBS_VALUE_social_expenditure +
    socialExp_lag1 + OBS_VALUE_health_exp + healthExp_lag1 +
    OBS_VALUE_hosp_beds + hospBeds_lag1 + OBS_VALUE_gdp + OBS_VALUE_unemp +
    OBS_VALUE_hdi + OBS_VALUE_life_exp + (1 | REF_AREA)
   Data: data_lagged

      AIC       BIC    logLik -2*log(L)  df.resid
   6495.0    6560.0   -3233.5    6467.0       758

Scaled residuals:
    Min      1Q  Median      3Q     Max
-5.0433 -0.4683 -0.0107  0.4330 11.7165

Random effects:
 Groups   Name        Variance Std.Dev.
 REF_AREA (Intercept) 438.2    20.93
 Residual             209.4    14.47
Number of obs: 772, groups:  REF_AREA, 41

Fixed effects:
                               Estimate Std. Error t value
(Intercept)                   2.140e+03  7.276e+01  29.407
```

```
mortality_lag1                2.948e-01  2.335e-02  12.627
OBS_VALUE_social_expenditure -7.100e-02  5.858e-01  -0.121
socialExp_lag1                1.248e-01  5.755e-01   0.217
OBS_VALUE_health_exp          6.857e+00  1.903e+00   3.603
healthExp_lag1               -4.987e+00  1.880e+00  -2.652
OBS_VALUE_hosp_beds           1.278e-04  1.499e-04   0.853
hospBeds_lag1                -1.226e-04  1.486e-04  -0.825
OBS_VALUE_gdp                 2.072e-04  1.426e-04   1.453
OBS_VALUE_unemp               1.231e+00  2.517e-01   4.890
OBS_VALUE_hdi                 3.860e+02  5.472e+01   7.053
OBS_VALUE_life_exp           -2.948e+01  1.057e+00 -27.890

Correlation of Fixed Effects:
              (Intr) mrtl_1 OBS_VALUE_s_ sclE_1 OBS_VALUE_hl_ hltE_1
mortlty_lg1   -0.868
OBS_VALUE_s_   0.003  0.049
soclExp_lg1   -0.004  0.008 -0.750
OBS_VALUE_hl_ -0.156  0.164 -0.649        0.542
hlthExp_lg1    0.195 -0.161  0.536       -0.645 -0.878
OBS_VALUE_hs_ -0.019  0.035  0.053        0.031 -0.013        -0.017
hospBds_lg1    0.020 -0.036 -0.051       -0.029  0.010         0.017
OBS_VALUE_g    0.145  0.030  0.085        0.020  0.013        -0.047
OBS_VALUE_n    0.057 -0.143 -0.120       -0.102  0.016         0.006
OBS_VALUE_h    0.031 -0.075 -0.071       -0.106 -0.081         0.035
OBS_VALUE_l_  -0.839  0.717  0.019        0.051  0.160        -0.181
              OBS_VALUE_hs_ hspB_1 OBS_VALUE_g OBS_VALUE_n OBS_VALUE_h
mortlty_lg1
OBS_VALUE_s_
soclExp_lg1
OBS_VALUE_hl_
hlthExp_lg1
OBS_VALUE_hs_
hospBds_lg1   -0.998
OBS_VALUE_g    0.038        -0.038
OBS_VALUE_n    0.005        -0.006  0.186
OBS_VALUE_h   -0.066         0.066 -0.325       0.340
OBS_VALUE_l_   0.042        -0.044 -0.010      -0.244      -0.557
fit warnings:
Some predictor variables are on very different scales: consider rescaling.
You may also use (g)lmerControl(autoscale = TRUE) to improve numerical stability.
```