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Life expectancy during the Covid-19 pandemic: A semi-parametric difference-in-differences analysis

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Abstract

The scope of this paper is to investigate the causal effects of the COVID-19 pandemic on life expectancy over a sample of 47 countries split into two groups. The first one includes countries that have adopted general lockdown measures (treatment group), while the second one consists of countries that have imposed social distancing measures other than a national lockdown (control group). The investigated period starts from the first confirmed European case back (25.01.2020) until 28.07.2020 and covers the first wave of the pandemic for the sample countries. The empirical results based on a Semi-Parametric Difference-in-Differences framework, suggest a decline in life expectancy at birth estimated to 1.38 years on average even though the countries who did implement the lockdown measures were motivated and willing to do so. However, the decrease in life expectancy would have been double (2.9 years) in the absence of such willingness to adopt the policy. Lastly, the findings support the argument that national lockdown would be an effective policy tool to the hands of regulators and health practitioners to mitigate the negative effects of the pandemic infection it is pursued by motivated and willing participant countries.

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1. Introduction

The COVID-19 pandemic has severely stressed health systems all over the world in an unforeseen way, potentially leading to increases in morbidity and mortality rate (see for example Connor, et al, 2020; Vandoros 2020; Trias-Llimós and Bilal 2020). These increases, however, seem to negatively affect life expectancy triggering significant consequences in all aspects of social life (Marois et al, 2020). To give but an example of the rapid penetration of the pandemic to humanity, it is estimated that over 30,5 million Covid-19 cases have been reported globally, leading to nearly 952,000 deaths as of 19 September 2020 (Johns Hopkins University, 2020).

It is noteworthy that the impact of this unprecedented situation on public health would have been even worse by the absence of restrictive measures to curb the spread of the pandemic (e.g., lockdowns, physical distancing, compulsory masking, flight cancellation, etc). This paper contributes to the existing literature since it is the first study so far that examines the impact of the national lockdown adopted by 33 countries on life expectancy at birth. In other words, this study investigates the links of life expectancy, which is a long-term issue with the effect of a short-run policy of a national lockdown.

Based on the above, the relevant study investigates possible causal effects of an exogenous policy (e.g., national lockdown) on life expectancy at birth due to COVID-19. It is worth mentioning that the life expectancy at birth concept may seem a bit unexpected, simply because a view of COVID-19 as transient in terms of affecting the lives of those currently being born is not highly relevant, as it is, says, affecting the continued life expectancy in the next year, of someone who is old enough (e.g., over 80 years old). However, we try to exemplify these issues by first examining the effects of mortality rates.

For this reason, the flexible Semiparametric Difference-in-Differences (SDID) approach developed in Abadie (2005) is employed to estimate how the effect of treatment (national lockdown) varies with changes in individual characteristics. The reason for using this method over the traditional linear DID estimator is that the former is mostly suited for longitudinal surveys with a baseline and follow-up rounds (e.g., lockdown periods) as in this case (see Houngbedji, 2016 and Abadie 2005). One of the reasons that justify the use of a (semiparametric) difference-in-differences approach over the traditional (parametric) DID analysis, apart from its simplicity is the ability to deal with many of the endogeneity problems that typically arise when making comparisons between heterogeneous individuals (see among others Krapf et al, 2017; Abadie, 2005; Meyer, 1995). In addition to accounting for endogeneity, the relevant SDID estimator allows us to compute conditional treatment effects (Krapf et al, 2017).

Despite the profound interest of the scientific community in studying the consequences of COVID-19 on public health (see among others Connor et al, 2020; Elgar et al, 2020; Vandoros, 2020; Nivette et al, 2020), little attention has been paid to the causal effects of the restrictive measures adopted to mitigate the spread of the pandemic infection on life expectancy at birth.

In a recent study, Vandoros (2020), employs a DID analysis to study whether there was a relative increase in deaths outside the pandemic has increased compared to what would have been expected in the absence of the pandemic (counterfactual scenario). The sample employs data related to the number of deaths not related to COVID-19 in England and Wales over the period 2015‑2020. The empirical findings postulate that there were an additional 968 weekly deaths that officially did not involve COVID-19, compared to what would have otherwise been expected. This study contributes to the literature since it looms the situation in the early stages of the pandemic crisis, and thus gives valuable information to the policymakers in the short term.

Connor et al, (2020) examine the impact of gender-based differences in the healthcare workforce on the economic, and social systems during the pandemic crisis. Specifically, this study focuses on the impact of gender on women's SARS-CoV-2 exposure and disease risks, and overall health status during the pandemic. The empirical results unravel that the increased risk of certain negative health outcomes and reduced healthcare access experienced by many women are typically exacerbated during the COVID-19 crisis.

In another study, Elgar et al, (2020) claim that COVID-19 mortality rates are related to differences in income and other specific dimensions of social capital such as trust, group affiliations, civic responsibility, and confidence in public institutions. This study employs data at a country level related to income inequality, several aspects of social capital, number of deaths by COVID-19 in a sample of 84 countries. They conclude that several country differences in mortality and morbidity rates are coupled with economic and social divisions within them.

Nivette et al (2020), by employing data before and during the pandemic crisis attempts to investigate the patterns of non-compliance with COVID-19 related public health measures. Moreover, this study disentangles the characteristics that increase the risk of non-compliance among young adults. The empirical results indicate that non-compliance, especially with hygiene-related measures, is more prevalent in males, and individuals with higher education, and a non-migrant background. In addition, young adults with low trust, also depict a low compliance rate with the pandemic measures.

The most related work to ours is the recent study of Llimós and Bilal (2020), where they examine the impact of COVID-19 on the annual life expectancy in the region of Madrid. This study estimates the expected changes in annual life expectancy accounting for the excess mortality over the period from 9.3.2020 to 10.05.2020. The empirical findings support a decline in life expectancy at birth of 1.9 and 1.6 years for men and women, respectively. The authors argue that the relevant figures could be even bigger since their estimates are based on the existing mortality pattern. Moreover, they argue that a decline in mortality rate is also possible due to the existence of a "*harvesting*" effect, as happened in other flu pandemics.

In a subsequent study, Marois et al (2020) provide first estimates of the potential direct impact of the COVID-19 pandemic on life expectancy for several countries and regions (North America and Europe, Latin America, and the Caribbean, Southeastern Asia, and Sub-Saharan Africa). They employ a microsimulation model based on several assumptions (e.g., mortality rate, prevalence rate, fertility, etc) that calibrates the life histories of 100,000 individuals by five-year age groups over a period of 52 weeks (one year). The empirical findings support that in all prevalence scenarios, life expectancy would drop even by 9 years (North America and Europe). However, life expectancy will not be substantially affected when the prevalence COVID-19 rate does not exceed 2%.

2. Data and Methodology

2.1 Sample and variables

The sample consists of an unbalanced panel data set comprising of 47 countries, over the period 25.01.2020 to 28.07.2020 (T = 186). All the variables were obtained from Roser et al (2020) and extracted on 30 July 2020.[1] The starting date for the national lockdown measure adopted by

[1] Retrieved from: https://ourworldindata.org/coronavirus.

each sample country is shown in Table 1. As it is evident, the majority of the (treatment) countries implemented this restrictive measure shortly after the declaration of the pandemic by the World Health Organization (11.03.2020).[2]

Table 1: National lockdown coverage: Dates and Countries

Date	AL	AT	BE	BG	HR	CY	CZ	DK	FI	FR	DE	GR	HU	IR	IT	LV	LI	LT	LU	MD	MC	ME
09.03.2020																						
10.03.2020																						
11.03.2020 Pandemic																						
12.03.2020																						
13.03.2020																						
14.03.2020																						
15.03.2020																						
16.03.2020																				`		
17.03.2020																						
18.03.2020																						
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25.03.2020																						
26.03.2020																						
27.03.2020																						
28.03.2020																						
29.03.2020																						
30.03.2020																						
31.03.2020																						

Date	NL	MK	NO	PL	PT	RO	RS	SK	SI	ES	UA	UK
09.03.2020												
10.03.2020												
11.03.2020 Pandemic												
12.03.2020												
13.03.2020												
14.03.2020												
15.03.2020												
16.03.2020												
17.03.2020												
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02.04.2020												
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04.04.2020												
05.04.2020												
06.04.2020												
07.04.2020												
08.04.2020												
09.04.2020												

Notes: Light shaded areas denote the pre-lockdown period, while dark shaded areas represent the lockdown period. AL = Albania, AT = Austria, BE = Belgium, BG = Bulgaria, HR = Croatia, CY = Cyprus, CZ = Czech Republic, DK = Denmark, FI = Finland, FR = France, DE = Germany, GR = Greece, HU = Hungary, IR = Ireland, IT = Italy, LV = Latvia, LI = Liechtenstein, LT = Lithuania, LU = Luxembourg, MD = Moldova, MC = Monaco, ME = Montenegro, NL = Netherlands, MK = Northern Macedonia, NO = Norway, PL = Poland, PT = Portugal, RO = Romania, RS = Serbia, SK = Slovakia, SI = Slovenia, ES = Spain, UA = Ukraine, UK = United Kingdom.
Source: Authors' elaboration from Wikipedia and various national websites.

[2] However, Slovakia is the only country that adopted national lockdown measures nearly one month after the declaration of the pandemic (08.04.2020).

The dataset is based on a combination of data from the Clio Infra project (see Zijdeman, and Filipa, 2015), the United Nations Population Division (United Nations, 2019), and global and estimates for world regions from Riley (2005).

2.2 Methodology and research design

One of the assumptions in the interpretation of using difference-in-differences estimators to measure the effect of policy intervention as a causal effect is that, in the absence of the treatment, the outcome variable follows the same trend in treated and untreated groups (Vandoros, 2020; Card and Kruger, 1994). This assumption may not be credible if selection for treatment is correlated with characteristics that affect the dynamic of the outcome variable (Imbens and Wooldridge, 2009; Hirano et al, 2003).

Abadie (2005) introduces the SDID estimator addressing the imbalance of characteristics between treated and untreated groups through a reweighting scheme that allows differences in observed characteristics to create nonparallel outcome dynamics for the treated and untreated groups. Since the characteristics are treated nonparametrically any estimation error caused by functional misspecification is avoided (Chang, 2018). Furthermore, the SDID estimator allows for the use of covariates to describe how the average effect of the treatment varies for different groups of the treated population. The estimator is based on reweighing the trend for the untreated participants using a semiparametric estimator of their propensity score using a polynomial series of covariates (Abadie 2005).

Following the SDID methodology, the effect of national lockdown can be disentangled by identifying two groups. The first group includes 34 countries (treatment group), that pursued the measure of the national lockdown. The second group (control group), comprises the rest 13 countries (Belarus, Estonia, Iceland, Malta, Sweden, Switzerland, Japan, Malawi, Nicaragua, South Korea, Taiwan, Timor, and Uruguay) that did not impose a general (national) lockdown but only transitory protective measures (e.g., school closures, social distancing, COVID testing, health checks, etc).[3]

We begin our analysis by estimating with OLS the following linear benchmark model

$$Life\ expectancy_{it} = b_o + b_1 Treated_i + b_2 GDP_{it} + b_2 Population_{it} + b_3 Median\ age_{it} + b_4 Male\ smokers_{it} + b_5 Female\ smokers_{it} + b_6 Poverty_{it} + b_7 Hospital_{it} + b_8 Diabetes_{it} + \varepsilon_{it} \quad (1)$$

We must mention that in the absence of a (formal) theoretical model, we tried to better envision the behavioral responses by which the independent variable and the dependent variable are connected. In other words, the above specification shows how life expectancy varies with the economic, demographic, and medical characteristics of the individuals (male and female smokers, diabetes prevalence).

[3] For the empirical application of the SDID estimator, we used the "*absdid*" command in Stata, developed in Houngbedji (2016). The relevant command estimates the average treatment of the treated (ATT) by comparing change over time of the outcome of interest across treatment groups while adjusting for differences between treatment groups on the observable characteristics at baseline that are correlated to the propensity score (Houngbedji, 2016).

The dependent variable in Eq. 1 is the life expectancy at birth in country *i* at day *t* and remains constant throughout the sample period. The dependent variable of life expectancy is obtained from the OECD Health Statistics database and refers to the life expectancy at birth in 2019.[4] Life expectancy at birth is defined as how long, on average, a newborn can expect to live, if current death rates do not change.[5] Gains in life expectancy at birth can be attributed to several factors, including rising living standards, improved lifestyle and better education, as well as greater access to quality health services. This indicator is presented as a total and per gender and is measured in years (see OECD, 2021).

$Treated_i$ is a dummy variable equal to one for the countries that adopted the national lockdown and zero otherwise. In other words, the policy intervention is simply a dummy variable in this benchmark linear OLS model without any Difference-in-Difference correction. GDP denotes the per capita gross domestic product at purchasing power parity in constant 2011 USD dollars, drawn from the World Bank (World Development Indicators Database). Population denotes the number of people divided by land area (density), measured in square kilometers obtained by the World Development Indicators. Median age denotes the median age of the population, drawn from the UN Population Division (World Population Prospects, 2017 Revision). Male and female smokers denote the share of males and females who smoke. These variables are available from the World Development Indicators, sourced from World Health Organization and Global Health Observatory Data Repository. Poverty denotes the share of the population living in extreme poverty, obtained by the World Bank Development Research Group. Hospital denotes the hospital beds available per 1,000 people and can be used as a proxy of the health infrastructure, available from the OECD, Eurostat, and World Bank. Diabetes denotes diabetes prevalence as a percentage of the population aged 20 to 79 in 2017. The variable is obtained by various sources such as the World Development Indicators Database, the International Diabetes Federation, and the Diabetes Atlas. Finally, ε_{it} is the error term.

Table 2 presents the summary statistics for the sample variables used in this study. It appears that the diabetes prevalence exhibits the lowest standard deviation among the sample variables equal to 1.997, while the GDP per capita is the highest. The relevant variable is positively skewed (0.863) and the (excess) kurtosis value suggests a platykurtic distribution (>3). On the contrary, the dependent variable (life expectancy) is negatively skewed (-1.209) and does not follow the normal distribution, which is also the case for all the rest variables. The rest of the variables are positively skewed (heavy-tailed) revealing a leptokurtic distribution.

[4] The OECD Health Statistics database offers the most comprehensive source of comparable statistics on health and health systems across OECD countries, and includes data found in the publication *Health at a Glance*. It provides data on the health status of the population including obesity (overweight, obese), suicide and life expectancy, health care financing, health care resources, social protection, health care utilization, the pharmaceutical market, long-term care resources and utilization, non-medical determinants of health, expenditure on health, and demographic and economic references, with coverage being provided for OECD and selected non-OECD countries as far back as 1960.

[5] https://data.oecd.org/healthstat/life-expectancy-at-birth.htm

Table 2: Summary statistics

Variable	Observations	Mean	Median	Min	Max	Standard deviation	Skewness	Kurtosis
GDP	7,372	33,504	32,606	1,095	94,278	17,875	0.863	4.672
Population	7,686	602.5	106.7	3.404	19,348	2,862	6.356	41.65
Median age	7,558	41.21	42.30	18	48.20	5.415	-2.701	11.90
Male smokers	7,063	34.52	33.10	15.20	78.10	11.39	0.987	5.107
Female smokers	7,063	21.57	21.30	4.400	44	8.423	0.034	3.056
Poverty	5,300	3.259	0.500	0.100	71.40	11.27	5.206	30.33
Hospital	7,686	5.355	4.530	0.900	13.80	2.918	1.255	4.262
Diabetes	7,686	6.414	5.760	3.280	11.47	1.997	0.701	2.581
Life expectancy	7,872	79.68	81.32	64.26	86.75	4.047	-1.209	4.887

Notes: GDP denotes the per capita gross domestic product at purchasing power parity in constant 2011 USD dollars, Population denotes the number of people divided by land area (density), measured in square kilometers, Median age denotes the median age of the population, Male smokers denotes the share of males who smoke, Female smokers represents the percentage of female smokers, Poverty denotes the share of the population living in extreme poverty, Hospital, denotes the hospital beds available per 1,000 people, Diabetes, denotes the diabetes prevalence as a percentage of the population aged 20 to 79 in 2017 and finally Life expectancy denotes the life expectancy at birth in 2019.

3. Results and discussion

The empirical findings of the benchmark model are presented in Table 3. As it is evident, countries that imposed restrictive measures (e.g., general lockdowns) faced a 2.9 decrease (95% *CI* from -3.107 to -2.776) in life expectancy relative to countries that did not, since the relevant dummy variable (*Treated*) is negative and statistically significant. This means that the absence of willingness and motivation to implement the policy intervention measure of the national lockdown (counterfactual), the pandemic infection would have an inversely related effect on life expectancy.

The rest of the estimated coefficients provide mixed results. Specifically, male smokers and diabetics are positively correlated with the dependent variable, while the number of hospital beds available in the sample is negatively and statistically significant correlated with life expectancy at birth (-0.557). This means that an increase in the medical care resources in terms of bed availability tends to decrease life expectancy at birth by almost six months (1/2 years). The negative effect is in alignment with the recent study of Hosokawa et al, (2020), in which for males, curative care beds per 1000 residents in Japan are negatively correlated with life expectancy at birth, while there is no significant correlation between the total number of beds (for males and females) and life expectancy in Japan. This lack of correlation might be attributed to the fact that hospital beds are well-deployed in Japan. The related empirical findings supporting the existence of a negative relationship between health care resources (e.g., beds availability) and life expectancy at birth is also consistent with previous studies that found that providing an excessive number of beds was negatively associated with health outcomes (see Jebeli et al, 2019).

Table 3: OLS regression results (benchmark model)

Dependent variable: *Life expectancy*	
Treated	-2.942***
	(0.0845)
GDP	0.000131***
	(2.62e-06)
Population	0.000841***
	(0.000109)
Median age	0.460***
	(0.00892)
Male smokers	0.0442***
	(0.00368)
Female smokers	-0.0298***
	(0.00286)
Poverty	-0.0468***
	(0.00315)
Hospital	-0.557***
	(0.0163)
Diabetes	0.250***
	(0.0139)
Constant	58.41***
	(0.438)
Observations	4,991
R-squared	0.835

Notes: Treated is a dummy variable taking value one for countries that imposed national lockdown and zero otherwise, GDP denotes the per capita gross domestic product at purchasing power parity in constant 2011 USD dollars, Population denotes the number of people divided by land area (density), measured in square kilometers, Median age denotes the median age of the population, Male smokers denotes the share of males who smoke, Female smokers represents the percentage of female smokers, Poverty denotes the share of the population living in extreme poverty, Hospital, denotes the hospital beds available per 1,000 people, Diabetes, denotes the diabetes prevalence as a percentage of the population aged 20 to 79 in 2017, Life expectancy denotes the life expectancy at birth in 2019. Robust standard errors in parentheses. Significant at *** $p<0.01$.

However, these counterintuitive results pose significant concerns on the validity of the estimated results obtained by the OLS model. The main problems that arise in such a case are associated with the endogeneity and reverse causality that appeared in the benchmark model. For example, the median age variable which comes at the right-hand side (RHS) of the regression equation (see Eq. 1) is endogenously determined in the model, since countries with longer life expectancy will also experience greater population aging, due to the existing negative relationship between fertility rates and life expectancy. Moreover, the negative relationship between the lockdown measures and life expectancy at birth is not a surprising finding since life expectancy and treatment likelihood are highly correlated with the number of cases in a region/country. In other words, high levels of COVID-19 infections reduce life expectancy and lead countries to adopt lockdown measures to curb the spread of the pandemic. To overcome these problems, we rely on the estimated results of the SDID model as they can be described below.

Table 4 presents the empirical results of the SDID econometric analysis. Specifically, Model (1) reports estimates of the average life expectancy at birth. Model (2) shows how life expectancy varies with economic (GDP per capita, extreme poverty), demographic (e.g., population, hospital beds), and medical characteristics (e.g., male and female smokers, diabetes prevalence). The coefficients reported in (1) and (2) are estimated using a logit specification of degree 4 to estimate the propensity score (SLE).[6]

Table 4: SDID regression results (control & treatment sample)

Dependent variable: *Life expectancy*	**(1)**	**(2)**
SDID estimator		
Constant	-1.158***	-1.606***
	[-1.588 to -0.727]	[-2.78 to -5.99]
Covariates		
GDP	-	0.0000485**
		[9.74e-06 to 0.00008]
Population	-	0.0117***
		[0.008 to 0.014]
Male smokers	-	-0.103
		[-0.250 to -0.043]
Female smokers	-	-0.360***
		[-0.472 to -0.247]
Poverty	-	-0.492***
		[-0.756 to -0.227]
Hospital	-	-0.296
		[-0.795 to -0.204]
Diabetes	-	-1.134***
		[-1.684 to -0.584]
Observations	4,991	4,991

Notes: The country-daily variation is captured by a variable that is equal to one for the period after the imposition of the lockdown imposed by the sample country and zero otherwise. This dummy indicates the binary treatment variable. It is required and should be coded as 0 or 1, with 0 indicating an untreated observation (e.g., a period before the imposition of the lockdown) and 1 indicating a treated observation (e.g., a period after the lockdown mandate). GDP denotes the per capita gross domestic product at purchasing power parity in constant 2011 USD dollars, Population denotes the number of people divided by land area (density), measured in square kilometers, Male smokers denotes the share of males who smoke, Female smokers represents the percentage of female smokers, Poverty denotes the share of the population living in extreme poverty, Hospital, denotes the hospital beds available per 1,000 people, Diabetes, denotes the diabetes prevalence as a percentage of the population aged 20 to 79 in 2017, Life expectancy denotes the life expectancy at birth in 2019. Time and country dummies are included but not reported. Robust confidence interval in brackets. Significant at *** $p<0.01$.

A careful inspection of the relevant table reveals some important findings. First, if we isolate all the additional covariates affecting life expectancy at birth (e.g., income effect, health conditions, population density, etc), we notice that there is a decrease in the post-treatment period compared to the control group (see column 1). The relevant SDID coefficient is negative (-1.158) and statistically significant, while the 95% confidence interval ranges from -1.588 to -0.727 during the first wave of the pandemic. This finding indicates that the policy intervention change (national lockdown) adopted by the 33 sample countries reduces annual life expectancy at birth by 1.2 years since these countries were willing, motivated by health safety considerations, and ready to do so. In other words, countries that imposed restrictive measures such as national lockdowns

[6] We have also used a linear polynomial function (LPM) of degree 4 to approximate the propensity score and the results were quite similar. To preserve space, the empirical findings are available from the authors on request.

experienced a decline in life expectancy at birth by almost 1,5 fewer years compared to countries that did not implement these measures (e.g., three years from the 2019 LE levels). The relevant estimate is in alignment with the study of Llimós and Bilal (2020).

Second, similar findings are reported when several explanatory variables enter the model (see column 2). In this case, the SDID estimator remains negative and statistically significant, though its magnitude is slightly larger than the previous estimate (1.606 compared to 1.158). Specifically, annual life expectancy at birth will be reduced by 1.606 years, 95% *CI* (-2.78, 5.99), while the rest of the variables have a negative and statistically significant correlation with life expectancy except for the male smokers and hospital beds as it is documented by previous studies (see among others Hosokawa et al, 2020; Miladinov, 2020; Shafi and Fatima, 2019).

All in all, this study argues that the national lockdown measure coincides with reductions in life expectancy[7]. However, the magnitude of the reduction rate would have been larger in the case of an absence of willingness, motivation, and readiness of the participant countries to implement this intervention. In that case, the estimated reduction in life expectancy would have been by almost three years from the current 2019 level (see Table 3). The relevant finding justifies the effectiveness of the national lockdown as a restrictive policy tool to combat the novel coronavirus disease. Combining the two important findings, this study supports the notion that short-run health policies (e.g., national lockdown) incur long-term implications (e.g., reduction in life expectancy growth). A similar result is also documented in the study of Verstraeten, et al (2016), where it is argued that a short-run policy change (decolonization) incurs negative effects on life expectancy growth in the Caribbean states. A subsequent study by Montez et al, (2020) for the US seems also to support this claim.[8] In this case, the link between life expectancy which constitutes a long-term issue with the short-run policy of a national lockdown can be explained through the channel that people's health may be compromised at birth. This could be partly justified by the fact that health resources have moved to take care of the reported COVID-19 infection cases, rather than early premature births. On the other hand, life expectancy at birth usually can be recovered to its former level and trajectory after a pandemic as happened in the case of the Spanish flu back in 1920. This happens since life expectancy is affected by mortality in all age groups, not just among infants. As a result, the final "*health footprint*" of COVID-19 on life expectancy at birth though negative as illustrated in this study might be transitory.

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[7] An interesting case is that of Taiwan and South Korea that belong in the group that did not impose a lockdown. Yet, these countries are among the very few that have had very few cases and even less fewer deaths associated with the pandemic. The reason for that is that they followed alternative and very consistent strict policies of travel controls and restrictions as well as contact tracing at the very first indication of suspected cases. As such even though there was no lockdown there was also a much smaller strain of their health systems that mitigated any adverse health effects such as loss in LE at birth. It is the mounting number of cases that has led to the strain of health systems around the globe that has resulted in reduced LE as a result.

[8] This study supports that shifts in state policy measures (e.g. liberal or conservative) predict life expectancy and US longevity.

4. Conclusions

This study employs a flexible SDID approach, to investigate the effect of a short-run health policy (e.g., national lockdown) on a long-run health issue (life expectancy). The econometric analysis suggests a structural link between the adoption of lockdown measures by the national governments to face the pandemic crisis and life expectancy at birth. The results indicate that the most stringent policy intervention such as a national lockdown incurs a decrease in life expectancy by 1.38 years on average. The negative relationship remains robust under several SDID specifications. In the absence of a willingness to adopt such a policy by the countries involved would have resulted in life expectancy at birth being reduced by a larger amount equal to 2.9 years (e.g., more than the double).

However, to efficiently trace the potential sources for this decline, one must disaggregate life expectancy at birth into age-specific mortality rates, since causes of LE decline include inter alia direct deaths from COVID-19, affecting primarily older age groups, and indirect deaths due to resource constraints where health facilities have been overwhelmed. The latter affects all age groups. The above issues constitute possible avenues for future research toward the global interest of the scientific community to the consequences of COVID-19 in life expectancy at birth.

Lastly, this study has significant implications for policymakers and health practitioners, since a decrease in life expectancy due to the pandemic could imply a higher death toll as a result of the imminent second wave of the pandemic, pushing the national healthcare systems to their limits. Therefore, future research may shed light on this issue by extending the sample and including more covariates (spatial characteristics, demographic conditions, education level, etc).

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