Dissertation

Economics Meets Mortality

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Introduction

This dissertation consists of three chapters corresponding to three different research analyses. All three empirical studies aimed to demonstrate the deep interconnections between the economy and mortality, emphasising the need for policies that account for how economic stability influences death rates.

The first chapter, titled 'The Silent Killer: The Impact of Unemployment on Mortality', investigated the relationship between unemployment and mortality. To this end, sensitive representative panel micro data on half of the Hungarian population were obtained (Admin3 dataset). The final sample used for estimations was from 2004 - 2016 and included only adults who were unemployed at least once during this period. The methodology employed two-stage least squares (2SLS) regression with time and industry fixed-effects (FE), using an instrumental variable (IV) approach. In this case, unemployment was instrumented by mass lay-offs at firms. This reduced bias as mass dismissals are non-selective. It also enabled a tentative causal interpretation of the results. The estimations confirmed a positive causal relationship between unemployment and mortality. It was revealed that, comparing 100,000 currently employed individuals to 100,000 unemployed ones, nine more died in the unemployed group. Heterogeneous treatment effects were detected, and differences were revealed across sexes, age groups, and regions. It was found that only men's mortality was influenced by unemployment. Only the 'Old' (the last 14 years of work before retirement age) age group's mortality was significantly impacted by unemployment. The most affected region by the relationship between unemployment and mortality was 'Northern Hungary'.

As a final step, three aggregate variables were analysed in the context of the individual-level findings. These were suicide, alcohol consumption, and divorces in Hungary. They enabled a contextual interpretation of the results and revealed some possible drivers behind the relationship between unemployment and mortality. The novelty of the research lies in its methodological approach, enabled by rich individual-level data capturing the heterogeneous effects of sex, age, and region. The mechanism presented in this chapter is unconventional in mortality research, where survival models are more standard. In addition, potential factors influencing the relationship between unemployment and mortality are unveiled.

In the same vein, the second chapter focused on the link between unemployment and suicide (titled 'On the Edge of Despair: The Connection Between Unemployment and Suicide'). Here, two analyses were done. The first used various methodological approaches (pooled OLS with time dummies, FD, within and between estimators, and TWFE) to connect unemployment to suicide worldwide. Towards this goal, country-level aggregate data of over 160 countries for 20 years (2000 - 2019) were obtained. Countries were then divided into three age brackets based on median age. Results mostly aligned with the literature and showed a positive correlation between unemployment and suicide in the period under study.

The objective of the second subchapter was to investigate whether Covid-19 significantly impacted the Hungarian suicide rate, accounting for unemployment. The literature suggested that there had been a significant increase in male suicide in Hungary during the pandemic (Bálint et al., 2022). To test the stability of these results, the period under study was extended by several years (2009 - 2023 as opposed to 2015 - 2021), and the mediator unemployment rate and its lags were also considered. The estimation method used was interrupted time-series regression (ITS). Compared to the literature, the results remained stable; however, larger shifts in suicide trends were observed in areas where it was difficult to attribute the changes to the pandemic.

The third and final chapter (titled 'Analysing Covid-19 Death Outcomes: An Ex-Ante Approach') was an extension and robustness check of a previously published paper (Kovács and Mihályi, 2021). It also examined the impact of Covid-19 but from a different perspective. Here, the goal was to explain as much of the variability of 'Mean Cumulative Excess Death' as possible during the two years of the pandemic. For this purpose, 30 explanatory variables were compiled for over 200 countries and territories. The methodology consisted of two steps: Lasso regression performed variable selection and was followed by an OLS regression that measured the explained variance in the outcome. Overall, the findings of this chapter aligned with our 2021 paper, reinforcing one of our main conclusions: healthier nations experienced significantly fewer deaths during the pandemic. In the final estimation, using only ex-ante variables, an explanatory power of about 60% was achieved. This offered a contextual perspective on the varied Covid-19 outcomes.

Chapter 1

The Silent Killer: The Impact of Unemployment on Mortality

1. Introduction

Most would agree that better economic performance increases the health and longevity of a country's citizens. It appears rather trivial that there should be a connection between unemployment and mortality, yet establishing causality is difficult. Confounding factors such as disease, age, race, sex, region, education level, religion, etc., influence both; thus, untangling cause from effect is difficult.

Therefore, the most important aim of this chapter was to convince the reader of a causal relationship between unemployment and mortality.[1] The analysis was conducted on the Admin3 individual-level dataset, which is representative of the Hungarian population and contains observations of about 5 million people. Instrumental variable estimation was employed on this panel of 14 years. To avoid biased results, unemployment was instrumented by mass layoffs at firms. This helped to avoid overstating the strength of the impact of unemployment on mortality. Moreover, to better understand the driving mechanism of this correlation, several aggregate-level factors were assessed and compared based on the estimation results.

The novelty of this research was thus three-fold:

1. This was the first Hungarian micro-level empirical analysis of the relationship between unemployment and mortality. Data availability and sensitivity make these types of estimations rare.
2. Estimating unemployment with mass lay-offs eliminated much bias, showing a more causal and accurate result than most literature.
3. Considering the aggregate national statistics in the context of the micro-level estimation results painted an integrated picture of the channels through which unemployment indirectly influenced mortality.

[1] Unemployment is associated with various physical and mental diseases, but most of these data are based on hospitalisation cases, doctors' records, admissions, while deaths are well-kept factual data. All previous examples can only be recorded if one seeks help for their problems, making official lists biased.

2. Literature Review

The empirical literature on the relationship between unemployment and mortality can be divided into two types of studies according to the data used: individual and aggregate. Results generally confirm a positive relationship between unemployment and mortality, regardless of the data level. Nonetheless, the literature review was organised according to the data type used. Several interesting papers on the relationship between unemployment and general health are also presented to shed light on the drivers behind the mechanism.

2.1 Individual-Level Studies

Since various confounding factors influence the connection between unemployment and mortality, it is best examined using detailed individual-level data. In Hungary, Bíró and Elek (2020) reported an odds ratio of 1.7 for 4-year mortality by comparing laid-off workers aged 35–45 with a 1:1 matched control group. A Finnish study examined the link between long-term unemployment and mortality, finding that unemployed individuals faced a higher risk of death (Blomgren and Valkonen, 2007). The researchers also stressed the importance of regional differences, noting that employment opportunities varied greatly depending on the area. This is also why regional differences will be considered in this chapter.

Sweden has been the focus of much research on the unemployment-mortality relationship. A 2001 Swedish twin registry study confirmed a positive correlation between unemployment and mortality (Nylén et al., 2001). The research also found that part-time and overtime work reduced the strength of this correlation. A later study using the same dataset emphasised the role of factors such as low education levels and personality traits in shaping this relationship (Voss et al., 2004). Additional findings showed that smoking, alcohol use, illness, and low socioeconomic status were more common among unemployed individuals, uncovering a few of the possible engines of this mechanism. External causes of death were strongly correlated with unemployment during the study's follow-up period. Within twin pairs, the unemployed twin faced a 1.5 times higher risk of death than their employed sibling. Divorce and increased use of sleeping pills were also more frequent among unemployed twins (Voss et al., 2004).

2.1.1 Lay-Offs

This chapter employed mass lay-offs as an instrumental variable for unemployment, a method previously used in empirical research. Finnish studies have shown that workplace downsizing and closures provide a cleaner measure of unemployment's effects by eliminating biases (Martikainen et al., 2007; Junna et al., 2020). These studies found that downsizing and closures increased mortality, particularly from substance use and accidental deaths. Notably, men who did not find reemployment faced increased somatic mortality as well (Junna et al., 2020). A U.S. study further highlighted that when accounting for state-level unemployment, dismissals had a moderate but significant reduction in the risk of death, demonstrating the importance of interpreting job loss within a broader economic context (Granados et al., 2014). In Hungary Elek et al. (2020) found that involuntary unemployment, especially through mass layoffs, was associated with increased short- and long-term health care utilisation, higher consumption of medications for mental illness, and elevated mortality risk. Their results suggested that the mental health consequences of job loss played a significant role, and that social and health systems should consider these impacts when addressing unemployment.

2.1.2 The Role of Sex and Age

Numerous studies have underscored the significance of sex in the relationship between unemployment and mortality, consistently finding a stronger correlation for men. Unemployed men appeared to suffer more severe consequences than women (Lundin et al., 2009; Roelfs et al., 2011). For example, Martikainen (1990) found that, after controlling for individual background, unemployed men had higher relative mortality rates from accidents and violence than from diseases. A Belgian study also found sex differences, showing that adjusting for factors such as educational level, home ownership, living situation, and migrant background significantly weakened the relationship between unemployment and mortality (Vanthomme and Gadeyne, 2019). Research from Norway also uncovered differences between sexes, with unemployed men experiencing higher hospital admission rates and mortality compared to unemployed women (Heggebø, 2022). Clemens et al. (2014) also found a significant relationship between unemployment and mortality, but only for men. They showed that an excess mortality of 85% was significant for unemployed men, but none of the results for women were significant. A study on the 1992–1996 Swedish recession revealed that unemployment led to substantial increases in suicide and cancer-related mortality among men (Vågerö and Garcy, 2016). Additionally, transport accident deaths were higher among unemployed men, particularly in younger age groups. The study also found that low-educated, low-income, and single men were more vulnerable to mortality risks when unemployed (Vågerö and Garcy, 2016). In Canada, Mustard et al. (2013) found that the age-adjusted mortality hazard ratio increased by 1.37 for unemployed men and 1.27 for unemployed women, with the strength of this relationship weakening with age. A U.S. study found that higher unemployment rates predicted increased mortality for men aged 60 and under, even after accounting for confounding factors. Specifically, a one-percentage-point increase in the unemployment rate was associated with a 6% rise in the probability of death within one year (Halliday, 2014). An Italian study similarly found that unemployed men faced a significantly higher mortality risk even after adjusting for age, residence, behavioural risk factors, health status, and sociodemographic characteristics. However, they did admit these controls somewhat weakened the relationship (d'Errico et al., 2019). Given these findings, this chapter takes sex into account as an important factor in the relationship between unemployment and mortality.

A few articles have mentioned that age also played a crucial role in shaping the unemployment-mortality relationship. While unemployment in old age was associated with increased mortality risk, especially for older men (Montgomery et al., 2013), a meta-analysis of 42 studies found that mortality risk was actually higher among those in early to mid-career than those in late career (Roelfs et al., 2011). To capture these variations, this chapter also considered four distinct age groups.

2.1.3 Unemployment, Divorce, and Alcohol Abuse

The relationship between unemployment and divorce remains debated (Roy, 2011). Early studies suggested a positive correlation (Jones, 1989; Lester, 1996), while later research found the opposite (Amato and Beattie, 2011; González-Val and Marcén, 2018). Some findings indicated that the impact of unemployment on divorce depended on whether the husband or wife lost their job (Tumin and Qian, 2017). Specifically, one study found that a husband's unemployment during separation reduced the likelihood of divorce. In contrast, another paper found that female unemployment decreased divorce rates while male unemployment increased them in the long run (Alola et al., 2020). Divorce itself has well-documented negative health consequences, including increased accidents, violence, and alcohol abuse (Metsä-Simola and Martikainen, 2013). It has also been linked to numerous health issues that can contribute to mortality (Sbarra et al., 2011). In Eastern Europe, several region-specific dynamics — such as the disintegration of former empires, rising familial instability including divorce and domestic violence, and the sudden emergence of both emigration and immigration — may have contributed to the sharper and more abrupt mortality crisis observed (King et al., 2022). For this reason, divorce is considered in the context of this chapter's results.

A Swedish study found that the relationship between long-term unemployment and all-cause mortality follows a cubic pattern for men over time (Garcy and Vågerö, 2012). Alcohol-related diseases and external causes were identified as primary drivers of this connection. Unemployment has been found to increase alcohol abuse (Stefansson, 1991), which in turn led to serious health consequences (Rehm et al., 2010). Studies indicated that individuals often turn to alcohol in response to unemployment-related despair (Forcier, 1988; Popovici and French, 2013; Mangot-Sala et al., 2021). Stuckler et al. (2009) showed that an increase in unemployment of more than 3% had a substantial impact on deaths from alcohol abuse, using data from 26 EU countries. Furthermore, Scheiring et al. (2021) showed that the reduction in industrial employment was strongly connected to the mortality crisis in Hungary. They proposed that the increased death rates were due to hazardous alcohol consumption. In Hungary, findings from over 80 interviews conducted by Scheiring et al. (2020); Scheiring and King (2022) suggested that the primary health risks linked to unemployment and income decline arose not necessarily from a lack of material resources, but from the psychological effects of stress and social stigma. Harmful health behaviours were found to be influenced by more than just cultural persistence or low levels of education; even individuals with relatively high education and income experienced increased drug and alcohol use during times of economic instability. King et al. (2022) emphasised that while substance abuse was a major factor in both Eastern Europe and the United States, the substances involved differed: alcohol was predominant in Eastern Europe, whereas opioids were central in the U.S. Therefore, alcohol consumption is considered a speculated driver of the mechanism in this chapter.

2.1.4 Unemployment, Suicide, and Homelessness

Several studies have demonstrated that unemployment increased the risk of suicide in developed countries such as England, Wales, Sweden, Denmark, and Canada (Moser et al., 1984; Iversen et al., 1987; Jin et al., 1995; Gerdtham and Johannesson, 2003). Notably, an early study in England and Wales found that women whose husbands became unemployed experienced higher mortality rates than other married women (Moser et al., 1984). While suicide is analysed separately in another chapter of this dissertation, it will also be analysed in this chapter.

Unemployment has also been linked to homelessness (Calvo et al., 2018; Flaming et al., 2021), which increases vulnerability to infectious diseases (Rudge et al., 2008; Liu et al., 2020), malnutrition (Seale et al., 2016), hypothermia in cold weather (Zhang et al., 2019), and heat strokes in warm temperatures (Harris and Albrecht, 2024). These conditions pose significant health risks, including mortality.

2.2 Aggregate-Level Studies

Most aggregate data-based studies on the relationship between unemployment and mortality come from Europe. Like individual-level findings, aggregate-level research suggested a positive correlation between unemployment and mortality.

For instance, Bonamore et al. (2014) examined 23 European countries between 2000

and 2012 and found that, in low-unemployment environments, an increase in the unemployment rate was associated with decreasing mortality, though the effect weakened over time. A Greek study using quarterly data from 1999 to 2013 found that a 1% increase in regional unemployment was significantly associated with a 0.3% increase in overall mortality. However, controlling for local population factors and time-varying confounders weakened this relationship (Laliotis and Stavropoulou, 2018).
Theodossiou et al. (2008) also found that a 1% increase in national unemployment rates led to a 1.54% increase in mortality. Their study examined variations by sex, geographic region, age group, and the influence of alcohol consumption and smoking, revealing differences in the strength of the unemployment-mortality link across these factors. Another study analysing 11 European countries between 1971 and 2001 identified two distinct effects of unemployment on mortality: a slight temporary decrease and a much more substantial permanent increase (Bender et al., 2013). Specifically, a 1% rise in unemployment was associated with a 0.2% temporary decrease in mortality but also correlated with a 1.5% permanent increase in mortality rates.

2.3 The Mitigating Effects of Unemployment Benefits

Recent studies from 2021 and 2024 have highlighted the mitigating effects of unemployment benefits on mortality. In Canada, researchers found that these benefits significantly reduced mortality among the unemployed (Shahidi and Parnia, 2021). Their research also revealed that benefit recipients differed from non-recipients in several ways: they had worked more weeks in the previous year, were more likely to have worked full-time, were predominantly men, had a higher likelihood of being born in Canada, and were more likely to reside in Eastern Canada. Additionally, recipients were less likely to be in the lowest income quartile and more likely to own their home (Shahidi and Parnia, 2021). These insights suggested that unemployment benefits may not always reach those who need them the most. Shahidi and Parnia (2021) also discovered that despite their mitigating effects, unemployment benefits did not eliminate the increased mortality risk associated with unemployment. Compared to employed individuals, mortality among unemployed men receiving benefits was 24%

higher, while for those not receiving benefits, it was a striking 58% higher. A similar pattern emerged for women: unemployed women receiving benefits had a 22% higher mortality rate compared to employed women, whereas those not receiving benefits had a 54% higher mortality rate. While the impact of benefits on reducing mortality diminished over time, it remained significant (Shahidi and Parnia, 2021). Finally, registered unemployment in Hungary was linked to lower mortality, which might suggest that unemployment benefits offered some protective effect (Scheiring et al., 2021). Similarly, Stuckler et al. (2009) showed that each additional US$10 per person invested in active labour market programs reduced the impact of unemployment on suicide rates by 0.038% in 26 EU countries.

Beyond overall mortality, unemployment benefits have also been linked to reductions in specific causes of death. For instance, Martins et al. (2024) found that a higher weekly benefit allowance for the unemployed significantly decreased opioid overdose mortality in the United States. This finding underscores the importance of considering unemployment and prevention policies when addressing public health concerns.

2.4 Questioning the Unemployment-Mortality Association

Several studies have challenged the correlation between unemployment and mortality. One of the earliest papers on this topic, published in 1984, analysed post-war Scotland and found little evidence of a consistent relationship between unemployment and mortality among individuals aged 15 to 74 (Forbes and McGregor, 1984). While the relationship was insignificant and even negative in younger age groups, it became significant and positive among older individuals. However, adjustments in the lag structure altered the estimated coefficients to negative, demonstrating the instability of the results. Stuckler et al. (2009) found no consistent evidence across the EU that all-cause mortality rates rose with higher unemployment, although the sensitivity of mortality to economic crises varied considerably between populations, partly due to differences in social protection.

Similarly, Roelfs et al. (2015) questioned the consistency of this relationship in a meta-study analysing 36 articles from 15 countries. Their findings indicated gender differences in the unemployment-mortality link but found no evidence that the aggregate unemployment rate moderated this association. Additionally, they noted that controlling for health behaviours, such as smoking and alcohol consumption, significantly impacted the strength of the relationship. They also observed that factors like age, region, sex, and socioeconomic status were often insignificant predictors of this correlation, depending on the study. A Finnish paper further questioned the link between unemployment and mortality by showing that, after controlling for socio-demographic factors, much of the mortality disparity across unemployed income quintiles could be explained (Tarkiainen et al., 2012). Moreover, research from South Korea indicated that the relationship between mortality and the economy shifted over time. Between 1989 and 2012, the connection evolved from weakly pro-cyclical to strongly counter-cyclical, highlighting concerns about the direction of causality (Lee and Kim, 2016).

Cross-country comparisons have also produced mixed results. A study comparing Germany and the USA found a significant relationship between unemployment and mortality in the USA but failed to replicate this finding in Germany (Mcleod et al., 2012). The researchers suggested that these differences stemmed from demographic and skill-level variations. In Germany, unemployed individuals tended to be older, whereas in the USA, they were often low-skilled. They noted that "the relative risk of dying was highest for unemployed high-skilled Germans and minimum-skilled Americans and lowest for unemployed medium-skilled Germans and high-skilled Americans" (Mcleod et al., 2012). Additionally, dividing the data between East and West Germany revealed significant regional differences, but accounting for race in the USA did not alter the findings. These results highlighted the inconsistencies in the unemployment-mortality relationship and suggest that its strength depends heavily on the dataset and context. On the other hand, a French study found that a 1-point increase in the unemployment rate was associated with a decrease of 6 deaths per 100,000 population (Buchmueller et al., 2007). This relationship remained consistent even after controlling for geography and population size. The researchers noted that the effect was stronger in recent periods, attributing it to changes in labour market conditions. In addition, a negative link was identified between unemployment and mortality from traffic accidents and a significant negative effect on mortality among the elderly (65 and over) (Buchmueller et al., 2007). Ruhm (2015) found that during severe national recessions in the U.S., overall mortality rates decline significantly more than would be predicted based on unemployment alone. Finally, Bíró et al. (2020) found that poor physical and mental health in Hungary was strongly associated with lower employment rates, particularly in disadvantaged regions. This again raised concerns about the direction of causality between unemployment and mortality.

3. Data

The data used in this analysis were from the Admin3 database provided by HUN-REN KRTK (HUN-REN, 2025). Admin3 contains panel data made by connecting information from the National Health Insurance Fund (NEAK), the State Treasury (MÁK), the Educational Authority (OH), the former Ministry of Finance (PM), and the National Tax and Customs Administration (NAV). It consists of anonymous, individual data for a randomised 50% of the Hungarian population (approximately 5 million individuals) from 2003-2017 at a monthly frequency (Sebők, 2019).

3.1 The Instrumental Variable - 'Mass Lay-Off'

When a person is dismissed individually, the mental and emotional strain tends to be greater, as the dismissal may feel more personal and raise doubts about their performance or value compared to colleagues. In contrast, mass layoffs are often perceived as less targeted, which can lessen the psychological impact. Consequently, the effects of individual dismissal may be more severe. However, in the case of solo lay-offs, bias arises for multiple reasons: For example, those who suffer from disease or are considered old are more likely to be dismissed from work and die. Thus, as mentioned in the 'Introduction', the so-called 'Mass Lay-Off' was used in this study to decrease this bias in estimations (see 'Methodology'). Mass firings are non-selective of the firm's workforce. If someone is dismissed, they automatically become unemployed the following month unless they find a new job within 3 weeks, which is challenging. Now, lay-offs increase unemployment, but should not have a strong correlation to mortality unless through the channel of unemployment. Hence, the variable 'Mass Lay-Off' was an instrument for unemployment and could be used to establish a causal relationship showing that losing one's job (and source of income) increases the probability of one's death. The instrument was defined for firms of at least 10 workers to avoid overstating the number of "mass" dismissals. "Mass" firings meant that at least 40% of the firm's workforce was laid off from one month to the next, and in case of acquisitions or mergers, a maximum of 20% were reemployed by the same new employer in the next 12 months.[1] This condition was necessary to eliminate the chance of "selective firing". This also meant that the first and last 12 months of observations were not considered, so all analyses were for 2004-2016.

3.2 External Validity - A Comparison of Admin3 and HCSO

Since Admin3 is privately owned, sensitive data, it was necessary to compare it to national statistics published by the Hungarian Central Statistical Office (HCSO) to show external validity. Towards this end, aggregate data for unemployment and mortality were downloaded from the HCSO website.

3.2.1 The Explanatory Variable - 'Not-Employed'

First and foremost, it must be mentioned that accounting for illegal employment is impossible. Thus, all unemployment data might be biased upward. The HCSO uses the definition of the International Labor Organization (ILO) for unemployment. Thus, according to the HCSO, an unemployed person "had no job and was not on temporary leave from a job, has been actively seeking employment in the past four weeks, and would be able to start work within two weeks" (KSH, 2025e). Several parts of this definition need to be addressed. First, it is unclear what "actively seeking" means and how it is measured (if it could be quantified). The other problem is "would be able to start work within two weeks". The issue with this is again measurement limitation. Both parts of the definition could conceal selection bias that reduces the credibility of the data. The national labour statistics are based on the so-called 'Labourforce Survey', a multistage, stratified, probabilistic sample. The published data are the result of a weighted estimate. To enable comparison to the Admin3 data, the inactive

[1] Several robustness checks were performed, see 'Sensitivity Analysis' of 'Methodology'.

population was manually added to the unemployed. Population data in the 15 to 74 years range was available on the HCSO website (KSH, 2025a), so unemployment (unemployed+inactive) per population for the ages 15 to 74 was calculated.

In contrast, defining unemployed individuals in the Admin3 database was more complex. In Admin3, there is a variable capturing unemployment benefits from the government to the individual, but to get such a transfer, one must be officially registered as 'unemployed'. This dramatically decreases the number of unemployed. Hence, a different variable was used instead. If there was no employment on the 15th day of the month, the individual was identified as 'Not-Employed'.[2][3]This meant that this data also contained the inactive population, which is why inactive individuals were added to the HCSO unemployed data, as mentioned above.

The unemployment data of Admin3 and the HCSO are compared in the graph below (see Graph 3.1).

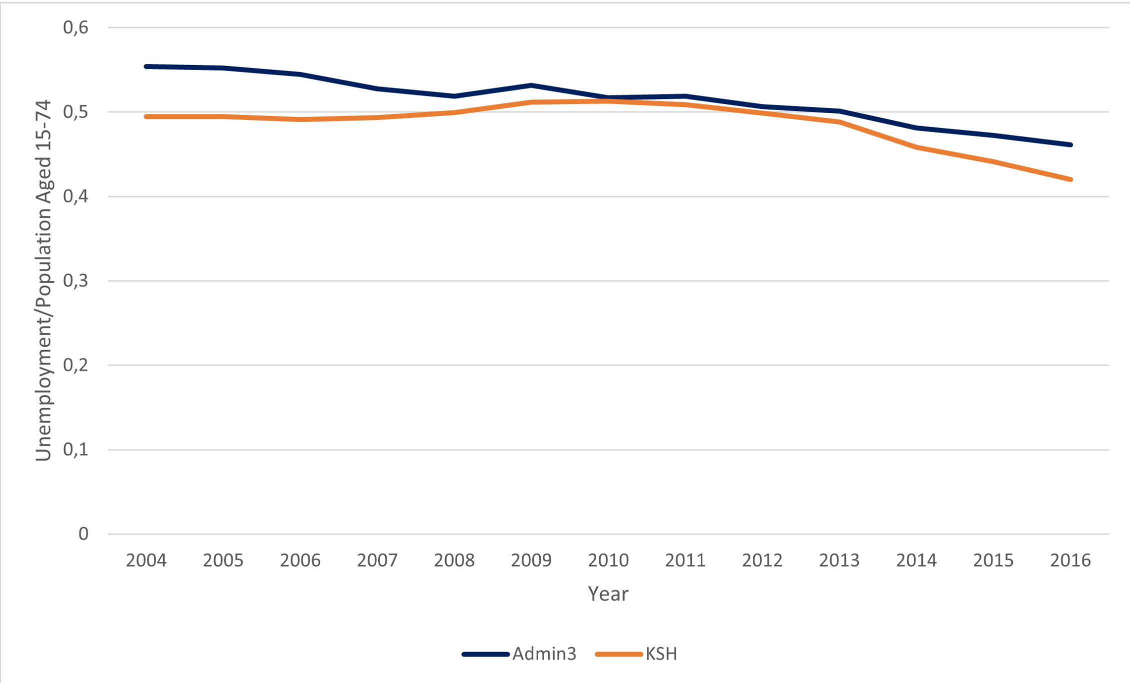

Figure 3.1: Comparison of Admin3 and HCSO Unemployment for People Below 75

Fortunately, the trends of the two sources of unemployment data were quite similar.

[2] See more on "j_nap" in HUN-REN (2023)

[3] Robustness checks with different definitions of 'Not-Employed' were made, see 'Sensitivity Analysis' of 'Methodology'.

For the analyses, a minimum age threshold of 18 was set in Admin3 (student jobs should be considered a side hustle to studying). This meant that individuals who did not pass 18 were dropped, while those who turned 18 during the period under study were only accounted for once they became adults. There were a few arguments against this threshold. One could claim that many people - especially those who enter tertiary education - do not enter the labour market until later in their lives or that the length of unemployment, as well as the consequences of it, tend to grow more severe as people age. Hence, the cut-off could be set higher. However, given the limited period of Admin3, this would have eliminated any feasible analysis for the active, younger generation. Furthermore, excluding observations above the retirement age (65 years) was considered but ultimately rejected, as female workers can retire after 40 years of employment, which would again introduce bias into the results.

As a final step, the sample was further refined to include only individuals who experienced at least one episode of job loss during the observation period (the probability of this was approximately 0.86). This restriction was conceptually appropriate, as it allowed for a more nuanced analysis of "job loss", instrumented by the occurrence of 'Mass Lay-Off'. The idea was that the characteristics of those who were never unemployed were probably very different. By excluding them from the sample, a more fine-grained comparison could be made between those who suffered at least one episode of unemployment.

3.2.2 The Explained Variable - 'Mortality'

The national mortality data were obtained from the HCSO website (KSH, 2025c) for ages 30-64. This age constraint was necessary if a comparison to the Admin3 data was to be made.[4] Mortality per population was then calculated (KSH, 2025h).

Like in the case of the HCSO data, the subpopulation mortality rate was also calculated in the Admin3 sample and the two are shown below (see Graph 3.2).

[4]The reason was that the age threshold of 18 in the Admin3 sample (see 'The Sample') meant that people in Admin3 were more rapidly ageing than the HCSO data that included the whole population, since the mortality of children was much below the mortality of adults. Hence, the population's mortality would have been substantially lower in the HCSO data than in the Admin3 sample.

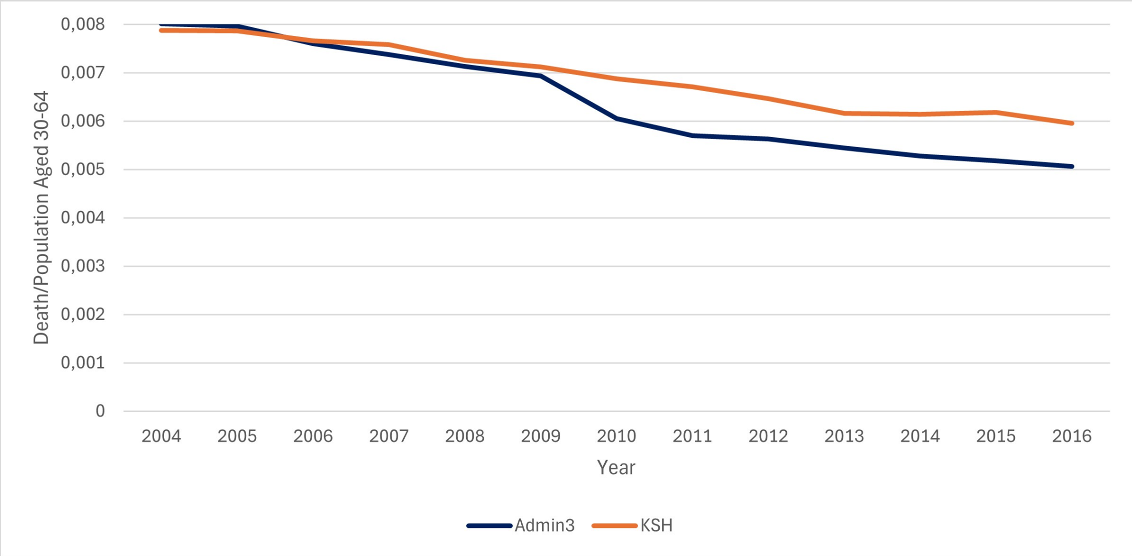

Figure 3.2: Comparison of Admin3 and HCSO Mortality for People Aged 30-64

The slight but emerging difference in mortality between the Admin3 and HCSO datasets may be due to the differing definitions used by the institutions that compiled the data. Death in the Admin3 dataset was based on Tasks of the National Health Insurance Fund of Hungary (NEAK) data (HUN-REN, 2023), while death on the HCSO website was based on the so-called "death certificate", which is managed by HCSO (KSH, 2025f). Additionally, in the final Admin3 sample, only individuals matched at the firm level were retained, which could explain the widening discrepancy between the two sources of mortality data.

Finally, in estimations, the cut-off of mortality was arranged so that only deaths after a maximum of 12 months of unemployment were accounted for, beyond which the impact of a one-time dismissal, as measured by the instrument of 'Mass Lay-Off', should fade.[5] As mentioned in the 'Literature Review', unemployment benefits, though limited in amount and duration, naturally help to offset the expected impact of unemployment on mortality (Scheiring et al., 2021).

[5]Robustness checks using various post-unemployment time intervals were conducted, see 'Sensitivity Analysis' of 'Methodology'.

3.3 The Sample

The descriptive statistics of the three samples are in Table 3.1. The 'Total' sample corresponded to about 445 million observations when accounting for employed and unemployed. The refined 'Not-Employed' sample shown in the second column captured the characteristics of individuals classified as unemployed specifically during their period of unemployment. Finally, the third column presents the characteristics of all individuals at the time of their 'Mass Lay-Off.'

Sample ~Observations	**Total** ~445 million		**Not-Employed** ~163 million		**Mass Lay-Off** ~1.6 million	
Variable	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Sex	0.496	-	0.470	-	0.486	-
Age	41.65	13.15	42.452	16.051	44.091	10.832
Mortality	0.0003	0.0182	0.0009	0.0300	0.000004	0.0021

Table 3.1: Descriptive Statistics by Sample

Across all groups, the proportion of males and females was close to even, with minor differences between samples. The average 'Age' was highest among individuals affected by a 'Mass Lay-Off' (44.1 years), which raised concerns about selection bias. 'Mortality' was generally low across all groups, but was highest among the 'Not-Employed' sample (0.09), which aligned with expectations. Interestingly, 'Mortality' among individuals affected by a 'Mass Lay-Off' was extremely low (0.0004), indicating that mass layoffs themselves were not strongly linked to an immediate risk of death. This finding supports the idea that the broader experience of unemployment, rather than the layoff event itself, primarily influences mortality.

3.4 Health History and Age

In Hungary, poor physical and mental health has been closely linked to lower employment rates (Bíró et al., 2020), making it essential to investigate whether the health status of individuals who were currently unemployed or affected by mass lay-offs differed significantly from those who remained employed at the time (but were unemployed at some point). Elek et al. (2020) has already demonstrated a significant association between unemployment, increased healthcare utilisation, and elevated mortality risk. This raised the critical question of whether declining health contributed to unemployment or whether unemployment resulted in worsening health, which could lead to death. Since some individuals, such as those suffering from illness or older workers, are both more likely to be laid off and to die, it was crucial to compare whether those affected by 'Mass Lay-Off' differed significantly in their health and age characteristics before dismissal from those who were not fired.

Table 3.2 presents the descriptive statistics of the health history and age of the final sample's individuals (only those who were unemployed at least once), allowing for a comparison between periods when individuals were 'Employed' and when they were 'Not-Employed', as well as those who were part of a 'Mass Lay-Off'. It is worth noting that health data were only available from 2009 onward. This drastically decreased the number of observations. 'Outpatient' is the sum of monthly outpatient visits, 'Prescription' is the sum of monthly prescription fillings, and 'GP' is the number of monthly general practitioner visits.

Ever Unemployed After 2009						
Sample (∼Observations)	**Employed** (∼135 million)		**Not-Employed** (∼100 million)		**Mass Lay-Off** (∼1.1 million)	
Variable	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Outpatient	0.515	1.617	0.611	1.812	0.415	1.398
Prescription	0.860	2.198	1.456	3.074	0.974	2.405
GP	0.464	0.950	0.500	0.947	0.470	0.916
Age	41.056	11.638	46.354	15.893	42.395	10.729

Table 3.2: Descriptive Statistics of 'Ever Unemployed After 2009' Sample

Then, to ensure exogeneity, the individuals' lagged prior health states ('Outpatient' visits, filled 'Prescription', and 'GP' visits) and age were used to estimate the likelihood of 'Not-Employed' and 'Mass Lay-Off'. 'Mass Lay-Off' should not be influenced by an individual's prior health status or age.[6] If this condition holds, we could consider 'Mass Lay-Off' truly exogenous to individual characteristics, making it a strong instrumental variable (IV) for 'Not-Employed', which health-related factors could otherwise bias. The results of a fixed effect (FE) regression (time and industry) with cluster-robust standard errors are presented below (see Table 3.3).

VARIABLES	Not-Employed	Mass Lay-Off
Outpatient	0.00141***	-1.65e-05***
	(1.45e-05)	(3.29e-06)
Prescription	1.99e-05*	-5.77e-07
	(1.20e-05)	(2.72e-06)
GP	0.00359***	1.35e-06
	(2.56e-05)	(6.02e-06)
Age	5.74e-05***	-5.28e-06***
	(2.61e-06)	(4.57e-07)
Constant	0.0152***	0.00973***
	(0.000105)	(1.86e-05)
Observations	75,865,486	73,725,546
R-squared	0.010	0.796

Cluster-robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3.3: FE Result - Health History and Age on Unemployment and Mass Lay-Off

Fortunately, health history did not significantly influence the occurrence of 'Mass Lay-Off', except for 'Outpatient' visits, where the sign indicated an unexpected, but tiny decrease in the likelihood of experiencing a 'Mass Lay-Off'. This suggested that controlling for prior health status when using 'Mass Lay-Off' as an IV was unnecessary. On the other hand, 'Not-Employed' was significantly affected by the individual's health

[6]However, 'Mass Lay-Off' may lead to a deterioration in their health following dismissal.

history, which was expected. 'Age' was significant in both estimations and thus was used as a control in all estimations.

3.5 Subsamples - Sex, Age, and Region

As pointed out by the literature (see 'Individual-Level Studies' in 'Literature Review'), considerable differences regarding the relationship between unemployment and mortality existed between various subgroups of society. To account for these, several variables were used to divide the sample into smaller subgroups to identify the most affected individuals (heterogeneous treatment effects). The sample was split between the sexes, four age groups, and the eight regions of Hungary.

Altogether, 4 age groups of employees were defined:

1. Young: From the age of 18 to 35.
2. Middle-Aged: From the age of 36 to 50.
3. Old: From the age of 51 to 64.
4. Very Old: From age 65 (retirement age) and above.

Based on the district-level data of Admin3, counties were manually created, which were then summed to regions according to the HCSO database (KSH, 2025g). Thus, the relationship between 'Not-Employed' and 'Mortality' could be compared in the 8 regions of Hungary:

- Western Transdanubia
- Central Transdanubia
- Northern Hungary
- Northern Great Plain
- Southern Great Plain
- Southern Transdanubia
- Pest
- Budapest

3.6 Aggregate Data

In empirical research, context is everything. Many components drive the mechanism between unemployment and mortality. These elements are the channels through which unemployment is indirectly associated with deaths. Thus, as a final step to this analysis of unemployment and mortality, following the result of the literature (see 'Literature Review'), a few potentially critical aggregate-level factors were considered in the context of the individual-level results. These factors were only considered on the aggregate level using data from the HCSO. Altogether, three such factors were examined:

- Suicide
- Alcohol Consumption
- Divorce

For the analysis, suicide, alcohol consumption, and divorce data from the HCSO were downloaded to match the Admin3 estimation results. This was done to enable contextual considerations. Filters based on sex, age group, and region were used to show differences between subpopulations on the aggregate level following the result of 'Treatment Heterogeneity' (i.e., the suicide of males versus females and the divorce rate in Central Transdanubia versus the Southern Great Plain). The regions and age groups of the HCSO data could not be an exact match to the individual level of Admin3 because of the structure of the HCSO data and changes in their definitions. However, the HCSO data were a very close approximation of regions and age groups in the Admin3 data.

4. Methodology

This research aimed to find a causal relationship between unemployment and mortality. Identifying a causal relationship is difficult, as many factors influence both variables. For example, some things affect unemployment and mortality similarly, such as age or illness. Furthermore, employees in dangerous jobs tend to have an increased probability of dismissal and death compared to less hazardous workplaces. On the other hand, one could argue that very high mortality in a population will eventually lead to very low unemployment, so under certain circumstances, even the direction of causality is somewhat questionable.

Simply assuming that becoming unemployed predicts death is an oversimplification and will lead to biased results. However, if an appropriate instrument for unemployment were found and results were still significant, then the evidence would point in the direction of causality. Thus, such an instrument was created, and a dummy for the so-called "Mass Lay-Off" (explained in the 'Data' section) was created. Mass lay-offs increase unemployment naturally, as many people are dismissed from the same employer.[1] Therefore, the so-called two-stage least squares (2SLS) regressions were used, where the first stage measured the impact of mass lay-off on unemployment, and the second stage used mass lay-off as an IV to estimate its effects on mortality (second stage). 2SLS allowed for a causal interpretation of the results. If mass lay-offs were to predict mortality, then results would be less biased and would indicate causality.

Furthermore, the estimations of this research were all fixed-effect regressions, simultaneously accounting for time and industry fixed effects. Changes in the dummy variable 'Non-Unemployed' were considered as "treatments" (de Chaisemartin and D'HaultfŒuille, 2017) to the individual. The outcome of the treatment was either "death" or "no death". In the Admin3 panel dataset, both 'Not-Employed' and its

[1] As the goal was to establish a causal relation between unemployment and mortality, the event of mass firings was an appropriate instrument, but at the same time, it made it impossible to test how, for example, long-term unemployment impacted mortality compared to the short run.

counterfactual (i.e., “never treated” – never fired) could be found.[2]
As this analysis was done on panel data, using time-fixed effects was relatively straightforward. The decision to include industry-fixed effects was necessary to account for the seasonal unemployment of many industries, such as agriculture, tourism, education, etc. Mass lay-offs in seasonal occupations are standard, so results would have been biased without accounting for industries. Furthermore, there is an increased probability of death in the case of some hazardous occupations, where dismissals might decrease mortality. Thus, issues with monotonicity would have arisen if the instrumental variable had affected individuals from different industries differently. Consequently, reckoning with industries was essential. In the Admin3 database, there were altogether 17 different industries, which were the following:

- Agriculture
- Fishery
- Mining
- Manufacturing
- Electricity, gas, steam, and water supply
- Construction
- Trade
- Accommodation, food service
- Transport, storage, postal services, telecommunications
- Financial intermediation
- Real estate activities, business services
- Public administration, defense, compulsory social security
- Education
- Health and social care
- Other community, social services
- Household activities
- Extra-territorial organizations

The four stages of estimation are below:

1. Naive Estimation: The relationship between ’Not-Employed’ and ’Mortality’ in the Admin3 database was shown. This overestimated the strength of the correlation because it included all the biases mentioned above (e.g., health).

[2]It must be mentioned that continuous treatments are challenging to interpret (Callaway et al., 2024).

$$\text{Mortality}_{st} = \beta_0 + \beta_1 \text{Not-Employed}_{st} + \lambda_s + \gamma_t + \varepsilon_{st} \tag{4.1}$$

where,

β_0 is the constant.

β_1 is the estimated coefficient of the endogenous variable 'Not-Employed'.

λ_s is the industry fixed effects.

γ_t represents the time fixed effects

ε_{st} is the estimation error.

2. First Stage Regression: Estimated the correlation between 'Not-Employed' and 'Mass Lay-Off' in the Admin3 database. Lay-offs should increase 'Not-Employed'; hence, this step showed how good of a proxy 'Mass Lay-Off' was to 'Not-Employed'.

$$\text{Not-Employed}_{st} = \alpha_0 + \alpha_1 \text{Mass Lay-Off}_{st} + \lambda_s + \gamma_t + \nu_{st} \tag{4.2}$$

where,

α_0 is the constant.

α_1 is the estimated coefficient of 'Mass Lay-Off', which will instrument the endogenous variable 'Not-Employed'.

λ_s is the industry fixed effects.

γ_t represents the time fixed effects

ν_{st} are the first stage residuals.

3. Reduced Form Estimation: The connection between 'Mass Lay-Off' and 'Mortality'. 'Mass Lay-Off' should not lead to death, so the estimation results show a reduced form of the true impact. However, by using dismissals of at least 40% of the workforce instead of 'Not-Employed' as the explanatory variable, confounding was reduced because 'Mass Lay-Off' are considered non-selective.

$$\text{Mortality}_{st} = \varsigma_0 + \iota_1 \text{Mass Lay-Off}_{st} + \lambda_s + \gamma_t + \omega_{st} \tag{4.3}$$

where,

ς_0 is the constant.

ι_1 is the estimated coefficient of 'Mass Lay-Off'.

λ_s is the industry fixed effects.

γ_t represents the time fixed effects

ω_{st} is the estimation error.

4. Instrumental Variable Regression (Second Stage): In this step, 'Not-Employed' was instrumented by 'Mass Lay-Off', and thus, the 'true' impact on mortality was shown. Fitted values of the endogenous regressor, 'Not-Employed', were used for the estimation. This step reduced variation; the leftover variation came only from individuals dismissed in a mass lay-off process. The idea was that 'Mass Lay-Off' did not directly impact 'Mortality'; it indirectly had an impact through the 'Not-Employed' that followed 'Mass Lay-Off'.

$$\text{Mortality}_{st} = \pi_0 + \zeta_1 \widehat{\text{Not-Employed}}_{st} + \lambda_s + \gamma_t + \upsilon_{st} \tag{4.4}$$

where,

π_0 is the constant.

ζ_1 is the estimated coefficient of the predicted values of $Not - Employed_{st}$ from the first stage.

λ_s is the industry fixed effects.

γ_t represents the time fixed effects.

υ_{st} is the estimation error.

4.1 Sensitivity Analysis

Subsamples were studied separately to identify possible heterogeneous treatment effects. As explained in the 'Literature Review', certain groups could be more severely affected by unemployment than others. Thus, subsamples for the two sexes, four different age groups, and all regions of Hungary were considered to examine the change in the impact of unemployment on mortality.

Several alternative sample specifications were also explored to assess the robustness of the results. Mortality outcomes were examined at various intervals following dismissal, specifically after 3 months, 2 years, and 5 years. The analysis also incorporated a more lenient definition of mass lay-offs, considering cases where only at least 30% of the workforce was dismissed. Separate estimations were conducted for firms employing a minimum of 50 and 100 workers. Finally, individuals who were never unemployed during the study period were compared with those who experienced at least one unemployment episode.

5. Results

The Stata output tables of the four base and all other estimations can be seen below (see Tables 5.1 - 5.4).

As explained before (see 'Methodology'), the 'Naive' estimation results were expected to be biased upward. The coefficient of 'Not-Employed' was significant and positive, suggesting that 'Not-Employed' was associated with an increase of 0.78 percentage points in the probability of death ('Mortality').

The 'First Stage' results confirmed that the more people were dismissed in 'Mass Lay-Offs', the greater the 'Not-Employed' (as explained in 'Data' and 'Methodology'). The estimated coefficient was significant and showed that an increase in 'Mass Lay-Off' increased 'Not-Employed' by 48 percentage points. This was expected as it usually takes time to find a new job after dismissal.

The 'Reduced Form' coefficient was much smaller than in the case of the 'Naive' estimation, which was expected as only those who were part of a 'Mass Lay-Off' process were considered. Nevertheless, the coefficient was significant and positive, indicating that an increase in 'Mass Lay-Offs' increased the probability of death ('Mortality') by 0.05 percentage points.

The 'IV' results uncovered a causal relationship between 'Not-Employed' and 'Mortality' since the base assumption was that mass dismissals increase mortality through unemployment. This showed that if 'Not-Employed' was true, the probability of 'Mortality' was expected to increase by 0.094 percentage points, one-eighth of the 'Naive' result. This meant that comparing 100,000 currently employed (but as some point unemployed) individuals to 100,000 currently 'Not-Employed', 9 more died in the presently unemployed group. Given that the base probability of death in this 'Ever-Unemployed' sample, this result suggested that mortality increased by approximately 1.92% if one became unemployed. The likelihood of death went from 4.9% to 5%.

Overall, the results confirmed what was suspected: unemployment increased the

	(1) 'Naive'	(2) 'First Stage'	(3) 'Reduced Form'	(4) 'IV'
VARIABLES	Mortality	Not-Employed	Mortality	Mortality
Mass Lay-Off		0.479***	0.000450***	
		(0.00102)	(0.000118)	
Not-Employed	0.00778***			0.000939***
	(6.17e-05)			(0.000247)
Age	0.000222***	-3.68e-05***	0.000222***	0.000222***
	(1.66e-06)	(2.02e-06)	(1.66e-06)	(1.66e-06)
Constant	-0.00635***	0.0214***	-0.00618***	Probability:
	(5.66e-05)	(8.32e-05)	(5.62e-05)	0.049
Observations	116,619,234			
R-squared	0.003	0.032	0.003	0.002

Cluster-robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: The structure of the table follows the logic behind the regressions: The first column contains the results of the so-called 'Naive' estimation, where becoming 'Not-Employed' predicts a change in the probability of death ('Mortality'). The second column corresponds to the so-called 'First Stage' of the 2SLS estimation. It presents how well 'Mass Lay-Offs' correlate with 'Not-Employed'. The third column displays the outcome of the so-called 'Reduced Form' regression. It estimates the connection between 'Mass Lay-Off' and 'Mortality'. The fourth and final column reveals the outcome of the 'IV' regression. In this case, 'Not-Employed' was instrumented by the 'Mass Lay-Off' variable.

Table 5.1: Base Estimation Results

likelihood of death, as was found in other countries (Buchmueller et al., 2007; Martikainen et al., 2007; Mustard et al., 2013; Vanthomme and Gadeyne, 2019; Junna et al., 2020).

5.1 Treatment Heterogeneity

The search for the most affected subgroups (heterogeneous treatment effects) is presented below (see Tables 5.2 - 5.4). As mentioned earlier, the following variables were considered when dividing the sample: sex, age group, and region. Only the 'IV' coefficients of these are presented.

5.1.1 Variable - Sex

As mentioned before (see 'Data'), the difference between sexes in the relationship between unemployment and mortality was considered. The first column (see Table 5.2) corresponds to 'Male', and the latter to 'Female'.
Comparing the estimated coefficient of the 'IV' for males and females shows that men's mortality was more affected by 'Not-Employed' than women's. Not only was the coefficient insignificant for 'Female', but the coefficient for 'Male' was twice as big. These results aligned with the findings of the literature (Martikainen, 1990; Lundin et al., 2009; Roelfs et al., 2011; Halliday, 2014; Vågerö and Garcy, 2016; d'Errico et al., 2019; Heggebø, 2022) and suggested that becoming unemployed increased the probability of death by 0.12 percentage points for men. These results showed that accounting for the higher likelihood of death for men, the probability of death for unemployed men increased by approximately 1.7% compared to their currently employed counterparts. The likelihood of death increased from 7% to 7.12% for unemployed men.

5.1.2 Variable - Age

As pointed out by the literature, the impact of unemployment on mortality might be different for older people than for younger generations (Roelfs et al., 2011; Garcy and Vågerö, 2012; WB, 2021a). The results of the 'IV' Table 5.3 are presented below.

	'IV'	'IV'
	Male	Female
VARIABLES	Mortality	Mortality
Not-Employed	0.00120***	0.000530
	(0.000357)	(0.000323)
Age	0.000315***	0.000126***
	(2.75e-06)	(1.79e-06)
Probability	0.07	0.03
Observations	58,526,570	58,092,664
R-squared	0.004	0.001

Cluster-robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: The 'Probability' was calculated as the ratio of individuals who had passed away to the total number of observations in that category.

Table 5.2: 'IV' Results - Sex

	'IV'			
	Young	Middle Age	Old	Very Old
VARIABLES	Mortality	Mortality	Mortality	Mortality
Not-Employed	0.000183	0.000161	0.00336***	0.00349
	(0.000148)	(0.000390)	(0.000967)	(0.00370)
Probability	0.004	0.019	0.071	0.07
Observations	46,624,583	41,573,114	27,032,257	1,107,141

Cluster-robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: The 'Probability' was calculated as the ratio of individuals who had passed away to the total number of observations in that category.

Table 5.3: 'IV' Results - Age

Only the 'Old' age bracket result was significant, suggesting that becoming 'Not-Employed' increased the probability of death by approximately 0.34 percentage points. 'Old' were the people between the ages of 51 and 64, corresponding to the last 14 years of employment before retirement age.[1] Considering the base probability of death when 'Old' was 7.1%, the 'IV' estimation result suggested that the likelihood of death for the unemployed 'Old' workers increased by about 4.73% based on their probability of death in the 'Ever Unemployed' sample. The likelihood of death rose from 7.1% to 7.4% in this age bracket. These findings were consistent with the literature (Montgomery et al., 2013) and confirmed that older employees' mortality was the most sensitive to unemployment.

5.1.3 Variable - Region

The literature also suggested that there could be regional differences in the relationship between unemployment and mortality (Blomgren and Valkonen, 2007; Bender et al., 2013). Hence, each Hungarian region was analysed separately to capture these proposed differences (see Table 5.4).

As shown in the table above, only the results of 'Central Transdanubia', 'Northern Hungary', and the 'Northern Great Plain' were significant. Otherwise, all coefficients ranged from 0.0002 to 0.002. The strongest effect was observed in 'Northern Hungary' (one of the poorest regions of Hungary), where being unemployed increased the probability of death by 3.31% among individuals, relative to the region's baseline mortality rate in the 'Ever Unemployed' sample. The likelihood of death went from 4.9% to 5.1% in this region.

5.2 Sensitivity Analysis

Table 5.5 presents robustness checks exploring the relationship between unemployment and mortality under various conditions.

The first column examined the relationship between unemployment and mortality in the 'Total' sample (not just the 'Ever Unemployed'), without restricting it to individuals

[1] Ignoring that women can retire after 40 years of work in Hungary.

	'IV'			
	Mortality	Age	Observations	Probability
Western Transdanubia	0.000738	0.000227***	12,522,840	0.05
	(0.000861)	(5.06e-06)		
Central Transdanubia	0.00135*	0.000218***	14,818,985	0.048
	(0.000815)	(4.60e-06)		
Northern Hungary	0.00162**	0.000218***	13,718,658	0.049
	(0.000680)	(4.74e-06)		
Northern Great Plain	0.000962*	0.000219***	16,354,354	0.044
	(0.000536)	(4.42e-06)		
Southern Great Plain	0.000751	0.000226***	14,201,937	0.047
	(0.000625)	(4.78e-06)		
Southern Transdanubia	0.00101	0.000202***	10,360,478	0.046
	(0.000691)	(5.31e-06)		
Pest	0.000161	0.000214***	14,295,827	0.038
	(0.000746)	(4.78e-06)		
Budapest	0.000571	0.000235***	19,551,998	0.041
	(0.000871)	(4.18e-06)		

Cluster-robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: The 'Probability' was calculated as the ratio of individuals who had passed away to the total number of observations in that category.

Table 5.4: 'IV' Results - Region

VARIABLES	Employed	30%	3 months	2 years	5 years	50 workers	100 workers
			Mortality				
Not-Employed	0.00197***	0.00102***	0.000112	0.00243***	0.00548***	0.00112***	0.00119***
	(0.000242)	(0.000257)	(0.000114)	(0.000362)	(0.000594)	(0.000289)	(0.000303)
Age	0.000173***	0.000222***	5.10e-05***	0.000477***	0.00123***	0.000219***	0.000217***
	(1.33e-06)	(1.66e-06)	(4.39e-07)	(3.25e-06)	(7.35e-06)	(1.97e-06)	(2.17e-06)
Probability	0,043		0.049			0.047	0.046
Observations	158,846,233		116,619,234			81,950,535	67,943,835
R-squared	0.002	0.003	0.001	0.005	0.014	0.002	0.002

Cluster-robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: The 'Probability' was calculated as the ratio of individuals who had passed away to the total number of observations in that category.

Table 5.5: Robustness Checks

unemployed at least once. The coefficient on 'Not-Employed' was statistically significant at 1%. This meant that the probability of death increased by 4.6% if one was dismissed compared to someone not in the 'Total' sample. The likelihood of death increased from 4.3% to 4.5% for the unemployed.

Column "30%" shows the effect when "only" 30% of workers at a firm were laid off. A 'Mass Lay-Off' of this magnitude was associated with a statistically significant increase in 'Mortality' of about 0.00102. In this case, the probability of death increased by 2.1% if one became unemployed, and the likelihood of death increased to 5% for the unemployed.

Columns "3 months," "2 years," and "5 years" examined 'Mortality' at different time horizons after dismissal: Within 3 months, the estimated coefficient was small and not statistically significant, suggesting no immediate 'Mortality' impact. After 2 years, 'Mortality' increased significantly by 0.00243, indicating that the adverse effects of unemployment might accumulate over time. The unemployed individual's probability of death increased by 5%.[2] After 5 years, the effect grew to 0.00548, showing a substantial long-term increase in 'Mortality' following unemployment, comparable to the findings

[2]Naturally, the estimated coefficient also captured the effects included in the 'Base' estimation. In simple terms, when deaths occurring two years after dismissal were accounted for, it also captured deaths from both the first and second years, which explained the larger coefficient compared to the base results.

of (Bíró and Elek, 2020). The probability of death for the unemployed rose by 11.2% , thus the likelihood of death went from 4.9% to 5.45% in the case of the unemployed.[3] Columns "50 workers" and "100 workers" showed effects based on firm size: Among firms with at least 50 workers, being laid off was associated with a 'Mortality' increase of 0.00112, slightly higher than the effect observed for firms with at least 10 workers (0.000939). Here, the probability of death for the unemployed individuals increased by 2.4%, the likelihood of death was then 4.8%. Among firms with at least 100 workers, the increase was somewhat higher at 0.00119. The probability of death increased by 2.6% for the unemployed person, while the likelihood of death went from 4.6% to 4.72% for the unemployed. This suggested that layoffs had adverse consequences even in larger, possibly more stable firms.

Across all estimations, 'Age' was positively and significantly associated with 'Mortality', as expected — older individuals were naturally at higher risk of death. The findings were robust across different definitions of exposure and timing, showing that unemployment indeed increased mortality.

[3]Similarly, extending the horizon to 5 years captured a cumulative effect, leading to a larger observed impact compared to shorter time frames.

6. Broader Context - Possible Drivers of Mechanism

6.1 Health

As mentioned, Elek et al. (2020) and Bíró and Elek (2020) have previously shown a strong link between unemployment, healthcare utilisation, and mortality risk in Hungary. To better understand the potential mechanism linking unemployment and mortality, here it was also examined whether unemployment significantly predicted health, using the same variables as before ('Outpatient' visits, 'Prescription' fillings, and 'GP' visits). The result of the cluster-robust FE regression (time and industry) is in Table 6.1, where only a one-period lead of the health variables was used. Thus, the table shows the imminent association between unemployment and health.

VARIABLES	Outpatient	Prescription	GP
Not-Employed	0.0310***	0.0599***	-0.0436***
	(0.00123)	(0.00207)	(0.000692)
Constant	0.515***	0.828***	0.452***
	(0.000517)	(0.00109)	(0.000362)
Probability	0,49	0,49	0.5
Observations		101,131,280	
R-squared	0.004	0.003	0.006

Cluster-robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: The 'Probability' was calculated as the ratio of individuals who had passed away to the total number of observations in that category.

Table 6.1: FE Results - Leads of Health Variables on Unemployment

'Not-Employed' was found to be significantly associated with an increased number of 'Outpatient' visits (estimated coefficient: 0.03) and 'Prescription' fillings (0.06). On the contrary, the number of 'GP' visits was negatively correlated with 'Not-Employed' (-0.04). One explanation for this could be that 'GP' visits are often only routine and do not necessarily indicate illness. In addition, people most frequently visit their 'GP' to acquire a medical certificate to justify absence from work, which is unnecessary if one is unemployed. These results suggested that declining health may be a potential pathway linking unemployment to higher mortality.

6.2 Aggregate Data

Unfortunately, as wide-ranging as the Admin3 database was, it did not contain information on several important factors that might be the channels of the mechanism by which unemployment impacts mortality. As mentioned in the 'Literature Review', unemployment influences many other areas of one's life, a few of which were considered in this subchapter, too. Fortunately, the HCSO had detailed data on suicides, alcohol consumption, and divorces, which are presented below (see Graphs 6.1 - 6.8). Once again, cohort divisions based on sex, age group, and region were applied to match the subpopulation estimations done on the Admin3 sample. Everything was divided by the subpopulation in that category (KSH, 2025i,j) to enable magnitude comparisons.
It must be noted that while the estimation results presented in 'Results' were based on a selected sample of at least once unemployed individuals of Admin3, the HCSO data shown below were at the aggregate level. Thus, differences detected between subpopulations might support the story behind unemployment and mortality found in the IV results, but many might not.

6.2.1 Suicide

The distribution of male and female suicides (KSH, 2025d) in the period 2004-2016 is below (see Graph 6.1).

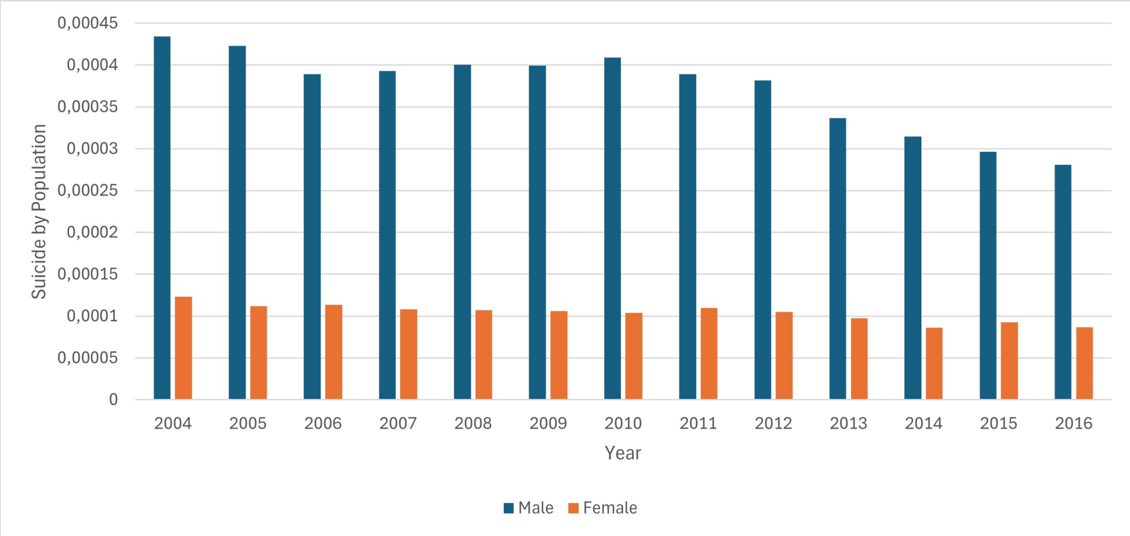

Figure 6.1: The Distribution of Suicides Between Sexes - 2004-2016

On the aggregate level, male suicides outnumbered female suicides by approximately 1 to 4. The 'IV' result for males was about twice as big as the results for females (not to mention that the coefficient of 'female' was insignificant). Thus, suicide was driven by males, as was the connection between unemployment and mortality.

The distribution of suicide per population based on age is shown in Graph 6.2. Unfortunately, the age groups could not be precisely matched to the Admin3 cohorts, but the threshold for each category was only 1-2 years different from the ones used in estimations.

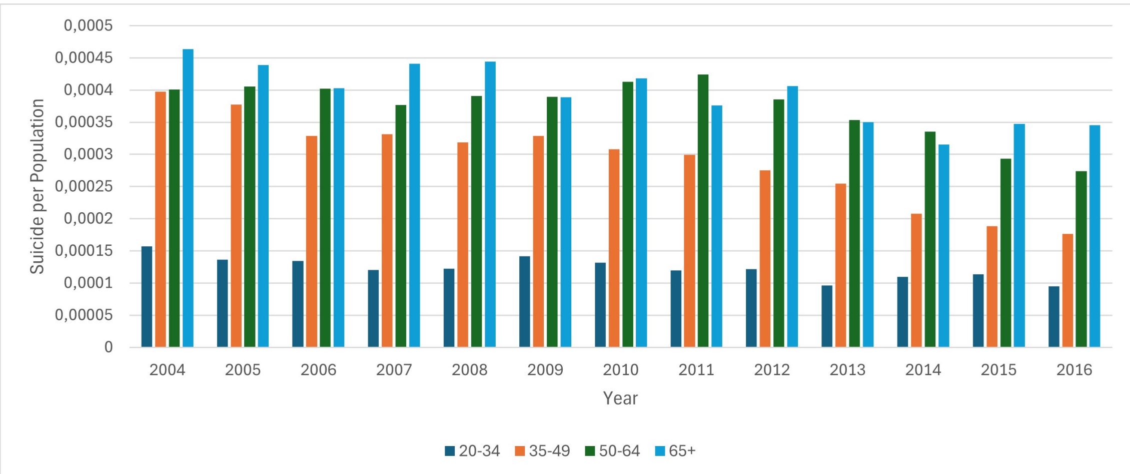

Figure 6.2: The Distribution of Suicides Between Age Groups - 2004-2016

Suicide was most common in the oldest (so-called 'Very Old') category, which was

unsurprising given that most of these people are pensioners. Older people usually suffer from various illnesses and might feel like a burden to society, so suicide is most frequent in their age group. Suicide was the second most common in the age category of 50-64 ('Old'). In the 'IV' estimations, unemployment influenced mortality the most in the 'Old' category. Hence, 'Old' workers are probably more likely to commit suicide, which strengthens the relationship between unemployment and mortality.
Finally, regional suicides were compared (see Graph 6.3).

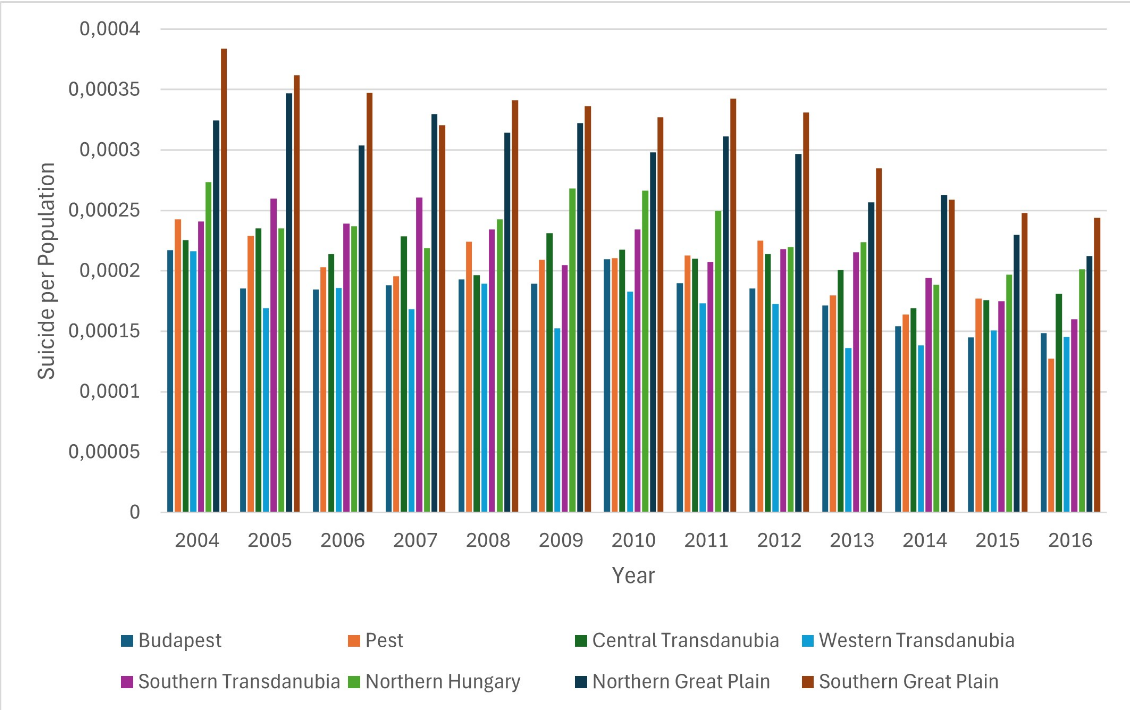

Figure 6.3: The Distribution of Suicides Between Regions - 2004-2016

By far, the most suicides occurred in the 'Southern' and 'Northern Great Plains'. This did not align with the micro-estimation results, where the strongest relationship between unemployment and mortality was found in 'Northern Hungary'. These diverging results probably reflected the different job opportunities in these regions; hence, they could not be tied to unemployment and mortality without more context.

6.2.2 Alcohol Consumption

One of Hungary's endemics is alcoholism (Elekes, 2014; Kovács and Tóth, 2015), which has been connected to mortality in the country (Kovács and Őri, 2010; Kovács and

Lajos, 2015). 2009 (about halfway through the period under study) was chosen to examine the patterns in alcohol consumption. The HCSO differentiated between four categories of alcohol consumption (KSH, 2025b):

- Big Drinker: For males, this meant that he drank more than 14 units of alcohol the week before. For females, 7 units.
- Drinks Often: Consumed alcohol at least once a week, but were not 'Big Drinkers'.
- Drinks Sometimes: Drank alcohol less than weekly.
- Abstinent: Did not drink at all.

I stress that this data was based on personal admission; thus, its reliability is questionable.

The differences between the two sexes' alcohol consumption habits are in Graph 6.4.

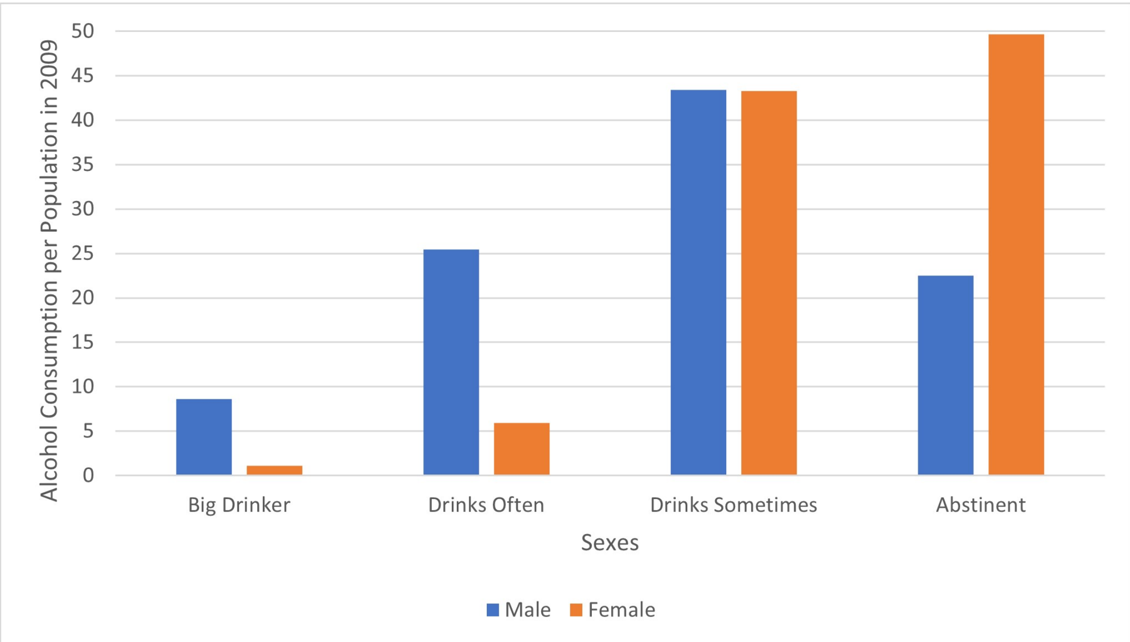

Figure 6.4: The Distribution of Male and Female Alcohol Consumption Habits in 2009

Men drank visibly more than women. 'Big Drinker' males outnumbered females 1 to 9. On the other hand, in the category 'Abstinent,' there were more than twice as many females as males. It can be assumed that as a result of unemployment, more males probably picked up drinking, which has severe health-damaging consequences, possibly leading to death.

The drinking categorisation of different age groups can be seen below (see Graph 6.5).

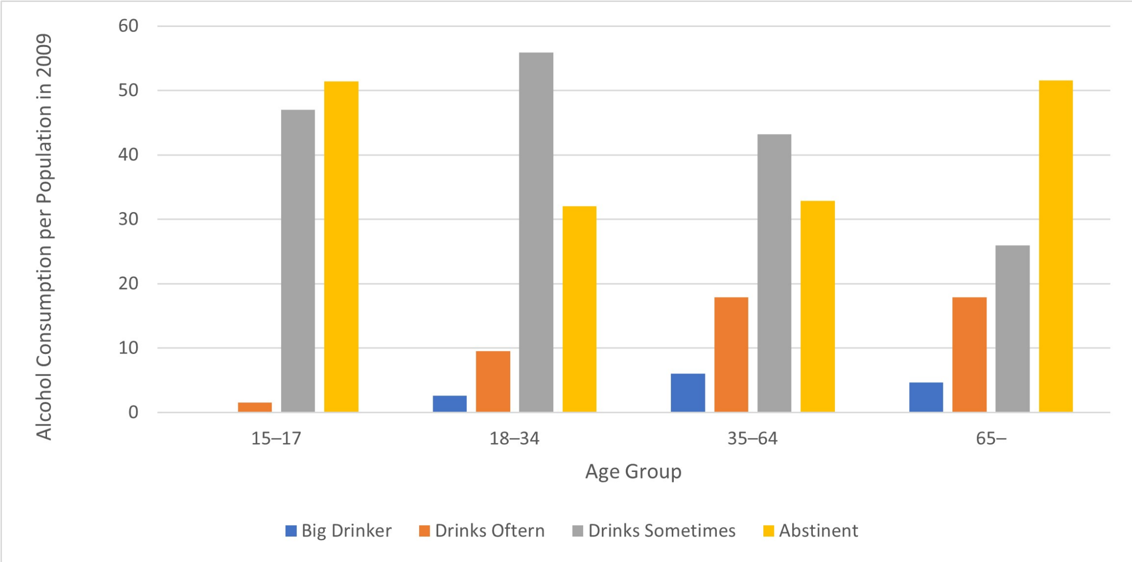

Figure 6.5: The Distribution of Alcohol Consumption Habits of Age Groups in 2009

People aged 35-64 were most likely to be 'Big Drinkers'. Since this age distribution of the HCSO data summed up two different age groups of the individual-level estimations, it was hard to interpret alcohol consumption in this context. It might be easy to conclude that developing an alcohol problem happens over time, and that is why not many from the younger group were 'Big Drinkers'. Middle-aged to old people were probably more likely to be alcoholics, which is dangerous to health and thus could lead to death.

Finally, the regional differences in alcohol consumption are presented (see Graph 6.6).

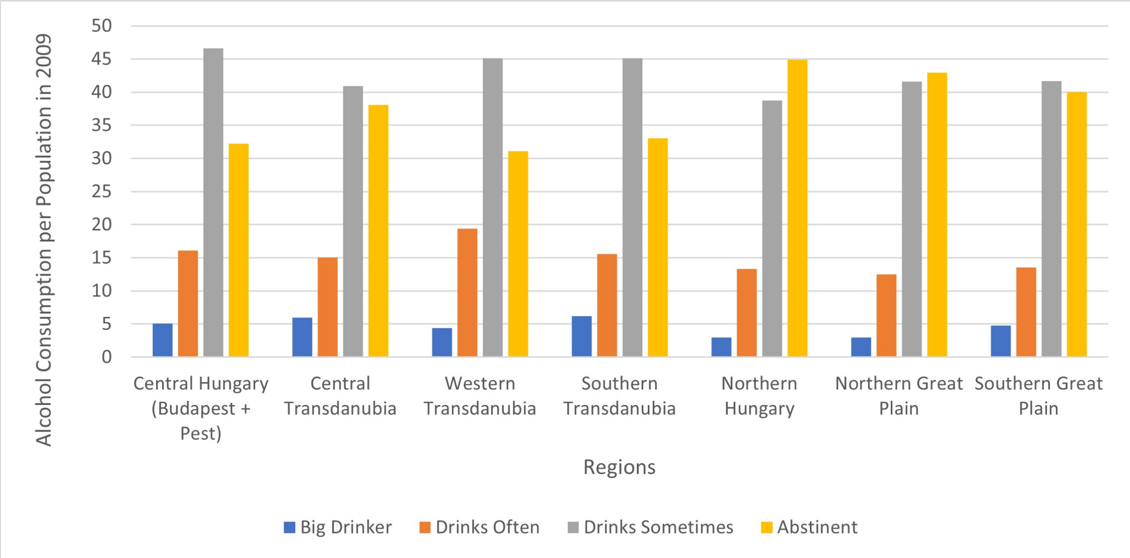

Figure 6.6: The Distribution of Alcohol Consumption Habits in Regions in 2009

Alcoholism (i.e., 'Big Drinker') was most common in 'Central Transdanubia', which also suggested that people in this area were more likely to suffer from alcohol-related issues, which could be life-threatening. Since the 'IV' result of this region was also significant, this supported the unemployment-mortality connection.

6.2.3 Divorce

The HCSO only has data on regions of the divorcee wife's residence and the divorcee husband's age group (KSH, 2025k,l). The distributions of which can be seen below (see Graphs 6.7 - 6.8). Of course, divorces should instead be interpreted in the context of the number of marriages and the generational trends of marrying age. Over time, the age at which people first got married increased, which meant that the time of the first divorce also got delayed. This was unique to every generation. Overall, the total divorce rate is almost 0.5 in Hungary. Even though the number of marriages has been decreasing, the number of divorces has decreased much less in comparison (Földházi, 2010, 2012, 2015).

Figure 6.7: The Distribution of Divorces Between the Age Group of the Husband - 2004-2016

Divorce seemed most common in the age group 35-49 (the 'Middle-Aged'). Unfortunately, this did not align with the results of unemployment on mortality.

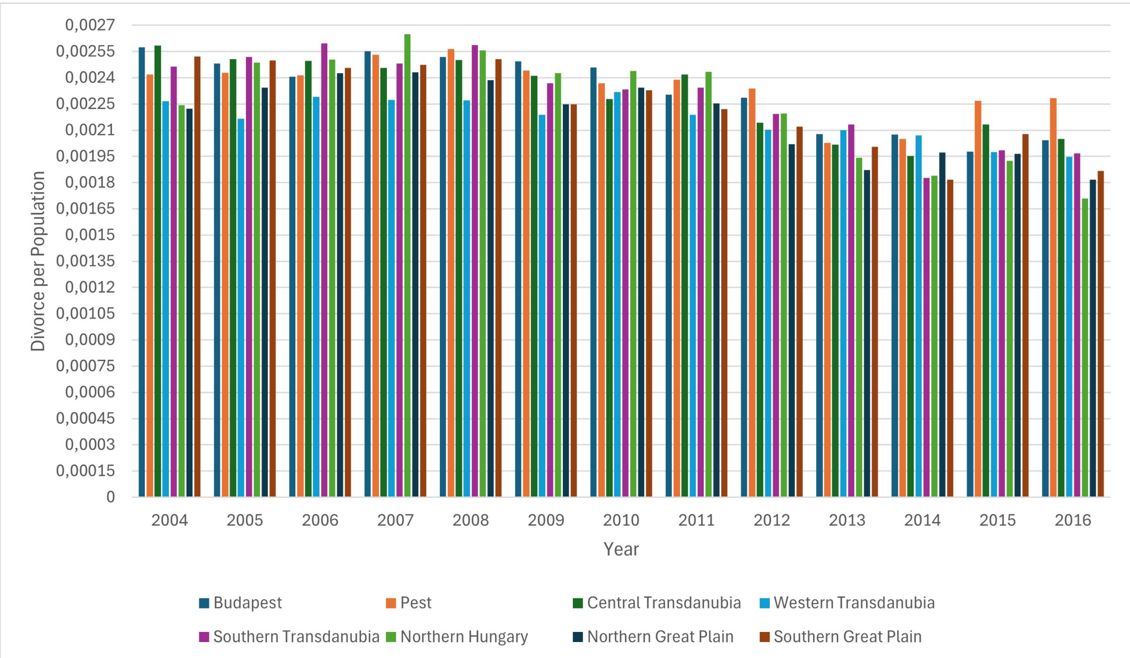

Figure 6.8: The Distribution of Divorces Between the Regions of the Wife's Residence - 2004-2016

Once regions were accounted for, the differences between divorce rates disappeared, so it could be concluded that although the number of divorces decreased in the period under study, the differences between regions were negligible. Hence, this could not be tied to unemployment patterns in the different areas.

As mentioned before, the factors examined above are just a few possible variables that could be part of the mechanism between unemployment and mortality. Since aggregate-level data is inappropriate for a deeper delve, little more could be shown. Still, two out of three examined factors were related to health, implying that unemployment indirectly influenced mortality through the worsening health of unemployed individuals. In conclusion, age and sex seemed important for suicides and alcohol consumption, which theoretically could both be tied to unemployment and mortality.

7. Conclusion

This study aimed to demonstrate that unemployment leads to increased mortality. This was done using the individual-level Admin3 dataset, which had data on half of the Hungarian population between 2003 and 2017 at a monthly frequency. The health history of individuals was found to be an insignificant predictor of dismissal in a mass lay-off process, but age had to be controlled for in all estimation. With the help of 2SLS accounting for time and industry fixed-effects, it was found that the probability of death increased by 0.09 percentage points if unemployed. To obtain this result, unemployment and mass lay-offs of at least 40% of firms' workforce were found to be significantly connected in the first stage. This was unsurprising given that dismissals should, in theory, increase the number of unemployed individuals. Then, in the second stage, mortality was explained by mass lay-offs used as instruments for unemployment to decrease bias in results. The findings suggested that given the base probability of death in the sample (which only considered those who were unemployed at least once during the period under study), mortality increased by 1.92% if one was fired in a mass lay-off. Results confirmed expectations by further diving into subsamples based on sex, age, and region. Finally, aggregate-level data from the Statistical Office (HCSO) was used to uncover the possible drivers behind this relationship. To achieve this, suicides, alcohol consumption, and divorces were considered.

All in all, the goal of this paper was attained. If unemployment increases, it can be expected that mortality will increase as well. The results are meaningful in two ways:

1. The mitigating effect of unemployment benefits, social education, and reintegration programs for the unemployed should be investigated for their power to weaken the relationship between unemployment and mortality. More affected subgroups of society were found to be older male workers, and regional differences were uncovered. Discovering what makes these people most affected by the connection between unemployment and mortality could also help policy-makers identify key characteristics of the most sensitive groups and target them better.

2. Moreover, studies discussed in the 'Literature Review' and the data examined in this paper also pointed to deteriorating health as one of the possible engines of this connection. This suggests that unemployment leads to disease, thereby increasing the risk of death. Thus, health policy should be a more significant part of unemployment policy.

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Chapter 2

On the Edge of Despair: The Connection Between Unemployment and Suicide

1. Introduction

Inarguably, the connection between a country's economic performance and its citizens' mental well-being is of great importance to the future growth of any nation. Comfort and security are the basis for production, and the rise of mental health issues (partially reflected in the suicide rate) is of growing concern to maintaining stable growth.

Suicide represents a complex human behaviour shaped by an array of psychological, social, and environmental determinants, making its underlying causes difficult to isolate. In general, the reasons for suicide can be divided into two categories:

- Macro-level: Broad, overarching conditions that affect societies and economies, including but not limited to economic conditions, political environment, cultural trends, etc.
- Personal: Changes in familial status, the passing of a loved one, depression, anxiety, illness, old age, etc.

Among these, the role of macroeconomic conditions — particularly unemployment — has been the subject of extensive scholarly debate. Given the cyclical nature of the economy and its influence on well-being, exploring how economic downturns affect suicide rates is a matter of both academic and policy relevance. The absence of detailed individual-level data made for an aggregate-level research on the relationship between unemployment and suicide.

First, a multi-country panel data analysis and then a focused case study on Hungary during the Covid-19 pandemic are presented in two subchapters. The first empirical subchapter evaluates the relationship between unemployment and suicide across a global sample using various econometric techniques. No study to date has examined this number of countries using such a wide range of estimation methods simultaneously. In contrast, the second chapter zooms in on the Hungarian context to explore short-term deviations in the suicide rate during the pandemic crisis. This subchapter is an extension and a robustness check of early results in the literature. Together, these two analyses aim to shed light on the relationship between unemployment and suicide.

2. Unemployment and Suicide – A Cross-Country Study

2.1 The Historical Relationship Between Unemployment and Suicide

The relationship between unemployment and suicide has long been debated. At first glance, it might seem straightforward and rather apparent that a higher unemployment rate should be associated with more suicides. This subchapter investigated whether a positive correlation between these variables was significant using aggregate panel data from over 170 countries (unprecedented in the literature). The methodological approach was multifold (unique in this body of research) but not without shortcomings; hence, all results should be interpreted with a grain of salt.

2.1.1 Economic Performance and Suicide

A key researcher and one of the voices of the empirical evidence of the relationship between unemployment and suicide was Harvey Brenner, who published a study on the positive connection between unemployment and suicide in 38 OECD countries, adding that other economic variables, such as the GDP per capita, might have a stronger impact (especially for those in the oldest age group) (Brenner and Bhugra, 2020). Many other researchers also got similar results to that of Harvey, indicating that the unemployment rate had a positive connection to suicides in various countries. (Iran (Noghanibehambari et al., 2021), Sweden (Johansson and Sundquist, 1997; Garcy and Vågerö, 2013), Australia (Morrell et al., 1993; Skinner et al., 2023), Greece (Madianos et al., 2014; Fountoulakis et al., 2015), Spain (Iglesias-García et al., 2017), England and Wales (Lewis and Sloggett, 1998), Mexico (Wang et al., 2020), Hungary (Fountoulakis et al., 2014a), Scandinavian countries (Babayeva, 2020), Turkic-speaking countries in Central Asia (Yüksel Okşak and Yilmaz, 2023), as well as, Italy (Preti and Miotto, 1999), and New Zealand (Blakely et al., 2003)). For example, Stuckler et al. (2009) showed that each 1% increase in unemployment was linked to a 0.79% increase in the suicide rate in Europe. Furthermore, using time series data from Hungary, Fountoulakis et al. (2014b) found that an increase in unemployment may be followed by a rise in the number of suicides 3 to 5 years later. Earlier (Platt, 1984) and more recent (Parmar et al., 2016; Amiri, 2022) meta-research analyses also confirmed the existence of a positive correlation between unemployment and suicide.

The experience of economic downturns and crises (the financial crisis of 2008-2009 and, more recently, the Covid-19 pandemic) also supported the positive connection between economic performance and suicide. Analyses of previous crises concluded that economic recession increased the suicide rate (Chang et al., 2013; Oyesanya et al., 2015; Harper et al., 2015). Interestingly, a Finnish study found that while unemployment was associated with excess suicides, high national-level unemployment decreased the strength of this relationship (Mäki and Martikainen, 2010). Similarly, Ruhm (2015) found that although suicides typically rise during economic downturns, this increase appears to be offset during severe national recessions.

On the other hand, Brenner's findings have also been disputed (Stern, 1983; Wagstaff, 1985). For example, a study in South Africa found no link between unemployment and suicide. Still, other macro-level (GDP, inflation), as well as personal indicators (divorce), were found to be significantly related to suicide (Phiri and Mukuku, 2020). Many suggested that the relationship between suicide and economic performance seemed entirely dependent on the period and the case under study. Such findings were drawn from US data (Ladd, 2019; Kunce, 2023), Italy (Platt et al., 1992), Argentina (Steinmetz et al., 2020), and various other European countries (Andrés, 2005; Laanani and Rey, 2015).

2.1.2 Men, Old-Age & Suicide

On the other hand, various papers identified noticeable differences between male and female suicide. The results of country-level data from Greece (Fountoulakis, 2019), Australia (Botha and Nguyen, 2022), Japan (Kuroki, 2010) and Hong Kong (Chan et al., 2007) suggested that increased unemployment rate affects the suicide of men more so than women. Using cross-sectional and panel data methods, several European (Ritter et al., 2013; Breuer, 2014) and OECD (Huikari and Korhonen, 2021) papers pointed to the same positive correlation. A regional study in the United States found a positive relationship between suicide and unemployment. They also noted that although men are more likely to commit suicide, they are less likely to do so due to unemployment (Snipes et al., 2012).

In addition, it is worth mentioning that generally, old-age suicide is more likely, as elderly people feel less capable and more burdensome day by day. For example, a study of the elderly in Italy revealed an alarming suicide rate in older age groups (Crestani et al., 2019). Another psychological paper drew attention to the risk of suicide in older men (De Leo, 2022), attributing the reasons to the loss of a loved one, loneliness and illness in addition to depression, loss of health, and independence. On the other hand, for example, during Covid-19, suicide among young age groups (Santomauro et al., 2021; Auger et al., 2023; Rodriguez-Jimenez et al., 2023) was on the rise.

2.1.3 Mitigating Effects of Unemployment Benefits on Suicide

Finally, the link between unemployment and suicide highlights the importance of employment policies and government interventions. For instance, a 2014 US-study tested whether the impact of economic downturns on suicide was reduced by unemployment benefit programs using data ranging from 1968 to 2008. They discovered that generous state unemployment benefit programmes offset the impact of unemployment on suicide, although the effects were small (Cylus et al., 2014). Another study of 25 EU countries investigated the link between working-age suicide and long-term unemployment to capture the mitigating effects of labour market policies in the period 1999-2017. Their results suggested an increased risk of suicide after long-term unemployment, as well as a decrease in suicides resulting from passive support policies. From the active policies, training and job creation were the most effective in reducing suicides (Goulas and Zervoyianni, 2023). In addition, a meta-study found that countries with active labour market programmes and sustained welfare spending in times of recession have experienced smaller increases in their suicide rates (Haw et al., 2014). A Japanese study that aimed to uncover the reasons for a decrease in the suicide rate between 2009 and 2018 found that prefectural education and intervention model programmes decreased male suicides, while municipal development programmes led to a decrease in overall suicide mortality (Okada et al., 2020). In the same vein, a Taiwanese study using monthly data between 1991 and 2012 showed that unemployment had a positive impact on suicide before the social welfare system was fully developed but not after (Chan et al., 2018). Another research involving 30 countries and over 50 years of data found that unemployment protection weakened the impact of unemployment on suicide during the Great Recession (Norström and Gronqvist, 2014). Finally, a research article on Italy found that with enough public unemployment spending, the effects of unemployment on suicide disappeared (Mattei and Pistoresi, 2019). On the other hand, an American study of 50 states with data ranging from 2000 to 2015 claimed that higher benefits had a negligible effect on suicide and that the effect was restricted to specific demographic groups in the United States (Kaufman et al., 2020).

In conclusion, the literature reveals a complex and context-dependent relationship between unemployment and suicide. While the general tendency points toward a positive association, the magnitude and direction of the effect can vary based on personal characteristics and institutional, cultural, and temporal factors. This study builds on these insights by applying multiple panel estimations across different age-tiered countries, allowing for a more granular and robust understanding of the unemployment-suicide dynamic.

2.2 Estimation

2.2.1 Data

The data on the suicide rate (per 100k population) was from Our World in Data (OWID), whose source was the World Health Organization (WHO) (Our World in Data, 2023a).[1] The unemployment rate data was also (as a percentage of the labour

[1] It is vital to mention that there is a difference in what is officially considered suicide in different countries, but in the absence of a standard definition, the data was taken as was.

force) from OWID, which acquired their compiled data from the World Bank (WB) (Our World in Data, 2023b). Finally, to account for business cycles, the GDP per capita (purchasing power parity constant 2021 international dollars) (Our World in Data, 2025a) was added as a control to all estimations. The descriptive statistics of all three variables are shown in Table 2.1. The period covered was between 2000 and 2019, and the number of country observations varied between 55 and 171 (see Appendix 3.6 for the complete list of countries).

Year	**Obs**	**Suicide Rate**				**Unemployment Rate**				**GDP/capita**			
		Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
2000	167	11.77	9.39	1.75	53.93	8.41	6.68	0.58	35.46	18148	21659	712	115589
2001	168	11.54	9.22	1.34	52.38	8.38	6.66	0.57	34.64	18259	21608	786	117733
2002	169	11.44	9.23	0.34	52.06	8.54	6.72	0.55	33.86	18419	21727	839	120263
2003	169	11.31	9.16	1.21	51.44	8.53	6.65	0.59	36.69	18851	22056	796	121923
2004	169	11.17	9.04	0.87	50.09	8.37	6.48	0.61	37.16	19643	22897	878	125289
2005	169	11.22	9.08	1.35	49.68	8.18	6.41	0.59	37.25	20218	23243	919	126450
2006	169	11.01	8.68	1.48	47.28	7.75	6.16	0.58	36.03	21035	24000	939	131937
2007	169	10.91	8.75	1.49	53.89	7.34	5.91	0.40	34.93	21686	24214	952	140436
2008	169	10.98	9.14	0.96	57.77	7.15	5.58	0.31	33.76	21862	23791	958	137534
2009	169	11.07	9.34	1.48	63.27	7.99	5.78	0.31	32.18	21039	22612	945	130638
2010	169	10.88	9.12	1.27	65.43	8.19	6.07	0.45	32.02	21615	23439	948	133098
2011	169	10.72	9.01	0.98	69.53	8.11	6.13	0.32	31.38	22089	24134	952	145591
2012	169	10.71	9.26	0.48	79.11	8.14	6.25	0.48	31.02	22322	24009	959	143831
2013	171	10.52	9.54	0.34	87.64	8.33	6.47	0.25	29.00	22240	23760	971	136454
2014	171	10.38	9.49	0.61	92.64	8.17	6.31	0.20	28.03	22470	23666	978	131899
2015	171	10.17	9.30	0.60	92.40	8.04	6.15	0.17	27.69	22771	23873	919	131747
2016	171	9.89	8.89	0.62	87.00	7.90	6.00	0.15	26.54	23043	24026	898	135356
2017	171	9.67	8.36	0.00	78.32	7.61	5.81	0.14	27.04	23496	24256	881	133846
2018	171	9.56	8.14	0.62	76.57	7.36	5.71	0.11	26.91	23967	24606	869	132890
2019	171	9.45	7.89	0.62	72.44	7.18	5.60	0.10	28.47	24318	24854	856	134106

Table 2.1: Descriptive Statistics by Year: Suicide Rate (per 100K pop), Unemployment Rate (% of labour force), and GDP/capita (PPP, const. int. 2021$)

In addition, to avoid comparing countries with vastly different age structures, the 'Median Age' data from 2019 (Our World in Data, 2025b) was used to create three separate age categories of countries. This step was necessary as older age is a major predictor of suicide (see 'Men, Old Age & Suicide'). The descriptive statistics of median age in the three age bracket categories of countries can be seen in Table 2.2. In addition, Appendix 3.3–3.5 presents the descriptive statistics of the suicide rate, the unemployment rate, and the GDP/capita across the different age brackets.

Age Bracket	**Observation**	**Mean**	**SD**	**Min**	**Max**
Young	1144	18.62	2.32	14.37	23.09
Middle	1127	28.16	2.77	23.21	34.19
Old	1120	39.83	3.23	34.33	47.26

Table 2.2: Descriptive Statistics of Median Age by Country Age Bracket

The following graph displays the relationship between the suicide rate and the unemployment rate for all 171 countries (see Figure 2.1) as two mean values for each country over time (aka the 'Between Estimator' - see later).

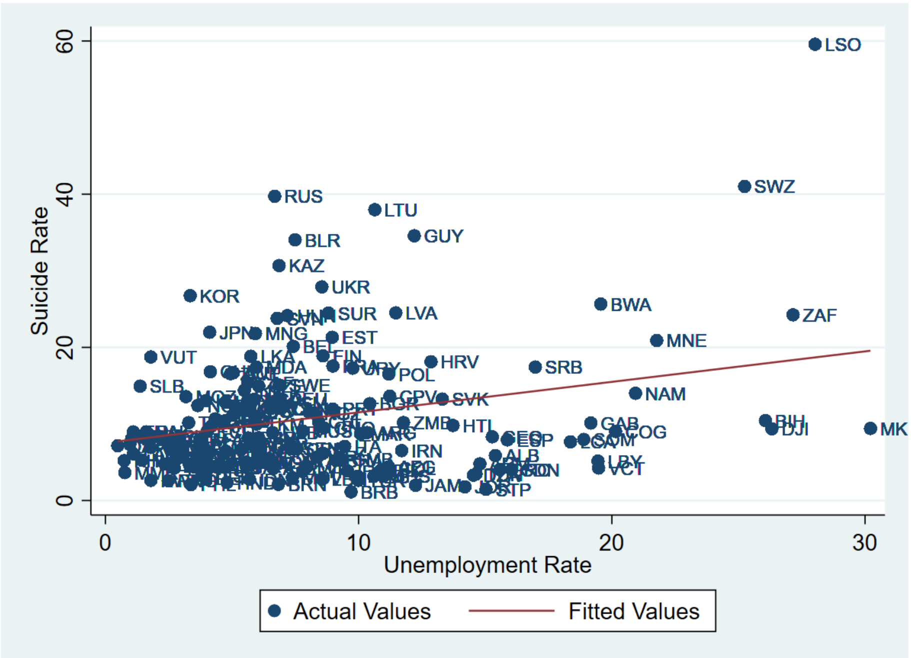


Figure 2.1: The Relationship Between the Unemployment Rate and the Suicide Rate

Note: The scatterplot displays the mean values of the two rates for each country between 2000 and 2019 (aka 'Between Estimator').

The unemployment rate, on average, seemed to have a positive relationship with the suicide rate, i.e., higher unemployment was associated with a higher suicide rate. To verify this, several issues had to be addressed.

2.2.2 Methodology

First, it was essential to account for the temporal dimension of the data. Hence, time dummies and differencing were considered to address time-based variation and reduce the risk of spurious results. Second, once a decision was made on how to deal with time, it also had to be contemplated how country-level differences should be included. Finally, the three variables under study changed continuously over time in the cases of all countries; thus, the clear absence of a counterfactual (control) was brought to the forefront. Several estimation approaches were used in the hopes of finding similar results, regardless of method. These were the following:

1. Pooled OLS with Time Dummies

$$S_{it} = \alpha_0 + \beta_1 U_{it} + \beta_2 G_{it} + \sum_{t=2}^{T} \lambda_t T_t + e_{it} \tag{2.1}$$

Where,

- S_{it} is the Suicide Rate for country i at time t,
- α_0 is the Constant,
- U_{it} is the Unemployment Rate,
- G_{it} is the GDP/capita,
- T_t are the Time Dummies (excluding the base period),
- e_{it} is the Error term.

'Pooled OLS' estimates the average relationship between the suicide rate and the unemployment rate, accounting for the GDP/capita, while time dummies excluding the base period (T_t) control for shocks or secular trends. However, 'Pooled OLS' assumes homogeneity across countries and does not account for unobserved country-level heterogeneity. As such, omitted variable bias may arise if country-specific effects are correlated with the unemployment rate and the GDP/capita.

2. OLS with First Difference (FD)

$$\Delta S_{it} = \alpha_0 + \beta_1 \Delta U_{it} + \beta_2 \Delta G_{it} + \Delta e_{it} \tag{2.2}$$

Where ΔS_{it} is the change (fist difference) in the Suicide Rate for country i between time t and $t-1$.

The 'FD' estimator helps remove unobserved, time-invariant heterogeneity by differencing out time-invariant heterogeneity across countries (ΔS_{it}, ΔU_{it}, and ΔG_{it}) and isolating the dynamic relationship between variables. However, differencing reduces degrees of freedom, may introduce noise if the original series is not difference-stationary, and assumes serially uncorrelated errors. It also cannot control for time-specific effects unless additional dummies are included, which may be problematic when differencing (Wooldridge, 2012).

3. Between Estimator

$$\bar{S}i = \alpha_0 + \beta 1\bar{U}i + \beta 2\bar{G}i + \bar{e}i \tag{2.3}$$

The 'Between Estimator' captures differences across countries by regressing averages of each variable ($\bar{S}i$, $\bar{U}i$, and $\bar{G}i$). This method is intuitive and straightforward if the goal is to explore whether countries with persistently higher or lower economic indicators also tend to have systematically higher or lower suicide rates. Additionally, this method avoids serial correlation and heteroskedasticity issues that can arise in panel estimations. However, the 'Between Estimator' only leverages between-country variation as it cannot capture within-country trends and ignores time-series dynamics. Moreover, it does not control for unobserved time-invariant heterogeneity, making the results vulnerable to omitted variable bias (Wooldridge, 2012).

4. Within Estimator (≈ *Country Fixed-Effects*)

$$\tilde{S}it = \alpha_0 + \beta 1\tilde{U}it + \beta 2\tilde{G}it + \tilde{e}it \tag{2.4}$$

The 'Within Estimator' controls all time-invariant characteristics at the country level (subtracting each country's average over time - $\tilde{S}it$, $\tilde{U}it$, and $\tilde{G}it$)), thus allowing for a more accurate assessment of within-country variation. This is particularly useful when the goal is to understand how variables like the unemployment rate or GDP/capita within a country influence changes in suicide rate rather than differences across countries. Unlike 'Pooled OLS', which assumes constant effects across all units, the fixed-effects model acknowledges that each country may have a unique baseline level of the suicide rate. Nonetheless, it assumes homogeneous slopes across countries and time and discards the possible invariance of the unemployment rate and GDP/capita, limiting the scope of interpretation (Wooldridge, 2012).

5. Two-Way Fixed Effects (TWFE)

$$S_{it} = \alpha_0 + \delta_i + \eta_t + \beta_1 U_{it} + \beta_1 G_{it} + e_{it} \tag{2.5}$$

'TWFE' controls country-specific (δ_i) and time-specific (η_t) effects. As a result, this method provides more accurate and unbiased estimates by addressing both dimensions of heterogeneity. However, its interpretation becomes complicated when treatment varies in timing or intensity across countries. The method assumes a parallel trends condition, and without a "never-treated" control group (counterfactual - no change in the unemployment rate and the GDP/capita), these assumptions may be violated (Imai and Kim, 2020; Goodman-Bacon, 2021). One solution to the absence of the never-treated group (the absence of a constant unemployment rate) is to consider late-treated groups as controls for the early-treated and vice versa when there is a variation in treatment timing (Goodman-Bacon, 2021). Further complications arise with heterogeneous treatment effects and ambiguity over defining what constitutes "treatment" in continuous or time-varying exposure contexts (de Chaisemartin and D'HaultfŒuille, 2017; de Chaisemartin and D'Haultfœuille, 2023; Callaway et al., 2024). Assuming that an increase in the unemployment rate meant the same thing in all countries is also a source of bias (de Chaisemartin and D'Haultfœuille, 2023). Moreover, it was unclear whether an increase or decrease in the unemployment rate and the GDP/capita should be considered "treatment" or whether changes in these variables should be considered as changes in dose (de Chaisemartin and D'HaultfŒuille, 2017).

2.2.3 Results

The results of several estimates are given in the tables below (see Tables 2.3 - 2.7). From the explanations above, it was clear that none of these methods were perfect for the type of data available, and thus, the results of all sensible possibilities are presented. Even though some of these methods were similar in their estimation procedure, they were not the same, and if their results were alike, then they could be considered robustness checks of each other. The idea was that if all estimation methods consistently pointed to the same relationship between unemployment and suicide rates, it made a case for a genuine underlying association rather than a result driven by model-specific assumptions.

Table 2.3 presents the 'Pooled OLS' results. The findings revealed notable age-related differences in how the economic variables relate to the suicide rate. Only for the youngest country bracket ('Young Age Bracket') was unemployment significantly and positively associated with an increased suicide rate (estimated coefficient: 0.783), suggesting that higher unemployment was linked to increased suicides in this country age cohort. The estimated coefficient for 'Middle Age Bracket' was positive but insignificant. The relationship turned negative in the case of the oldest country bracket; however, its coefficient was also statistically insignificant.[2] GDP/capita exhibited a small but statistically insignificant negative influence on the suicide rate, suggesting that greater economic prosperity may contribute to lower suicide incidence in these brackets. The explanatory power was notably higher for 'Young Age Bracket' (0.246) than 'Middle Age Bracket' and '3' (both 0.039), indicating that the economic variables included explained a larger share of the variation in the suicide rate among the youngest nations.

Table 2.4 displays the results of first-difference ('FD') OLS regressions, which estimated the year-over-year change in the suicide rate across three age brackets as a function of the changes in the unemployment rate and the GDP/capita. Unlike the 'Pooled OLS' results, the unemployment rate was no longer a significant predictor for 'Young Age Bracket', with a small negative but insignificant coefficient. However, the unemployment rate showed a positive and statistically significant association for both 'Middle Age

[2] It must be mentioned that countries with older age structures (greater 'Median Age' are usually more developed and hence might have social security systems in place during recessions.

VARIABLES	Suicide Rate (Young Age Bracket)	Suicide Rate (Middle Age Bracket)	Suicide Rate (Old Age Bracket)
Unemployment Rate	0.783**	0.234	-0.164
	(0.357)	(0.172)	(0.135)
GDP/capita	-0.000264	-0.00000676	-0.0000511
	(0.000267)	(0.0000218)	(0.0000400)
Time Dummies	included	included	included
Constant	5.692***	6.505***	20.05***
	(1.834)	(1.674)	(3.232)
Observations	1,144	1,127	1,120
R-squared	0.246	0.039	0.039

Cluster-robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2.3: Pooled OLS Results with Time Dummies by Country Age Bracket

Bracket' and 'Old Age Bracket' (estimated coefficients: 0.057 and 0.083), both significant at the 5% level. This marked a reversal from the previous model, where unemployment had a strong positive influence on the youngest nations. GDP/capita was statistically significant for 'Young Age Bracket' and '3' but was statistically insignificant for 'Middle Age Bracket'. Across all estimations, only limited explanatory power was achieved, suggesting that economic changes explained little of the year-to-year variation in the suicide rate. Furthermore, the autocorrelation of residuals was significant at the 5% significance level in all three age brackets (estimated autocorrelation of all age brackets: 0.06), hinting that the 'FD' was still time-dependent.
Table 2.5 presents the 'Between Estimator' results. The findings were broadly consistent with the 'Pooled OLS' results, particularly for 'Young Age Bracket', where the unemployment rate had a strong and significant positive association with suicide rates (estimated coefficient: 0.806). For 'Middle Age Bracket', the unemployment rate's coefficient was smaller and not statistically significant, but still positive, much like in

VARIABLES	FD Suicide Rate (Young Age Bracket)	FD Suicide Rate (Middle Age Bracket)	FD Suicide Rate (Old Age Bracket)
FD Unemployment Rate	-0.0481	0.0570*	0.0832***
	(0.144)	(0.0312)	(0.0264)
FD GDP/capita	-0.0000525*	-0.00000263	-0.0000710**
	(0.0000306)	(0.00000827)	(0.0000330)
Constant	-0.0680	-0.0484*	-0.163***
	(0.0488)	(0.0269)	(0.0495)
Observations	1,086	1,070	1,064
R-squared	0.002	0.004	0.018

Cluster-robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2.4: First Difference OLS Results by Country Age Bracket

the 'Pooled OLS'. For 'Old Age Bracket', it was negative but also insignificant — again echoing the direction of association observed in the 'Pooled OLS'. GDP/capita did not show significant influence in any age bracket under this method's specifications, suggesting that its cross-country variation was less clearly associated with the suicide rate.

Table 2.6 reports the results of the 'Within Estimator' (country fixed-effects). The 'Within Estimator' yielded a negative and statistically insignificant coefficient for the youngest country bracket compared to the previous estimations. For 'Middle Age Bracket', the unemployment rate was positive and statistically significant (estimated coefficient: 0.207), similar to the 'FD' and partially aligning with the 'Pooled OLS'. In 'Old Age Bracket', the unemployment rate was weakly positively associated with the suicide rate. GDP/capita was a significant negative predictor for 'Old Age Bracket' in the 'Within Estimator' (–0.000242), reinforcing its role observed in the 'FD' model for the same age bracket. The highest explanatory power was found in 'Old Age Bracket' (0.192), suggesting that economic conditions within countries were most

VARIABLES	Suicide Rate (Young Age Bracket)	Suicide Rate (Middle Age Bracket)	Suicide Rate (Old Age Bracket)
Unemployment rate	0.806***	0.214	-0.254
	(0.168)	(0.167)	(0.224)
GDP/capita	-0.000262	-0.000006	-0.00006
	(0.000234)	(0.00004)	(0.00006)
Constant	4.655***	6.452***	19.30***
	(1.663)	(1.970)	(3.732)
Observations	1,144	1,127	1,120
R-squared	0.299	0.033	0.030
Number of countries	58	57	56

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.5: Between Estimator Results by Country Age Bracket

relevant for understanding suicide trends in the oldest nations. Finally, although cluster-robust standard errors were used, the autocorrelation of residuals revealed a significant correlation over time in all three age brackets (estimated autocorrelation of all age brackets: 0.9). Hence, the inference could be biased.

Overall, these results underscore how sensitive the observed relationships were to the choice of estimator: while the 'Pooled OLS' and the 'Between Estimator' suggested a strong and positive association between the unemployment and the suicide rates — particularly among the youngest countries — the 'Within Estimator' and 'FD' revealed weaker or even opposing relationships.

Table 2.7 shows the results of a two-way fixed effects ('TWFE'). For 'Young Age Bracket', the unemployment rate's coefficient was negative and statistically insignificant (estimated coefficient: –0.831), aligning closely with the 'Within Estimator' and 'FD' results. This stood in contrast to the 'Pooled OLS' and the 'Between Estimator', where the unemployment rate had a strong and positive association with the suicide rate in

VARIABLES	Suicide Rate (Young Age Bracket)	Suicide Rate (Middle Age Bracket)	Suicide Rate (Old Age Bracket)
Unemployment Rate	-0.843	0.207**	0.095*
	(0.831)	(0.082)	(0.050)
GDP/capita	-0.000244	-0.00007	-0.000242***
	(0.000189)	(0.00004)	(0.00007)
Constant	16.70***	7.807***	23.23***
	(5.815)	(0.771)	(3.056)
Observations	1,144	1,127	1,120
R-squared	0.101	0.106	0.192
Number of countries	58	57	56

Cluster-robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 2.6: Within Estimator Results by Country Age Bracket

this age bracket. For 'Middle Age Bracket', the unemployment rate was positively and significantly associated with suicide (0.203), mirroring the 'FD' and 'Within Estimator', and partially the 'Pooled OLS'. In 'Old Age Bracket', the unemployment rate also showed a positive and significant relationship with suicide (0.152), again consistent with the 'FD' and the 'Within Estimator', and contradicting the 'Pooled OLS' and the 'Between Estimator', which either found a negative or non-significant association. The association with the GDP/capita were generally negative across all age brackets but remained statistically insignificant in the 'TWFE' as well. Due to the lack of a counterfactual, the notably high R-squared values in the 'TWFE' (0.882 to 0.958) should be taken with a pinch of salt.

The binscatter graphs of 'Middle Age Bracket' and 'Old Age Bracket' of the TWFE are shown in Figures 2.2a-2.2b.

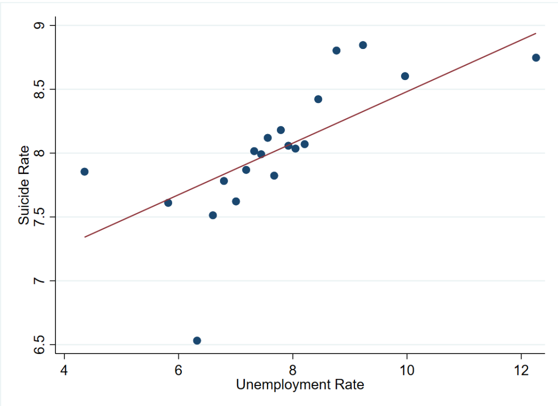
Since the residuals of the 'FD' and the 'Within Estimator' were still serially correlated, the result of the 'Pooled OLS', the 'Between Estimator', and the 'TWFE' should be

VARIABLES	Suicide Rate (Young Age Bracket)	Suicide Rate (Middle Age Bracket)	Suicide Rate (Old Age Bracket)
Unemployment Rate	-0.831	0.203**	0.152**
	(0.841)	(0.083)	(0.063)
GDP/capita	-0.000215	-0.00005	-0.0001
	(0.000155)	(0.00003)	(0.00008)
Constant	16.48**	7.501***	17.24***
	(6.291)	(0.690)	(3.129)
Observations	1,144	1,127	1,120
R-squared	0.882	0.958	0.914

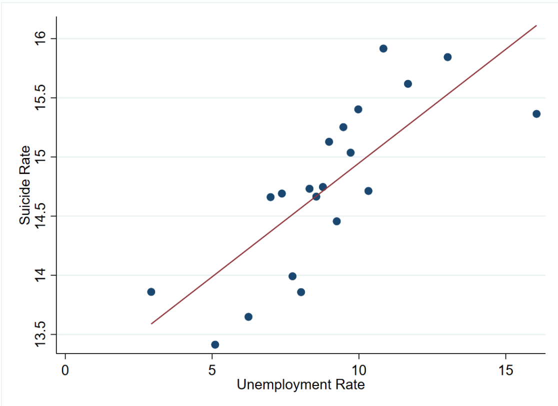
Cluster-robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2.7: TWFE Results by Country Age Bracket



(a) 'Middle Age Bracket'



(b) 'Old Age Bracket'

Note: Scatterplots are binscatters. The x-axis variable was divided into equal-sized bins and, for each bin, the average y-axis value is plotted. Country effects were absorbed and time was controlled.

Figure 2.2: The Relationship Between the Unemployment Rate and the Suicide Rate – TWFE

most reliable. According to these, there was a significant positive relationship between the unemployment rate and the suicide rate, albeit different across country age brackets.

2.2.4 Conclusion

Based on the results of all five estimation models, the influence of unemployment on suicide rates was shown to vary significantly by both age bracket and estimation strategy. Only the 'Pooled OLS' and the 'Between Estimator' suggested a strong positive association between the unemployment rate and the suicide rate for the youngest countries. Conversely, for the oldest nations, the unemployment rate exhibited a positive association with the suicide rate only in the cases of the 'Within Estimator', 'FD', and 'TWFE' methods. These inconsistencies implied that, unfortunately, the assumed positive association between unemployment and suicide rates could be spurious. The role of GDP/capita was even less consistent across methods. However, it showed a statistically significant negative association with the suicide rate — particularly for 'Old Age Bracket' in 'FD', and the'Within Estimator'. Taken together, the results highlight the importance of model selection when investigating the socioeconomic determinants of the suicide rate.

Since all significant coefficients indicated a positive relationship between the unemployment rate and the suicide rate, let us assume that this positive association existed and was not coincidental. If that were the case, the role of mental health in unemployment policies should receive considerable attention, as suggested by the literature (see 'Mitigating Effects of Unemployment Benefits on Suicide').[3]

[3] Limitations: Unfortunately, possible confounders were at work. Sick people, as well as the elderly, were both more likely to become unemployed and commit suicide. However, aggregate datasets made it impossible to control for such individual-level factors.

3. Hungarian Suicide During Covid-19

Building upon the cross-country analysis in the previous subchapter, this section turns to a single-country case study to explore the unemployment-suicide relationship within the unique context of the Covid-19 pandemic. This chapter aims to examine whether the unemployment-suicide association identified in the global dataset withstood the crisis conditions or whether the pandemic altered this relationship due to exceptional psychological, social, and institutional pressures. The literature (Bálint et al., 2022) explored this relationship with early data from 2020 and 2021. This subchapter is a robustness check of their results by

- extending the period under study by several years
- accounting for the mediator unemployment rate.

To this end, a brief introduction to suicides during Covid-19 around the world is presented first. Then, the Hungarian cases of suicide and unemployment during the pandemic are discussed. Using the estimation method of interrupted time-series (ITS), this chapter's analysis examined whether the suicide rate in Hungary changed after the start of Covid-19 and while accounting for the unemployment rate. The goal is to connect the unemployment and suicide rates; hence, all papers discussed were chosen for this purpose.

3.1 Various Impacts of Covid-19 on Suicide

Covid-19 emerged in late 2019 and quickly became a global crisis, bringing widespread health, economic, and social challenges. The early symptoms of the respiratory disease (SARS-CoV-2) were severe and often fatal. Although efforts to find a solution and develop a vaccine began immediately, an effective vaccine only became available a year later, in 2021. Thus, the pandemic called for emergency regulations for the common good, which limited personal freedoms. Most governments implemented many of the following measures to stop the spread of the disease: a ban on social gatherings, shutdowns of restaurants, theatres, and gyms, the introduction of online education, a ban on visiting hospitalised patients, etc. People were instructed to stay home and leave only when necessary. Even then, social distancing restrictions had to be met.

Given the uncertainty and fear caused by the pandemic, measures designed to protect the public were bound to have repercussions. The feeling of isolation, xenophobia (fear of the sick), and being stigmatised when sick are just a few to name. In addition, many people lost their jobs, leading to unexpected financial difficulties that paved the way to mental health problems. Experts warned at the start of the outbreak that the increased unemployment would contribute to the rising number of mental health issues (Hasnain Iftikhar and Moeeba Rind, 2020; de Miquel et al., 2022). In Latin America, depression and anxiety symptoms were identified along with a fear of Covid-19 (Caycho-Rodríguez et al., 2021). In both Turkey and Canada, young adults, females, LGBTQ/2S+ people, and low socioeconomic status groups were found to cope poorly with the new circumstances (Chankasingh et al., 2022; Çay et al., 2023). Furthermore, a multi-country study on depression and anxiety disorders (the main reasons for suicide) also concluded that Covid-19 had a greater impact on women and younger age groups (Santomauro et al., 2021; Rodriguez-Jimenez et al., 2023). A cross-national study of the USA, the UK, Australia, and Norway showed that time passing did not reduce the "toll" of the pandemic on mental health (Østertun Geirdal et al., 2021). As early as May 2020, a study was published warning of a possible increase in suicide as a result of increased unemployment during the pandemic (Bhatia, 2020).

Several researchers have investigated the various effects of the pandemic on suicide rates in different countries. The results were inconclusive. Some papers were unable to detect any change in the suicide rate during Covid-19 (John et al., 2020; Radeloff et al., 2021; Appleby et al., 2021; Stene-Larsen et al., 2022; Barlattani et al., 2023), while others found a decrease in suicide at the time of the pandemic. A reduction in suicides during a crisis might seem perplexing, but an explanation for this could be the temporary effect of the feeling of unity among individuals. The virus could be stopped only through unified common action (all had to stay home). This was known as the 'pulling together' period (Zortea et al., 2020). Consequently, a drop in suicide was observed in several countries (e.g., Canada (Isnar and Oremus, 2022), Italy (Grande et al., 2023), Taiwan (Chen et al., 2023), Finland (Partonen et al., 2022), and South Korea (Kim, 2022)). An interrupted time-series analysis of 33 countries also concluded that suicide during the pandemic was lower than expected (Pirkis et al., 2022).

Other studies revealed the opposite: an increase in suicide at the time of COVID-19. A rise in suicides was shown in various countries and cities (Mexico (Borges et al., 2022, 2023), Spain (Martínez-Alés et al., 2023), the city of Milan (Italy) (Calati et al., 2023), and Mexico City (Mexico) (García-Dolores et al., 2023)). Interestingly, during Covid-19, contrary to the usual 'male dominance' in suicide, female suicide was on the rise. These results were found in several empirical papers (a meta-analysis of 54 studies (Dubé et al., 2021), in Japan (Ueda et al., 2021; Tanaka and Okamoto, 2021; Sakamoto et al., 2021; Nomura et al., 2021; Yoshioka et al., 2022), the city of New Taipei City (Taiwan) (Su et al., 2023), and in the Kerman province of Iran (Pouradeli et al., 2023)). A study of hospital admissions due to suicide attempts in Madrid (Spain) also showed an increase in the hospitalisations of women specifically. Additionally, an increase in suicide was observed among young girls in Quebec, Canada (Auger et al., 2023).

3.2 The Case of Hungary

3.2.1 The Hungarian Unemployment Rate During Covid-19

Each country combats unemployment differently, as cultural dissimilarities make an approach feasible in one place and impossible in another. For instance, in Hungary, it has been shown that being laid-off increased the probability of enrolling in disability insurance 1.5-fold in the first 4 years (Bíró and Elek, 2020), indicating an intention to stay out of the labour market long-term, possibly leading to serious mental health consequences. The same study concluded that the four-year mortality rate after the lay-off increased 1.7-fold. Furthermore, another Hungarian paper showed that being unemployed could lead to an increase in the consumption of antidepressants (Elek et al., 2020), which is a medicine for depression - one of the reasons for suicide.

With the findings of these studies in mind, it seems that being laid-off in Hungary, at the very least, increases the probability of mental health issues. Hence, it is concerning that research by Köllő found that the Covid-19 pandemic was more detrimental to Hungary's labour market than the 2008-2009 financial crisis, and its impact lasted six months to a year (Köllő, 2022). He also suggested that the official employment numbers during the pandemic did not reflect reality. It is worrisome that according to his findings, employment in the public sector decreased, and the opportunities to work abroad shrunk, while the strict rules for applying for unemployment benefits remained. Sadly, pandemic-related unemployment benefit programs were delayed and meant little relief to receivers in international comparison (Köllő, 2020). He added that working from home was restricted to those with higher educational attainments. Köllő also found an increase in career switchers (Köllő, 2022). Furthermore, a study found that career-switching in 2020 was not very successful in Hungary, as both the participation and job-finding rates decreased (Kónya, 2020). Another article showed that unemployment increased mainly in the first wave of the pandemic, and those who lost their jobs had less stable employment statuses to begin with (Kónya and Krekó, 2020; Boza and Krekó, 2020). The authors of these articles also found that the greatest increase in unemployment was observed, unsurprisingly, in the hospitality sector; however, at the same time, there was an increase in the employment of highly qualified jobs, as well as very basic physical jobs. These changes were explained not by career-switchers but by new job market entrants, leavers, and new job trends. Regarding the long-term impact of Covid-19 on Hungary's unemployment rate, a study concluded that, unfortunately, those who became unemployed during the pandemic remained unemployed for a long time (Boza et al., 2022).

3.2.2 The Hungarian Suicide Rate During Covid-19

The definition of suicide in Hungary is the following: "The deliberate act to cause one's own death" (KSH, 2024). Based on the latest report (Zonda et al., 2013) that investigated suicides between 1970 and 2010 in Hungary, significantly more men commit suicide than women, and by far, most suicides are registered in the south-eastern region of the country. In addition, the annual peak is between May and July, which is also common in other countries.

Until now, only a few studies have investigated the effects of the pandemic on the suicide rate in the Hungary (Osváth et al., 2021; Lantos and Nyári, 2022; Bálint et al., 2022; Szeifert et al., 2023). All stated that contrary to most other countries, unfortunately, Covid-19 had significantly increased the suicide rate in Hungary. In addition, two studies found an increase in antidepressant consumption after the start of the pandemic (Elek et al., 2021; Purebl and Réthelyi, 2022). Furthermore, findings also indicated that, unlike Japan, where there was a rise in female suicide, in Hungary, male suicide increased after the start of Covid-19 (Osváth et al., 2021; Bálint et al., 2022; Lantos and Nyári, 2022).

3.3 Estimation

3.3.1 Data

The Hungarian Suicide Rate

All Hungarian suicide data (KSH, 2023b) were from the Hungarian Central Statistical Office (HCSO). To calculate the male suicide rate, the number of male suicides was divided by the male population in the ages of 15-74 to match the unemployment data (KSH, 2023a). [1] The monthly time-series of the Hungarian suicide rate between 1995 and 2023 is shown in Graph 3.1.

[1] I have considered using district-level data on antidepressant consumption but decided against it. First, to obtain a prescription for antidepressants, one needs a licensed psychiatrist, which is expensive in Hungary, not including the price of the medication. Second, it is my conviction that seeing such a therapist is still stigmatized in Hungary, and, as a result, many people would rather remain undiagnosed. Finally, during Covid-19, most practices were temporarily closed, so obtaining a prescription was more difficult.

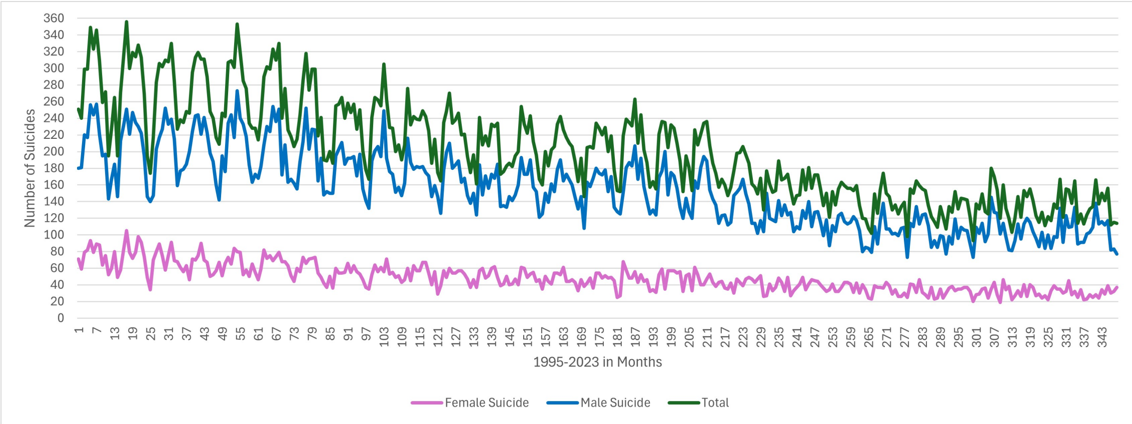


Figure 3.1: Hungarian Suicides by Sex (1995-2023)

In the years shown, approximately 75% of suicides were male; therefore, it was appropriate to only account for male suicides in Hungary. This meant that, in the coming estimations, only male unemployment was considered. It can also be seen that Hungarian suicides have been on a long-term declining trend, but a slight rise could be observed right around the time of the first summer of the pandemic (see "Month 307").

The Hungarian Unemployment Rate

Unfortunately, because of changes in the definition, credible monthly unemployment data in Hungary was only available after 2009. Hence, all estimations covered the time between 2009 and 2023. The monthly number of unemployed (ILO definition) (KSH, 2023a) data was used as collected by HCSO. The unemployed were divided by the population between 15 and 74 to determine the unemployment rate. [2]

A comparison of the male suicide rate and unemployment rate in the period under study is presented in Graph 3.2.

[2] The decision to include people over the age of retirement was justified because Covid-19 impacted the employment opportunities of older employees worse (Hollis-Sawyer, 2021; Goda et al., 2021) than any other age group, due to increased ageism (Jimenez-Sotomayor et al., 2020; Fraser et al., 2020; Werner et al., 2022). They had to face social stigma because they were more vulnerable to the virus, and they were less apt to switch to remote work than their younger colleagues. In addition, as discussed before, suicide is more common among older people (see 'Men, Old-Age & Suicide' in 'Unemployment and Suicide'), so it was important to include them in the measure of the unemployment rate as well.

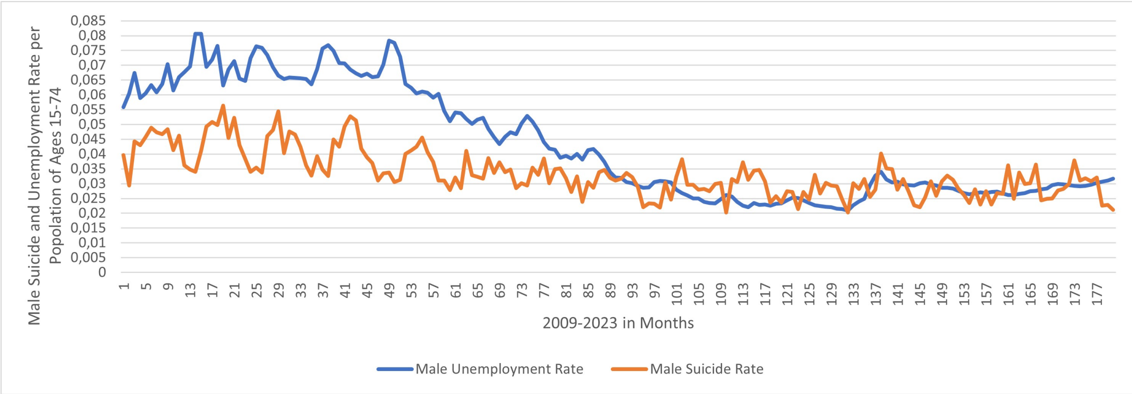


Figure 3.2: Hungarian Male Suicide and Unemployment Rate (2009-2023)

The male suicide rate is procyclical in Hungary, especially at the beginning of the period. It lags behind the unemployment rate by about 3 months but is much more volatile than the unemployment rate, which smooths out by the end of the period. This could be explained by the economic crisis of 2008-2009 and the consolidation period that followed.

3.3.2 Methodology

The goal of this research was to investigate the impact of Covid-19 on the Hungarian male suicide rate while accounting for its association with unemployment. To achieve this, following the methodology of the literature (Osváth et al., 2021; Bálint et al., 2022; Lantos and Nyári, 2022), four separate interrupted time-series regressions (ITS) were run. First, the results of the literature were replicated on the Hungarian male suicide rate during the pandemic. This meant an estimation of the monthly suicide rate for the period 2015 to 2021. Then, as a robustness check, I expanded the years under study to monthly observations between 2009 and 2023.[3]

Going one step further, as a second assessment, I also included the Hungarian monthly male unemployment rate as a mediator in the case of both estimations (the replication of the literature results and the robustness check of the lengthened period). The

[3] It is important to mention that, compared to 2021, the male suicide rate increased in Hungary in 2022, which might be related to the unfortunate development in the neighbouring country Ukraine, where war had started with Russia (March 2022). This event needs to be researched separately, and as it is not directly related to the pandemic, it was not considered in the following analysis.

first difference in the monthly male unemployment rate was taken, and stationarity was confirmed with the augmented Dickey-Fuller test. This way, the Hungarian male unemployment rate's trend did not disrupt the estimated time-series regressions of the suicide rate. Time lags with one, three and six-month delays in the monthly unemployment rate were added to the 'Extended' estimations to reduce bias and capture the dynamic relationship between unemployment and suicide. Naturally, the presumed effects of unemployment and its associated economic burden are significantly mitigated by unemployment benefits, which are available for a limited amount and duration; hence, the inclusion of lags in the estimations was necessary.[4]

The estimated equations of the interrupted time-series regressions were:

$$Y = \beta_0 + \rho_{1-12}M + \beta_1 T + \delta_1 D + \upsilon_1 P + \lambda_0 U_t + \lambda_1 U_{t-1} + \lambda_3 U_{t-3} + \lambda_6 U_{t-6} + \varepsilon \quad (3.1)$$

where,

Y is the monthly 'Male Suicide Rate'.

β_0 is the Constant.

$\rho_{1-12}, \beta_1, \delta_1, \upsilon_1, \lambda_0, \lambda_1, \lambda_3, \lambda_6$ are the estimated coefficients.

M are the 'Month Dummies'.

T is a continuous variable indicating 'Time'.

D is the 'Dummy for Covid-19' ($=0$ if before 2020, $=1$ if after 2020).

P is a continuous variable indicating the 'Time Since Covid-19' (before Covid-19, $P = 0$).

U_t is the contemporaneous, monthly 'FD Male Unemployment Rate'.

$U_{t-1}, U_{t-3}, U_{t-6}$ are the 1-month, 3-month, and 6-month lags of the 'FD Male Unemployment Rate'.

ε is the estimation 'Error'.

The appearance of Covid-19 was scheduled for March 2020.

[4] Longer lags could have been considered; however, due to the study's focus on the pandemic's impact on suicides and limited data availability, this approach was avoided to prevent excessive loss of relevant observations (i.e., 2020-2023).

3.3.3 Results

The estimations' results are below (see Tables 3.1 and 3.2). The column 'Literature' replicated the published literature results. At the same time, the column 'Extended' showed the results of the extended period.

VARIABLES	Literature Male Suicide Rate (2015-2021)	Extended Male Suicide Rate (2009-2023)
Constant	included	included
Month Dummies	included	included
Trend	-0.007***	-0.015***
	(0.002)	(0.001)
Covid-19 Dummy	0.323*	0.218**
	(0.174)	(0.01)
Time Since Covid-19	-0.005	0.024***
	(0.012)	(0.003)
Observations	84	180
R-squared	0.52	0.76

Everything is multiplied by 100
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.1: Interrupted Time-Series Regression Results – Hungarian Male Suicide Rate

The 'Covid-19 Dummy' was significant in both estimations, indicating that the appearance of the pandemic indeed had an influence on male suicide in Hungary. It appears that the 'Male Suicide Rate' increased after the outbreak (estimated coefficient: 0.323). Of course, with a longer time considered, the strength of this correlation decreased (0.218) as the impact of the pandemic diminished. The variable 'Time Since

Covid-19' was only significant in the 'Extended' results (0.024). This showed that probably in the period 2022-2023, the trend of male suicides changed more significantly than during the pandemic. This suggested that the impact of the pandemic on suicide rates may have been smaller than the effects of other crises. By simply extending the period under study, more notable changes in the trend of the 'Male Suicide Rate' could be detected. The residuals were autocorrelated in the 'Literature' results but were serially independent in the 'Extended' results.

The findings remained robust when the male unemployment was included as a mediator in the estimations (see Table 3.2). Although the mediator 'FD Male Unemployment Rate' showed a negative correlation with the 'Male Suicide Rate' (estimated coefficient: -22.55), considering its lags, the correlation changed to positive. It was significant and positive at the sixth lag (21.92). All estimated coefficients increased considerably once the male unemployment rate and its one, three and six-month lags were accounted for. The variable 'Time Since Covid-19' was again insignificant in 2015-2021 but was highly significant in the 'Extended' period (0.026). Furthermore, the sign of the variable switched here as well, which further confirmed the suspicion that the result found by (Bálint et al., 2022) were somewhat overstating the impact of the pandemic on Hungarian, male suicide. Once again, the residuals were only uncorrelated in the 'Extended' results, indicating that the 'Literature' results were also somewhat biased.

The graph (see Figure 3.3) depicts the 'Extended' interrupted time-series, including the mediators of male unemployment. This is a visual representation of the 'Extended' results above. The vertical orange line depicts the interruption in the time-series (timed to March 2020) of the Hungarian male suicide rate. The blue line before it shows its fitted values before Covid-19. After the vertical line, the blue line represents the so-called counterfactual, the hypothetical case of no interruption (i.e., no pandemic). The orange line after the vertical line shows the actual values of the Hungarian male suicide rate. The break in the Hungarian male suicide rate after the pandemic led to very slight changes in the variable compared to the variation later in time. Attributing these delayed increased deviations to the pandemic alone would likely be false.

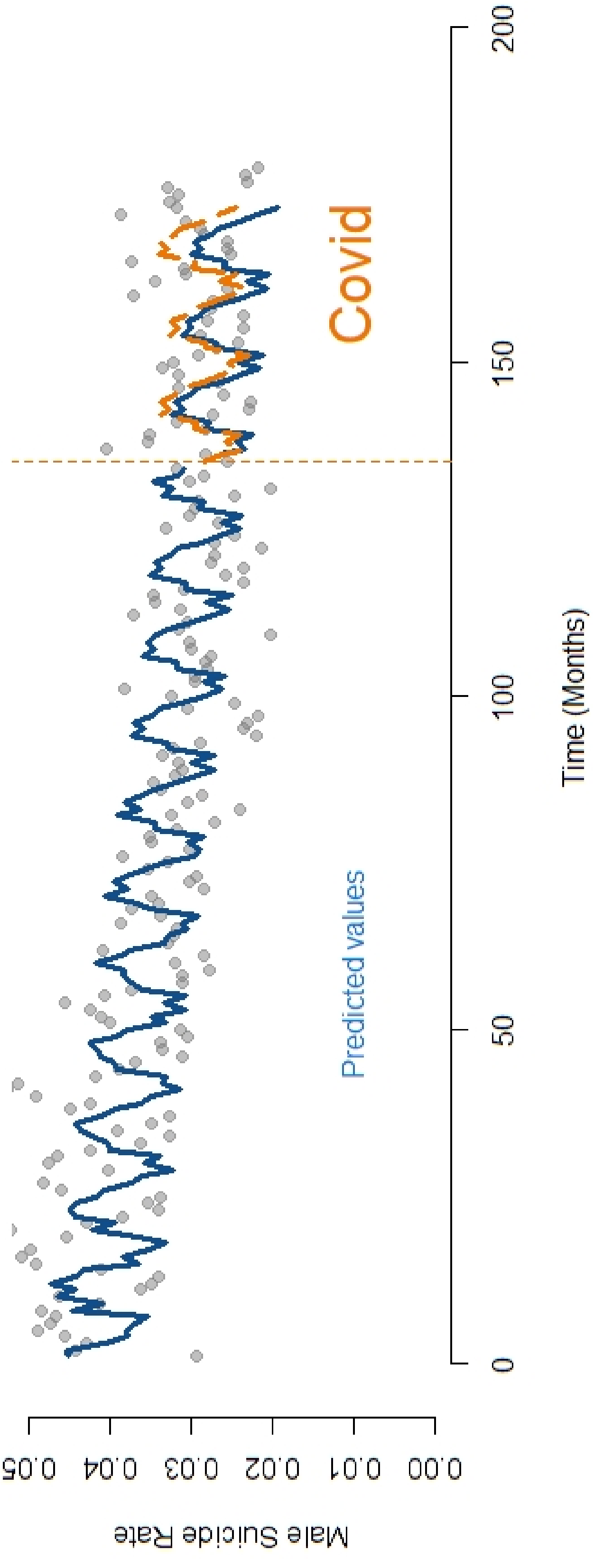


Figure 3.3: Interrupted Time-Series – 'Extended' Data – Monthly Hungarian Male Suicide Rate (2009-2023)

3.3.4 Discussion

This subchapter was a robustness check of the findings of Bálint et al. (2022). To achieve this, two alterations were made. The period under study was extended by several years in both directions (2009-2023). In addition, based on the results of the first subchapter, the male unemployment rate and its one, three and six-month lags were included as mediators for the male suicide rate. Extending the analysis's time series, the literature's results proved stable if overstated. More notable but delayed changes in the trend of the male suicide rate could be detected years after the pandemic, the reasons for which are unlikely to be due to Covid-19. Nonetheless, this could not be investigated further, as aggregate data did not allow it.

Finally, a considerable change in the suicide rate could occur as a result of the legalisation of euthanasia in the country. Thus, future data could change suicide rate patterns completely.

VARIABLES	Literature Male Suicide Rate (2015-2021)	Extended Male Suicide Rate (2009-2023)
Constant	included	included
Month Dummies	included	included
Trend	-0.007** (0.003)	-0.015*** (0.001)
Covid-19 Dummy	0.268 (0.208)	0.241** (0.1)
Time Since Covid-19	-0.003 (0.015)	0.026*** (0.004)
FD Male Unemployment Rate	-18.84 (44.23)	-22.55* (12.77)
Lag 1	0.906 (41.41)	-0.615 (12.61)
Lag 3	31.56 (41.35)	3.847 (12.83)
Lag 6	48.51 (38.04)	21.92* (12.44)
Observations	76	172
R-squared	0.54	0.76

Everything is multiplied by 100
Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3.2: Interrupted Time-Series Regression Results – Hungarian Male Suicide and Unemployment Rate

Appendix

Age Bracket	**Observation**	**Mean**	**SD**	**Min**	**Max**
Young	1144	9.41	9.75	1.29	92.64
Middle	1127	8.02	7.11	0.00	40.28
Old	112	14.75	8.52	0.34	53.93

Table 3.3: Descriptive Statistics of the Suicide Rate by Country Age Bracket

Age Bracket	**Observation**	**Mean**	**SD**	**Min**	**Max**
Young	1144	7.26	6.60	0.32	35.46
Middle	1127	7.73	5.62	0.10	33.29
Old	112	8.97	6.17	0.25	37.25

Table 3.4: Descriptive Statistics of the Unemployment Rate by Country Age Bracket

Age Bracket	**Observation**	**Mean**	**SD**	**Min**	**Max**
Young	1144	4783	4893	712	39995
Middle	1127	21149	23493	1360	145591
Old	112	38580	22555	3990	140436

Table 3.5: Descriptive Statistics of the GDP/capita by Country Age Bracket

AFG	AGO	ALB	ARE	ARG	ARM
AUS	AUT	AZE	BDI	BEL	BEN
BFA	BGD	BGR	BHR	BHS	BIH
BLR	BLZ	BOL	BRA	BRB	BRN
BTN	BWA	CAF	CAN	CHE	CHL
CHN	CIV	CMR	COD	COG	COL
COM	CPV	CRI	CYP	CZE	DEU
DJI	DNK	DOM	DZA	ECU	EGY
ESP	EST	ETH	FIN	FJI	FRA
GAB	GBR	GEO	GHA	GIN	GMB
GNB	GNQ	GRC	GTM	GUY	HND
HRV	HTI	HUN	IDN	IND	IRL
IRN	IRQ	ISL	ISR	ITA	JAM
JOR	JPN	KAZ	KEN	KGZ	KHM
KOR	KWT	LAO	LBN	LBR	LBY
LCA	LKA	LSO	LTU	LUX	LVA
MAR	MDA	MDG	MDV	MEX	MKD
MLI	MLT	MMR	MNE	MNG	MOZ
MRT	MUS	MWI	MYS	NAM	NER
NGA	NIC	NLD	NOR	NPL	NZL
OMN	PAK	PAN	PER	PHL	PNG
POL	PRT	PRY	QAT	ROU	RUS
RWA	SAU	SDN	SEN	SGP	SLB
SLE	SLV	SOM	SRB	STP	SUR
SVK	SVN	SWE	SWZ	TCD	TGO
THA	TJK	TKM	TLS	TON	TTO
TUN	TUR	TZA	UGA	UKR	URY
USA	UZB	VCT	VNM	VUT	WSM
ZAF	ZMB	ZWE			

Table 3.6: List of Country Codes Used in the Cross-Sectional Analysis

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Chapter 3

Analysing Covid-19 Death Outcomes: An Ex-Ante Approach

1. Introduction

The SARS-CoV-2 virus appeared in Wuhan, China, at the end of 2019, and on 11 March 2020, the World Health Organization (WHO) declared a global pandemic now known as Covid-19 (WHO, 2024a). The outbreak was sudden and unexpected; the early symptoms of the respiratory disease were severe, and even though the race for a solution and the development of a vaccine began right away, it was only realised a year later in 2021 (Hatcher et al., 2022). However, the characteristics of high-risk groups were shared early on: Older age and long-term underlying health conditions were identified as vulnerable to the disease (Pal et al., 2020).

One of the pitfalls of Covid-19 lies in its singularity (Borio, 2020). The last global pandemic occurred about 100 years ago (1918-1919, Spanish flu), and the world then was very different from the world today. Thus, nothing of this calibre has happened in the last couple of decades, and the advancements achieved in science have created a facade of safety. This is the first impediment to understanding the progression of the pandemic. A local outbreak turned into a global epidemic within weeks, which shocked the world.

The other catch in dealing with the latest pandemic lies in its duration. Covid-19 lasted about 1,5-2 years. For some countries, most infection cases occurred in the first year, but there was a delay for others. Doctors and healthcare professionals warned the public early on about overburdening the healthcare system (Lasater et al., 2021; Andel et al., 2021). Moreover, there are cases to this day, and there will be future cases. After the first vaccines became available, Covid-19 slowly blended into daily life, the new norm. These issues show the difficulties that researchers must consider in investigating Covid-19.

From the beginning of the outbreak, doctors and health experts alike began to question why Covid-19 outcomes were so drastically different across countries. In our previous study with Professor Péter Mihályi (Kovács and Mihályi, 2021), we presented early empirical evidence that national health indicators strongly predicted Covid-related mortality. The current chapter builds on that research with a more extensive dataset, an updated methodology, and an independent regression framework. While our earlier study provided the initial insight, the analyses and findings presented here are comprehensive. This paper contributes to a growing body of literature that finds strong relationships between priori public health status and pandemic outcomes (Elgar et al., 2022). Furthermore, structural or "endowment" factors — such as geography or population density — have also been highlighted in recent literature as important non-policy determinants of mortality (Pažitný et al., 2021; Ameh et al., 2022), which are supported by the results of this chapter as well.

Thus, this research investigates which pre-pandemic factors were most relevant in explaining the variation in Covid-19 outcomes, using a global sample of 131 countries. The analysis pays special attention to health indicators, policy capacity, and endowment variables, aiming to offer robust evidence for policymakers and scholars alike. The key contribution of this chapter's analysis lies in its scope: to my knowledge, no other published study has explored such a wide array of pre-pandemic variables across as many countries before. Consequently, the findings offer a unique perspective on the diverse Covid-19 outcomes observed worldwide, reflecting the combined impact of factors not previously considered in research.

2. Literature Review

In the beginning of the pandemic, most research focused on forecasting the spread of the disease with various methods of time-series analyses (Iftikhar and Rind, 2020; Ismail et al., 2020; Papastefanopoulos et al., 2020; Magyar et al., 2021; Aditya Satrio et al., 2021; Bhangu et al., 2021) as well as machine learning techniques (Niazkar and Niazkar, 2020; Khan et al., 2021; Bloise and Tancioni, 2021; Hasanah et al., 2023; Lyu et al., 2023). Later, an extensive literature on vaccine hesitancy was published as well (Costa-Font, 2022; Andrade, 2022; George et al., 2023; Boga et al., 2023; Alfasi, 2023; Backhaus, 2023). Since then, many papers aimed to explain the variability of Covid-19 outcomes among countries by pre-Covid-19 conditions using testing, infection, and death rates as outcome measures of the pandemic. Their data came from either only one country (Tóth G. et al., 2023) or as few as 10, (Cabo et al., 2020) to as many as over 180 countries in the world (Kong et al., 2020).

The following table was created to organise the related literature (see Table 2.1), listing the most commonly used explanatory variables in these papers. Of course, this is not an exhaustive list of all possible variable considerations but a constraint to arranging the articles explicitly connected to this chapter's research analysis. The first column indicates the names of the variables used, while the second column is the authors' names and the year of publication. Most of these papers considered aggregate-level data available in national statistics. They are organised and presented along the categories of 'Health Status', 'Policy Capacity', and 'Endowment'.

Health Status Measures: Related to individual health characteristics, which were a direct consequence of individual lifestyle. On the aggregate level, these variables captured the general health state of citizens.

- Body Mass Index: Height/body weight.
- Chronic Disease: People suffering from incurable diseases were more vulnerable to the virus.
- Habit of Smoking: Smoke weakens the lungs and shrinks their capacity, making them

weaker against respiratory diseases.

- Old Age: Older people have weaker immune systems and were thus defenceless against the virus.
- Life Expectancy: This is based on genetics, gender, and health conditions, which all correlate to the immune system.

The findings of these articles highlighted the most critical factors in explaining the variance among countries' Covid-19 outcomes. Older people were more vulnerable to the virus. However, countries with older age structures (greater average/median age, higher life expectancy) - typically more developed - did not suffer more Covid-19 deaths compared to younger, developing countries throughout the pandemic. Another risk factor for Covid-19 was obesity. Overweight countries did not experience more deaths than their "thinner" peers, because excess weight is also a sign of wealth. Finally, chronic patients were in the highest risk group of all, and a bigger proportion of these patients meant more deaths during the pandemic. Health-damaging habits, such as smoking, were associated with an increased Covid-19 death rate. However, spending on healthcare seemed to have paid off, as a greater number of nurses, doctors, and hospital beds meant fewer Covid-19 casualties. Healthcare spending also correlated with the economy's output level; richer countries (higher GDP/capita) were associated with fewer Covid-19 deaths.

Policy Capacity Measures: These were of the "macro-level", meaning that, they were presumably "similar" for everyone within a country. These variables were a direct consequence of national policies constrained by national wealth and institutional characteristics.

- GDP/capita: Reflects the wealth of the nation.
- Trade: Shows the amount of trade a country conducts.
- Development: Shows the stage of development in a country.
- Number of Nurses: Shows healthcare preparedness and wealth.
- Spending on Healthcare: Shows healthcare preparedness and wealth.
- Number of Hospital or nursing beds: Shows healthcare preparedness and wealth.
- Number of Doctors: Shows healthcare preparedness and wealth.

Geographically, the effect of landlocked (variable 'Island') had a decreasing influence on Covid-19 deaths, probably because of less connection with other countries through trade. Eminent air pollution increased the deaths of Covid-19, while higher average temperatures decreased pandemic-related deaths. In addition, the effects of trust among individuals and toward authorities all emphasised the importance of compliance with Covid-19 regulations. Similarly, vaccine hesitancy was closely related to the measures of trust. Last but not least, the influence of culture could not be underestimated, as the actions taken during the pandemic reflected the tremendous impact of cultural aspects.

Endowment: Included national characteristics that could not be influenced by policy.

- Density of Population: Crowded locations made it harder to keep social distancing rules.
- Island: Less international trade (no sea) meant less contact with the world.
- Particulate Matter: Air pollution weakens the lungs and the immune system of the people.
- Temperature: Cold weather and less sunshine were favourable conditions for spreading disease.
- Level of Trust: Shows shared values and unity within a nation.
- Cultural Factors: Unique habits and traditions of people from the same origin.

Significant Findings	Authors & Year of Publication
Health Status	
BMI	(Bollyky et al., 2022; Beaumont et al., 2022)
Prevalence of Chronic Illness	(Gunness and Lynn, 2020; Käffer and Mahlich, 2022a)
Prevalence of Smoking	(Xie and Li, 2020; Khan et al., 2021)
Older Age	(Cabo et al., 2020; Hulíková Tesárková, 2020; Dowd et al., 2020)
Life Expectancy	(Kong et al., 2020; Özyılmaz et al., 2022)
Policy Capacity	
GDP/capita	(Valev, 2020a; Haldar and Sethi, 2021)
Trade	(Zoungrana et al., 2022; Jeanne et al., 2022)
Development	(Valev, 2020b; Stojkoski et al., 2020; Zoungrana et al., 2022; Kumru et al., 2022; Shynkaryk et al., 2022; Fallah-Aliabadi et al., 2022)
Number of Nurses	(Kovács and Vántus, 2022)
Spending on Healthcare	(Mateusz and Andrzej, 2023)
Number of Hospital or Nursing Beds	(Buja et al., 2020; Arachchi and Managi, 2021; Hradský and Komarek, 2021)
Number of Doctors	(Asfahan et al., 2020; Ehlert, 2021; Jeanne et al., 2022)
Endowment	
Density of Population	(Hassan et al., 2020; Ahmed et al., 2021; Mogi and Spijker, 2022; Zoungrana et al., 2022; Tamasiga et al., 2022; Shi et al., 2023)
Island (has sea)	(Navarro, 2021; Kumru et al., 2022)
Particulate Matter (Air Pollution)	(Contini and Costabile, 2020; Hassan et al., 2021; Sarkodie and Owusu, 2021; Teja et al., 2023; Lackó, 2024)
Temperature	(Aabed and Lashin, 2020; De Angelis et al., 2021; Rizzo et al., 2022; Zahid et al., 2023)
Covid-19 Waves	(Bonfiglio et al., 2022a,b; Antolini et al., 2023; Mateusz and Andrzej, 2023)
Level of Trust	(Arachchi and Managi, 2021; Bollyky et al., 2022; Besley and Dann, 2022; Virág, 2022; Ságvári, 2022)
Cultural Factors	(Mogi and Spijker, 2022; Käffer and Mahlich, 2022b)

Table 2.1: Variable-Based Article Organization

3. Data

3.1 The Explained Variable - 'Mean Cumulative Excess Death'

An appropriate "outcome" measure had to be chosen to explain Covid-19 outcomes. Several studies used the Case Fatality Rate (CFR) as their dependent (Pažitný et al., 2021). Still, CFR required that individual cases were identified, which, especially in the beginning of the pandemic, was rather challenging. Not everyone infected with the virus developed symptoms (Johansson et al., 2021), greatly affecting the reported infection rate. Additionally, not all confirmed infections were reported. In general, reporting is a major hindrance in all pandemic-related research as the data had been collected and recorded hastily (Appleby, 2020). The stigma of infection (Ramaci et al., 2020; Peprah and Gyasi, 2020) and various personal incentives might have discouraged the sick from reporting. Finally, the lack of willingness to test (McElfish et al., 2021) and limited testing resources (Sim et al., 2021; Beaudevin et al., 2021) made it difficult to investigate every suspicious case. Thus, the official infection rate should be treated as a rough estimate of the actual rate (Phipps et al., 2020; Tradigo et al., 2020). Consequently, the testing and recovery data suffered from the same reporting bias. The least noisy data would be the only undeniable outcome: death.

Thus, choosing deaths as the outcome measure was straightforward: deaths were inarguable. One way to account for Covid-19 deaths is called 'Excess Death'. This aims to capture additional mortality attributable to the pandemic. Basically, 'Excess Death' calculates the difference between the actual number of deaths (registered deaths) and the estimated number of deaths that would have occurred had the pandemic not happened (counterfactual). Another way to account for deaths is called 'Cumulative Death'. This is achieved through aggregation over time.

The distinction between the two death measures is clear: the 'Excess Death' compared all deaths to an estimated counterfactual, whereas the 'Cumulative Death' summed all death registered as "Covid-19 deaths".[1] Excess death, of course, included deaths that occurred as a result of COVID-19 infection; hence, it was unsurprising that the two measures were strongly, positively correlated (Pearson correlation coefficient: 0.63 among 180 countries) (WHO, 2024c,b). On the other hand, the two death measures painted a different picture once the Spearman rank correlation (between countries) was considered (rho: -0.79) (WHO, 2024c,b). Below is a scatterplot of the logarithm of the two measures of deaths (see 3.1).

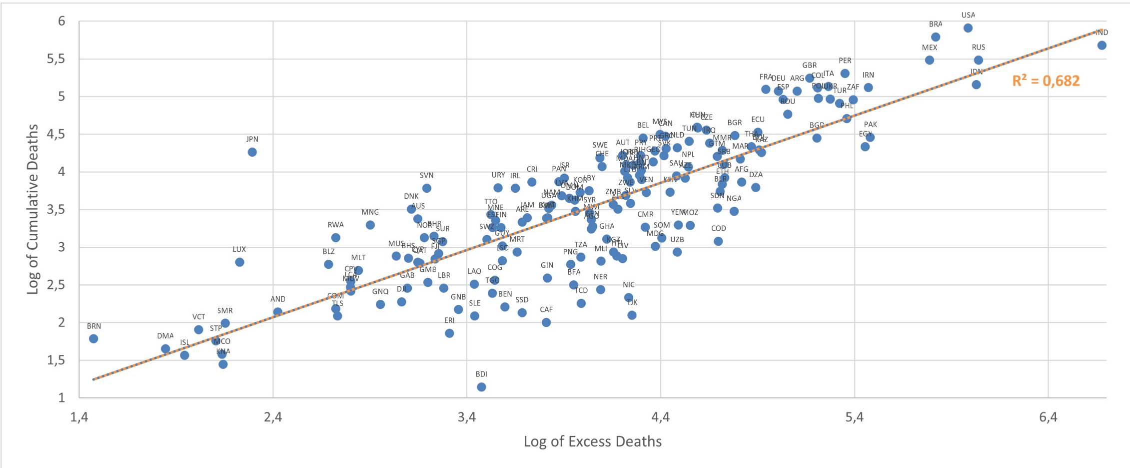

Figure 3.1: Scatterplot of Log Cumulative Excess and Log Cumulative Deaths

Source: (WHO, 2024c,b)

Many researchers have argued that 'Excess Death' was a more reliable measure of Covid's impact than 'Cumulative Death' as it accounted for indirect effects of Covid-19 and, as such, 'Excess Death' was independent of testing activity (Beaney et al., 2020; Tóth G., 2021; Ferenci and Tóth G., 2022; Eurostat, 2024). For one, 'Excess Deaths' captured the mortality dynamics during the pandemic by including the increase in overall deaths due to the virus and the decrease in other causes of death, like traffic accidents due to mobility restrictions. 'Excess Death' was also better to capture the

[1]What exactly constituted a 'Covid-19 death' was not clear (Beaney et al., 2020; Ferenci and Tóth G., 2022). Most people who died after catching the disease had severe underlying conditions to begin with, which could also have led to their deaths. Moreover, the term "died from Covid" was false and misleading. People did not die from Covid; they died from Covid-19 complications, for example, pneumonia as a result of long bedrest due to Covid-19 (Beaney et al., 2020; Tóth G., 2021; Ferenci and Tóth G., 2022).

true effects of Covid, as different types of mortality could have also been indirectly affected by the pandemic crisis (e.g., shortage of healthcare personnel) but were not counted as "Covid-19 deaths" (Castro et al., 2023) (e.g., suicides). In addition, deaths incorrectly diagnosed were also accounted for in the 'Excess Death' mortality.
Hence, this chapter used 'Excess Death' to measure Covid-19 outcomes. Using registered deaths as the outcome measure among different countries was not obvious, yet not unique either (Aghakhani et al., 2022). The 'Excess Death' data came from the WHO, which estimated the average cumulative excess deaths (henceforth 'Mean Cumulative Excess Death') between 2020 and 2021 (WHO, 2024c). One shortcoming of 'Mean Cumulative Excess Death' lay in its dependence on estimating expected deaths, also known as the counterfactual. In this case, the basis for the comparison was the years 2015-2019 if monthly mortality data were available or 2000-2019 if only annual mortality data were provided by the country (WHO, 2023). The WHO data was later divided by 100.000 population (WB, 2025) to match the measures of the independent variables.

3.2 The Explanatory Variables

Similarly to the literature, I used aggregate data from over 200 countries and territories worldwide. The latest year of observation before 2020 was always chosen for the pre-pandemic (henceforth 'ex-ante') variables. Together, this meant 30 independents.[2]
In the following, the names of the explanatory variables are listed, their respective units of measure, and their sources (see Table 3.1 -3.2). The variables considered were grouped into the same three categories as those in the literature 'Health Status, 'Policy Capacity', and 'Endowment'.

Health Status: Highlights the influence of individual lifestyle on health.

- Alcohol Consumption: Alcohol weakens the immune system.
- Prevalence of Overweight: A high BMI is associated with an increased risk of cardiovascular diseases and diabetes, both of which were associated with a heightened risk if infected with the virus.

[2]The reliability of the data was a serious limitation of this study. To compare countries, it was assumed that the data had been measured the same way and were equally genuine.

Variable	Measure	Year	Source
Health Status			
Alcohol Consumption	per capita, 15 years and older, litres of pure alcohol	2018	(WHO, 2021a)
Prevalence of Overweight	BMI greater than 25 among adults, crude rate	2016	(WHO, 2021f)
Prevalence of Insufficient Physical Activity	among adults, age-standardized, crude rate	2016	(WHO, 2021e)
Prevalence of Tobacco Use	current, percentage of adults	2018	(WB, 2021f)
Fruit Consumption	per capita, kilogramme	2017	(UN, 2022)
Meat Consumption	per capita, kilogramme (Daily meat consumption relative to the expected EU average of 165g per person in 2030.)	2019	(UN, 2024)
Non-Communicable Diseases	disability-adjusted life years per 100.000 population, both sexes, age-standardized rate	2019	(IHME, 2022a)
Self-Harm	suicide per 100.000 population	2019	(IHME, 2022b)
Life Expectancy	at 60 years of age, both sexes	2019	(WHO, 2021c)
Median Age	in years, population	2013	(WHO, 2021d)

Table 3.1: Health Status Variables

- Prevalence of Insufficient Physical Activity: Exercise is essential for good health.
- Prevalence of Tobacco Use: Smoking weakens the lungs and is associated with an increased risk of respiratory as well as cardiovascular diseases. Both of these made for high-risk groups.
- Fruit Consumption: Reflects conscious eating habits that influence health.
- Meat Consumption: Protein intake is essential for muscular health.
- Non-Communicable Disease: Chronic diseases weaken the body.

- Self-Harm: Reflects mental health.
- Life Expectancy: Reflects the wealth and health of a nation.
- Median Age: Reflects the age structure of a society. Younger people have stronger immune systems compared to older generations.

Policy Capacity: Captured factors that were a direct consequence of national policy and could influence pandemic outcomes.

- GDP/capita: Reflects wealth and the standard of living.
- Trade Openness Index: Reflects the exchanges of goods and services between countries. More trade meant more potential contact with the world, increasing the risk of virus spread during the pandemic.
- Human Development Index (HDI): Reflects the stage of development.
- Expenditure on Healthcare: Reflects wealth and priorities of a nation.
- Hospital Beds: Reflects wealth and healthcare preparedness.
- Nurses and Midwives: Reflects wealth and healthcare preparedness.
- Physicians: Reflects wealth and healthcare preparedness.

Endowment: Country characteristics that could not be influenced by policy potentially influenced Covid-19 outcomes.

- Population Density: Crowded locations were hotbeds for disease spread.
- Landlocked: Trade enabled by international connectivity on sea sped up disease spread.
- Exposure to Extreme Temperature: Hot weather (a proxy for sunshine) was unfavourable to the virus. Temperature is also closely tied to geographical location, which often shaped the history of nations.[3]
- Exposure to PM2.5: Air pollution weakens the lungs and makes people more susceptible to diseases.[4]

[3] For the variable 'Exposure to Extreme Temperature' the average of years 2020 and 2021 were considered as the climate did not change abruptly, and as such, the extreme heat in the years of the pandemic under study should be examined only.

[4] The variable 'PM2.5' was the average of years 2019 and 2020. The reason for including 2020 was simple: Air pollution does not happen overnight; therefore, accumulated pollutants lead to serious consequences by some delay in time. As the analysis aimed to explain the variation in average 'Mean Cumulative Excess Death' during 2020 and 2021, 2019 and 2020 were considered for the variable capturing air pollution.

Variable	Measure	Year	Source
Policy Capacity			
GDP/capita	per capita, current US dollars	2019	(WB, 2021a)
Trade Openness Index	as percent of GDP	2019	(OWID, 2024)
Human Development Index (HDI)	0-1	2019	(UNDP, 2024)
Expenditure on Healthcare	per capita, current, US current PPP	2018	(WHO, 2021b)
Hospital Beds	per 1000 population	2017	(WB, 2021b)
Nurses and Midwives	per 1000 population	2018	(WB, 2021c)
Physicians	per 1000 population	2017	(WB, 2021d)
Endowment			
Population Density	per square kilometre	2018	(WB, 2021e)
Landlocked	dummy (0=has sea, 1=landlocked)		
Exposure to Extreme Temperature	population exposure to hot days, less than 2 week, percentage of population	2020-2021	(OECD, 2024a)
Exposure to PM2.5	mean population exposure to PM2.5, microgrammes per cubic metre	2019-2020	(OECD, 2024b)
Trust	Share of 'Agree: Most people can be trusted'	2014	(EVS, 2024)
Political Participation	from 0 to 10 (most active)	2019	(EIU, 2024)
Political Regime	closed autocracies; electoral autocracies; electoral democracies; liberal democracies	2019	(V-Dem, 2024)
Hofstede Index	power distance; uncertainty avoidance; individualism/collectivism; masculinity/femininity; long/short term orientation; indulgence/restraint	2015	(HOFSTEDE, 2024)

Table 3.2: Policy Capacity and Endowment Variables

- Trust: Interpersonal trust was key to keeping to Covid-19 regulations.
- Political Participation: Reflects people's perception of their power. Thus, this is a proxy for how unified a nation was.
- Political Regime: Shows the country's system of government, which limited the strictness of regulations introduced during the pandemic.
- Hofstede Index: Capturs cultural aspects of the nations. The importance of cultural factors cannot be overstated; they show how people live in communities.

Many of these variables ('GDP/capita', 'Prevalence of Tobacco Use', etc.) were also used in the literature (see earlier). Still, the inclusion of several ('Self-Harm', 'Fruit and Meat Consumption', and 'Alcohol Consumption') were novel variable considerations. The descriptive statistics of all variables can be seen in Tables 3.3-3.4.

Variable	Mean	SD	Min	Max	Count
Mean Cumulative Excess Death/100K Population (2020-2021)	186.09	194.60	-178.55	923.12	203
Health Status					
Alcohol Consumption	6.1	4.16	0	20.5	199
Prevalence of Overweight	48.57	18.31	17.9	87.9	201
Prevalence of Insufficient Physical Activity	27.97	11.74	5.04	65.25	172
Prevalence of Tobacco Use	22.18	10.16	3.7	52.1	159
Fruit Consumption	77.73	49.4	6.14	381.76	179
Meat Consumption	136.18	81.94	10.03	346.17	191
Non-Communicable Diseases	21860.84	4976.96	12309.91	44700.53	205
Self-Harm	10.31	5.97	2.29	42.17	205
Life Expectancy	19.93	3.1	13.17	26.35	194
Median Age	28.39	8.75	15	45.9	194
Policy Capacity					
GDP/capita	15848.62	23648.52	261.25	185829.02	200
Trade Openness Index	90.81	57.33	22.82	382.35	170
HDI	0.73	0.16	0.39	0.96	200
Expenditure on Healthcare	1254.89	2050.72	18.51	10623.85	200
Hospital Beds	1254.89	2050.72	18.51	10623.85	200
Nurses and Midwives	4.73	4.62	0.07	20.16	202
Physicians	1.80	1.65	0	8.30	200

Table 3.3: Descriptive Statistics - Health Status & Policy Capacity

Variable	Mean	SD	Min	Max	Count
Endowment					
Population Density	291.08	1456.17	2.04	19083.37	203
Landlocked	0.21	0.41	0	1	198
Exposure to Extreme Temperature	21.61	21.66	0	86.33	204
Exposure to PM2.5	23.64	15.05	5.21	79.41	200
Trust	22.54	15.39	3.15	66.14	58
Political Participation	5.31	1.87	1.11	10	175
Political Regime	1.64	0.97	0	3	183
Power Distance	59.01	21.76	11	104	74
Individualism	46.23	24.09	6	91	74
Masculinity	49.24	19.48	5	110	74
Uncertainty Avoidance	68.87	23.19	8	112	74
Long-Term Orientation	45.81	23.27	3.53	100	90
Indulgence	44.97	21.94	0	100	91

Table 3.4: Descriptive Statistics - Endowment

4. Methodology

4.1 The 'Black-Box' Approach

The idea behind this research was that countries' Covid-19 outcomes resulted from their initial conditions, and hence, all actions taken during the pandemic were left out of the analysis. The goal was to find the variables that best explained the variance in 'Mean Cumulative Excess Death' during the pandemic. This led to the so-called 'Black-Box' estimation. The black-box model was as follows (see Figure 4.1).:

1. Measures that captured the nations' ex-ante conditions were the independent variables.
2. Actions (Covid-19 regulations as measured by the stringency index) taken during the outbreak made the black box itself.
3. Post-Covid-19 (ex-post) outcomes ('Mean Cumulative Excess Death') were considered the results of the ex-ante conditions and were the dependent variable of the estimation.

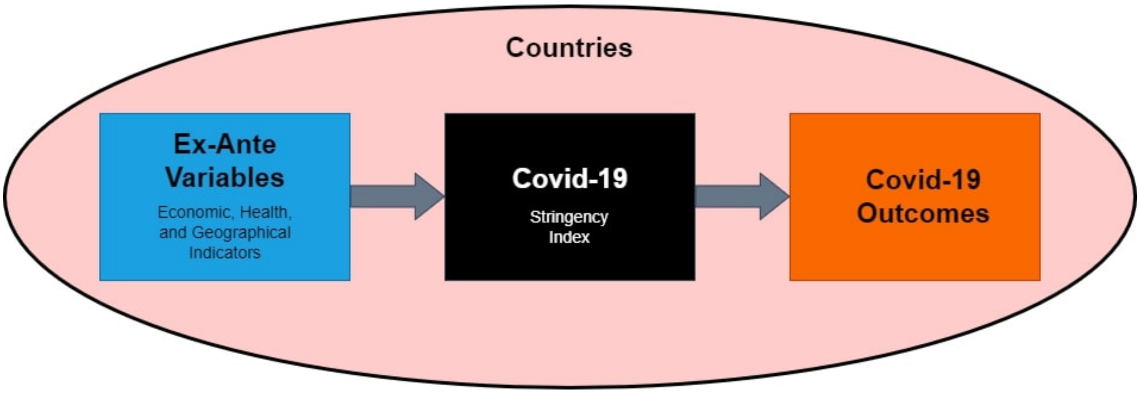

Figure 4.1: The Black-Box Model

The purpose of this analysis should not be misunderstood; it was to show the significance of the contextual background of different Covid-19 outcomes. Thus, the objective was not to dismiss the lockdown measures - the importance of delaying disease spread was inarguable - but to simply set them aside to investigate the variation in Covid-19 outcomes from a different perspective. The reason for doing so was reverse causality, which made the stringency index hard to include. It could have been that some countries imposed stricter lockdown measures because the number of infected dramatically increased, or they could have done so to prevent that from happening. Hence, including the stringency index in this type of estimation was impossible. Besides, strict regulations may have been in place, but a lack of trust and resources could have meant that people did not follow any rules imposed upon them. Several studies suggested that compliance with the governments' preventive measures heavily depended on several individuals and cultural factors (Pullano et al., 2020; Tang et al., 2022; Folayan et al., 2023; Blackburn et al., 2023; Kim, 2023). So, the effectiveness of the preventive measures was almost impossible to measure accurately. The estimated impact of the stringency index was also subject to testing activity. It was, however, unquestionable that swift and strict government actions were not only necessary but were very often successful in achieving their intention (Túri and Virág, 2021).

4.2 Estimation

The methodology of this chapter can be divided into two sequential steps as recommended by Athey and Imbens (2018):

1. Three Lasso regressions were run to select the best variables. This step was necessary because many of the considered variables were correlated. The goal was to reduce multicollinearity, so the Lasso performed a variable selection.
2. Once the most important variables were selected by Lasso, an ordinary least squares regression (OLS) estimated the explained variance in the outcome 'Mean Cumulative Excess Death'.

4.2.1 Lasso Regression

Lasso is a machine learning method. Thus, it maximizes predictive power, whereas regression focuses on explained variance. To this end, the data was separated into two sets: training (in this case, 70% of the data) and test (30% of the data) to first find the best variables (training) and then test the chosen variables' predictive power (test). Lasso shrinks some of the variables' estimated coefficients to zero, thereby performing variable selection, which results in a sparse model (James et al., 2013). It minimises the following:

$$\underbrace{\sum_{i=1}^{n}\left(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j x_{ij}\right)^2}_{RSS} + \underbrace{\lambda\sum_{j=1}^{p}|\beta_j|}_{PenaltyTerm} \tag{4.1}$$

where,

y_i are the values of the dependent 'Mean Cumulative Excess Death'

β_0 is the constant.

β_j is the estimated joint influence of the independent variables (x_{ij}) on 'Excess Death'.

λ is the tuning parameter (estimated separately) and shows how strong the penalty is. The higher the β_j is, the higher the penalty term, meaning that estimated coefficients are penalised, i.e., shrunk to zero.

The first half of Formula 4.1 corresponds to the residual sum of squares (RSS), which is the objective function of the OLS regression as well. The second term of the formula is the so-called shrinkage penalty term (constraint), which shrinks the coefficient estimates with small predictive power to zero to minimise the value of the function (James et al., 2013). Choosing an appropriate value of λ was crucial.

Thus, 10-fold cross-validation was performed to find the best λ to prevent overfitting and ensure that the model performs well on different subsets of the dataset. Cross-validation splits the data into 10 equal-sized folds, trains the model in 9 folds, and tests on the 10th. This process is repeated 10 times to test each fold once. As always, there was a trade-off between bias and variance, so the best λ was the one with the lowest mean squared error (MSE). Furthermore, while estimates are square equivariant in an OLS, in the case of Lasso, results change substantially because of the penalty term. Thus, the variables were standardised.[1]

Once Lasso chose the key variables an ordinary least squares (OLS) regression estimated

[1] The grid of possible λs was defined as s sequence of 100 number logarithmically spaced between 10^{10} and 10^{-2} as per (James et al., 2013). During the 10-fold cross-validation, the folds were randomly defined. This meant the Lasso results could change slightly each time the code was run.

their ability to explain 'Mean Cumulative Excess Death' during the first two years of Covid-19.

4.2.2 OLS

The equation of the OLS estimation is given below.[2]

$$\text{Mean Cumulative Excess Death}_i = \beta_0 + \sum \beta_n X_n + \varepsilon_i \tag{4.2}$$

where,

Mean Cumulative Excess Death$_i$ is the dependent.

β_0 is the constant.

β_n are the estimated coefficients of the explanatory variables (X_n) chosen by Lasso regression.

ε_i is the estimation error.

[2]As both estimation methods only run on complete cases, variables of the 'Hofstede Index' and 'Trust' had to be omitted from the regression analyses. The number of country observations was very low, in both cases around 60. As all other variables had over 150 country observations, these two had to be analysed in separate OLS regressions.

5. Results

5.1 Final Regression

The variables chosen by the Lasso regression were put into an OLS estimation, the results of which can be seen in Table 5.1).[1].

The OLS regression results show that a few variables from all three categories ('Health Status', 'Policy Capacity' and 'Endowment') were significant. The 'Health Status' variables suggested that healthier nations experienced lower 'Mean Cumulative Excess Death' during the pandemic. More 'Alcohol Consumption' (estimated coefficient: 5.711), elevated national obesity (6.622), as well as greater 'Tobacco Consumption' (2.471) were significantly associated with more deaths. In addition, nations characterized by an older demographic profile suffered more deaths compared to their younger counterparts as captured by the variables 'Life Expectancy' (-21.431) and 'Median Age' (9.554). In the category 'Policy Capacity', greater values of the variable 'GDP/capita' were significantly linked to fewer deaths (-0.005), which is expected as GDP/capita, to some degree, captures wealth. Finally, according to the variables in the category 'Endowment', 'Landlocked' nations experienced more deaths (59.913), opposite to the expectation that "Landbound" should mean less connectivity to the rest of the world and thus the virus. It was also surprising that less densely populated countries suffered more deaths (-0.052). An educated guess to explain this is that in more densely lived areas, there was probably a great reduction in fatal traffic accidents due to lockdowns. Last but not least, more political participation was associated with more deaths (12.925), but only at a 10% significance level. This could be because participation in the political sphere usually involves organised groups or mass activities, and gatherings were a hotspot for virus spread.

The explained variance in 'Mean Cumulative Excess Death' was 61%, meaning that with

[1]The list of countries used in the OLS regression can be found in the Appendix 6.1

VARIABLES	Mean Cumulative Excess Death per 100K Population (2020-2021)
Constant	-26.132***
	(143.8)
Health Status	
Alcohol Consumption	5.711*
	(3.239)
Life Expectancy	-21.431**
	(10.3)
Median Age	9.554***
	(3.139)
Prevalence of Overweight	6.622***
	(1)
Prevalence of Tobacco Use	2.471*
	(1.258)
Meat Consumption	-0.388
	(0.299)
Policy Capacity	
GDP/capita	-0.005***
	(0.001)
Physicians	6.323
	(12.27)
Endowment	
Landlocked	59.913**
	(28.03)
Population Density	-0.052*
	(0.03)
Exposure to Extreme Temperature	0.810
	(0.526)
Political Participation	12.925*
	(7.211)
Observations	131
R-squared	0.614

Heteroscedasticity robust standard errors in parentheses.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5.1: OLS Regression Results

just these ex-ante variables, about 60% of the differences in countries that registered deaths during the pandemic were accounted for. This indicates that Covid-19 outcomes should be interpreted in a circumstantial context and not just by crude numbers.

5.2 'Trust' and the 'Hofstede Index'

The variable 'Trust' was significantly and negatively associated with registered deaths (estimated coefficient: -3.831), which aligns with expectations. If citizens of a nation trust each other, then through unified action, they could have reacted better to the circumstances created by the pandemic and considerably slowed down the spread of the virus.

VARIABLES	Mean Cumulative Excess Death per 100K Population (2020-2021)
Constant	322.090***
	(42.312)
Endowment	
Trust	-3.831*
	(1.321)
Observations	57
R-squared	0.093

Heteroscedasticity robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 5.2: 'Trust' OLS Regression Results

The Hofstede OLS results (see Table 5.3 indicated that higher values of the 'Power Distance' (i.e., more authoritarian) were associated with increased 'Mean Cumulative Excess Death' (estimated coefficient: 3.863). An explanation for this could be that citizens of an autocratic country tend to learn that they can only count on themselves, which might have made them defy the rules imposed on them during Covid-19. In addition, 'Uncertainty Avoidance' was significantly and positively associated with deaths (3.224). As this variable captures the degree to which individuals avoid ambiguity and uncertainty, this was a shocking result - maybe the aversion to uncertainty was indeed rational in some nations. On the other hand, more 'Indulgence' means that one's own happiness and satisfaction are valued over society. As such, this cultural trait should have been linked to more deaths, but surprisingly, it was not (-2.989). Maybe self-perseverance was stronger than the power of unity in nations, and as such, for one's own good, they might have kept to pandemic regulations, which could have led to fewer 'Mean Cumulative Excess Deaths'. I would like to add that to be indulgent; monetary resources are needed, which might have led to this outcome.

VARIABLES	Mean Cumulative Excess Death per 100K Population (2020-2021)
Constant	-56.177
	(220.343)
Endowment	
Power Distance	3.863**
	(1.773)
Individualism	1.862
	(1.485)
Masculinity	-0.734
	(1.150)
Uncertainty Avoidance	3.224***
	(0.1)
Long-Term Orientation	-0.944
	(1.383)
Indulgence	-2.989**
	(1.404)
Observations	60
R-squared	0.353

Heteroscedasticity robust standard errors in parentheses.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5.3: 'Hofstede Index' OLS Regression Results

6. Conclusion and Discussion

The purpose of the analysis of this chapter was to conduct empirical research that best explained the variance in deaths during Covid-19 as an extension and robustness check for our published early findings with Professor Péter Mihályi (Kovács and Mihályi, 2021).

In general, the results of this chapter were similar to our 2021 paper in that one of the main conclusions of our research was that healthier nations had experienced significantly fewer deaths during the pandemic. This remained true even with a different dependent variable and many more country observations. On the other hand, the importance of 'Endowment' could not be denied; that is, characteristics that could not be influenced by policy, including extreme temperatures, a denser population, or having a coastal border, were all important in explaining the variance of deaths during the outbreak.

These findings are in line with a broader literature that connects structural and health-related factors with Covid-19 mortality (Pažitný et al., 2021; Ameh et al., 2022; Elgar et al., 2022). Studies have consistently shown that health systems, age structure, and lifestyle-related conditions (such as obesity and tobacco use) significantly shape pandemic outcomes. Similarly, geographic or demographic constraints — while outside the control of policymakers — play a persistent role in mortality differences across countries.

Overall, the goal of this chapter was achieved: Over 60% of the variation in 'Mean Cumulative Excess Deaths' could be explained. This signals that Covid-19 outcomes should always be considered in a country-context. Finally, the development and availability of various vaccines might have ended the latest infectious outbreak, but the lessons learnt should not be forgotten. As the future of viral diseases is uncertain, the lack of preparation has proven deadly. In sum, this paper strengthens the argument that ex-ante conditions mattered for pandemic outcomes and adds robustness to previous findings by using updated data and methods.

Appendix

ALB	ARE	ARG	ARM	AUS	AUT	AZE	BDI	BEL	BEN
BFA	BGD	BGR	BHR	BIH	BLR	BRA	BWA	CAN	CHE
CHL	CHN	CIV	CMR	COG	COL	COM	CRI	CUB	CYP
CZE	DEU	DNK	DOM	DZA	EGY	ESP	EST	ETH	FIN
FJI	FRA	GBR	GEO	GHA	GMB	GRC	GUY	HRV	HTI
HUN	IDN	IND	IRL	IRN	IRQ	ISL	ISR	ITA	JAM
JPN	KAZ	KEN	KGZ	KHM	KOR	KWT	LAO	LBN	LBR
LKA	LSO	LTU	LUX	LVA	MAR	MDA	MDG	MEX	MLI
MLT	MMR	MNG	MOZ	MUS	MWI	MYS	NAM	NER	NGA
NLD	NOR	NPL	NZL	OMN	PAK	PAN	PER	PHL	POL
PRT	PRY	QAT	ROU	RUS	RWA	SAU	SEN	SLE	SLV
SRB	SVK	SVN	SWE	SWZ	TCD	TGO	THA	TLS	TUN
TUR	TZA	UGA	UKR	URY	USA	UZB	YEM	ZAF	ZMB
ZWE									

Table 6.1: List of Included Countries in the OLS Regression

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