Social Distancing, Vaccination and Evolution of Covid-19: A Panel-Model Analysis

Eduardo Lima Campos[1]*, Rubens Penha Cysne[2] and Alexandre Madureira[3]

Abstract

This work discusses the impact of social distancing and vaccination on the monthly variation rate of new cases and deaths of COVID-19 around the world. A statistical panel-regression model was applied to daily data for 131 countries from March, 2020 to December, 2021. The setting of suitable control variables was essential to achieve reliable results. We found, as a possible consequence of strict social distancing, a decrease of around 5.5 percentage points in the growth rate of both new cases and deaths, before vaccination. The possible impact of progress in vaccination, in 2021 was even stronger: a decrease of 9 and 12 percentage points on the growth of new cases and deaths, respectively. As a final conclusion, our dataset and the method employed did not allow to exclude either the hypothesis that strict social distancing was an important measure to control the pandemic before the advent of vaccines, nor the conjuncture that the impact of vaccination has been stronger, mainly with regard to deaths.

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[1] EPGE Brazilian School of Economics and Finance (FGV EPGE) and National School of Statistical Sciences (ENCE/IBGE), Rio de Janeiro, Brazil. *Corresponding author

[2] EPGE Brazilian School of Economics and Finance (FGV EPGE), Rio de Janeiro, Brazil.

[3] EPGE Brazilian School of Economics and Finance (FGV EPGE) and National Scientific Computing Laboratory (LNCC), Rio de Janeiro, Brazil.

1. Introduction

Globally, the COVID-19 pandemic has sickened more than 300 million people and claimed the lives of more than 5 million until the end of 2021, according to John Hopkins University[4]. Social distancing policies at different levels, along with other types of non-pharmaceutical interventions, such as mandates to wear masks and efforts to test, track, and isolate individuals potentially exposed to COVID-19, have been implemented in many economies. Considering the unprecedented and worldwide economic disruption of these policies, it is important to measure their effects to control the pandemic. Recent studies with this goal are Alfano and Ercolano (2020), Cano et al. (2020), Ferguson et al. (2020), Maloney and Taskin (2020) and Price and van Holm (2021).

With the advent of vaccines against COVID-19, the focus changed from distancing policies towards vaccination, in order to raise immunity and control the pandemic, thus making it possible to ease previous strict measures. Although there is still no consensus on whether the available vaccines can actually prevent the transmission of the virus (WHO, 2021), evidence from epidemiological literature has established the effectiveness of COVID-19 vaccines in reducing the virus' transmission and curbing severe infections (see Voysey et al. (2021), Polack et al. (2020), Kim and Lee (2021), Lopez Bernal et al. (2021), Kissler et al. (2021) and Coccia (2022)).

This work aims to investigate and measure the possible association between social distancing and vaccination on the monthly variation rate of both new cases and deaths caused by COVID-19, using a statistical model for panel data. To correctly address these effects, it was essential to identify and incorporate suitable control factors, such as climate, economics and demographics, healthy systems capacity and natural evolution of pandemic.

We estimate the social distancing and vaccination effects on the COVID-19 evolution by a statistical panel-data model. As practical applications, our results add information to the discussion about the tradeoff of lockdown measures and make it possible to better understand why some countries with low vaccination rate experienced a new explosion of cases when they left the distancing measures. Our work also contributes to literature on the spread of the world's most recent pandemic as we propose an indicator for social distancing, incorporate a wider set of control factors to the model and use a data sample, which cover 131 countries over 640 days.

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[4] https://coronavirus.jhu.edu/map.html

2. Data

2.1 Cases and Deaths for COVID-19

The daily number of new cases and deaths caused by COVID-19 (measured per million[5]) was obtained in the World Health Organization website[6], for 131 countries that had registered values of the main variables of interest in this work from March 2020 to December 2021.

The data sample was divided into two sub-samples: (i) Mar/2020 - Dec/2020 and (ii) Jan/2021 - Dec/2021. In the first period, we investigated the effect of social distancing policies on COVID-19 cases and deaths before the start of the vaccination campaign. In the second period, we investigated the impact of the vaccination progress on new COVID-19 cases and deaths.

2.2 Social Distancing

The social distancing data were collected from the Google COVID-19 Community Mobility Reports database from Mar/2021-Dec/2021. These data represent daily percentage variations of some variables, compared to a pre-pandemics period in early 2020[7]. For example, if in the day t, the reported mobility value achieves -5%, it means that there are 5% less people on the streets, in relation to the benchmark period. The public transport stations category, which captures the trend of mobility through public transport terminals, was chosen as a proxy for social distancing[8]. The next step was to create a variable called Circulation Index, CI_{it}, defined as the inverse measure of social distancing (the greater the distancing, the lower the circulation)[9].

To illustrate, Figure 1 showcases the evolution of cases and deaths per million and the Circulation Index for USA, Mexico, Italy, United Kingdom, France e Brazil showing.

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[5]Cases per million = (Number of Cases/Population) *1,000,000. We consider cases per million of inhabitants, since a country X with the same growth rate as another country Y, but with a larger population, will tend to present more cases.

[6] https://covid19.who.int/

[7] https://www.google.com/covid19/mobility/. The availability of this data is limited by the Locating History tool on Google accounts, which must be turned on for this purpose, and they are anonymized. The benchmark used is the median of the baseline period.

[8] Maloney and Taskin (2020) use the same dataset, however they consider the workplaces category.

[9] CI was considered with a 21-day lag time, the suitable lag to reflect the impact of the distancing measures on registers of COVID-19. Then, CI_{it} denotes the circulation index in country i, 21 days before the day t. This also solves a possible endogeneity of the variable.
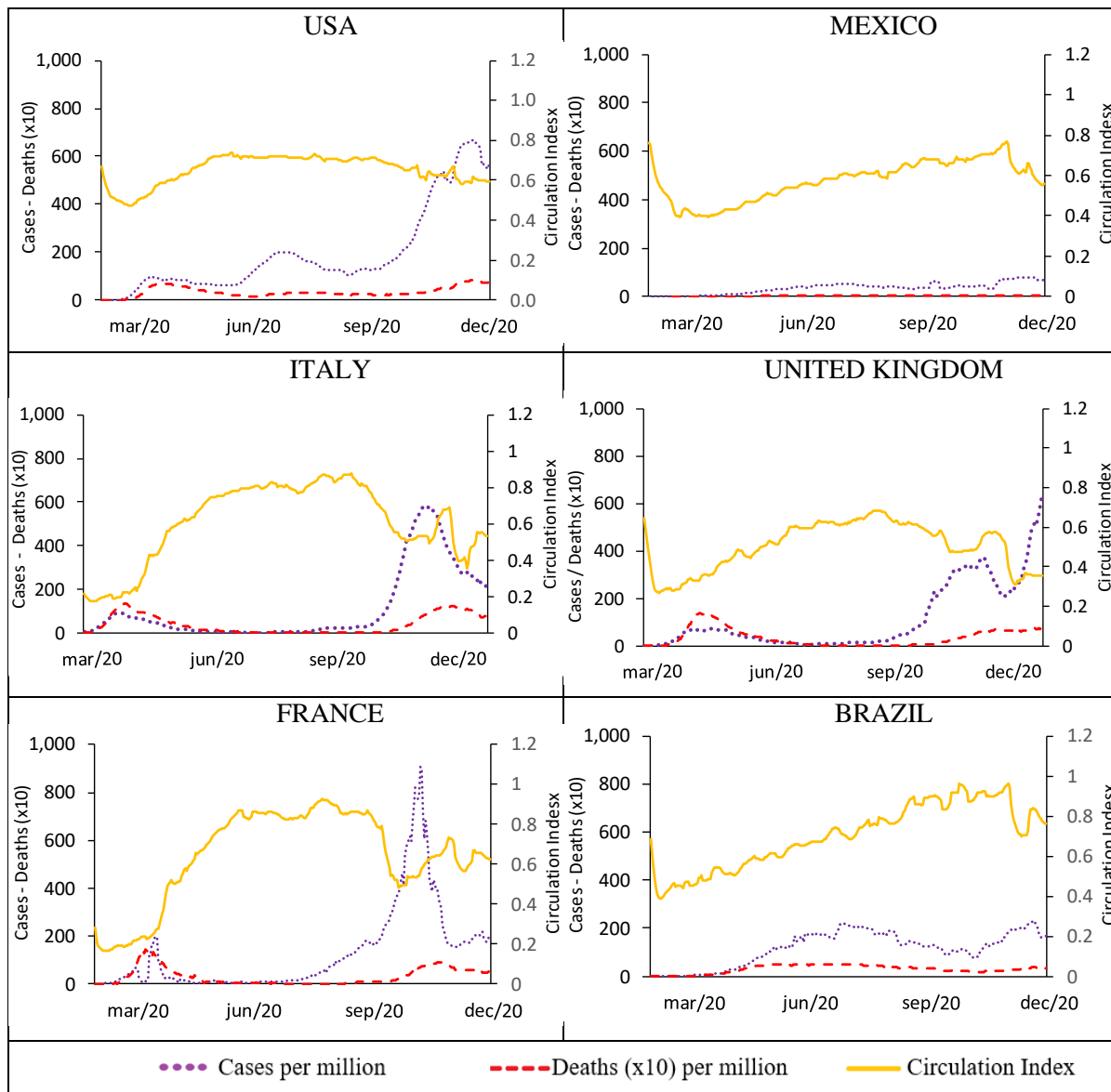
Note: As the effect of social distancing policies take around 3 weeks, the Circulation Index was delayed by 21 days.

Figure 1: Cases x Deaths*10 x Circulation Index 7-day moving average from Mar 2020 to Dec 2020

At the beginning of the pandemic, countries naturally applied several precautionary measures to help prevent the spread of the pandemic. Some of these precautions affected transport directly and indirectly, limiting mobility and promoting social distancing (Morgan Stanley, 2020). Some evidence of these effects are provided by Figure 1: higher (fewer) number of cases per million follows fewer (higher) values of the circulation index. A possible explanation is that, when there is an increase of

COVID-19 cases per million, the governments implement measures of prevent and control transmission, thus resulting in a reduction in the circulation index. Lower circulation tends to reduce disease contamination. After a few months with low transmission, precautionary measures are relaxed, the circulation index grows and, as a possible consequence, the transmission of COVID-19 also grows. Then, new preventive measures are taken to control the contamination.

For modeling purposes, we concluded from statistical tests the clearest effects observed if CI_{it} is divided into only two categories. Thus, we created the binary variable SD_{it}, called strict distancing:

$$SD_{it} = \begin{cases} 1, \text{if } CI_{it} < 40\% \\ 0, \text{if } CI_{it} \geq 40\% \end{cases} \tag{1}$$

SD_{it} assumes value 1 if circulation index is less than 40% and SD_{it} assumes value 0 if circulation index is greater/equal to 40%.

2.3   Vaccination

The daily vaccines doses (per million) were obtained in the Our World in Data website[10], for the 131 countries that had registered this variable up to December 31, 2021.

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[10] https://ourworldindata.org/covid-vaccinations
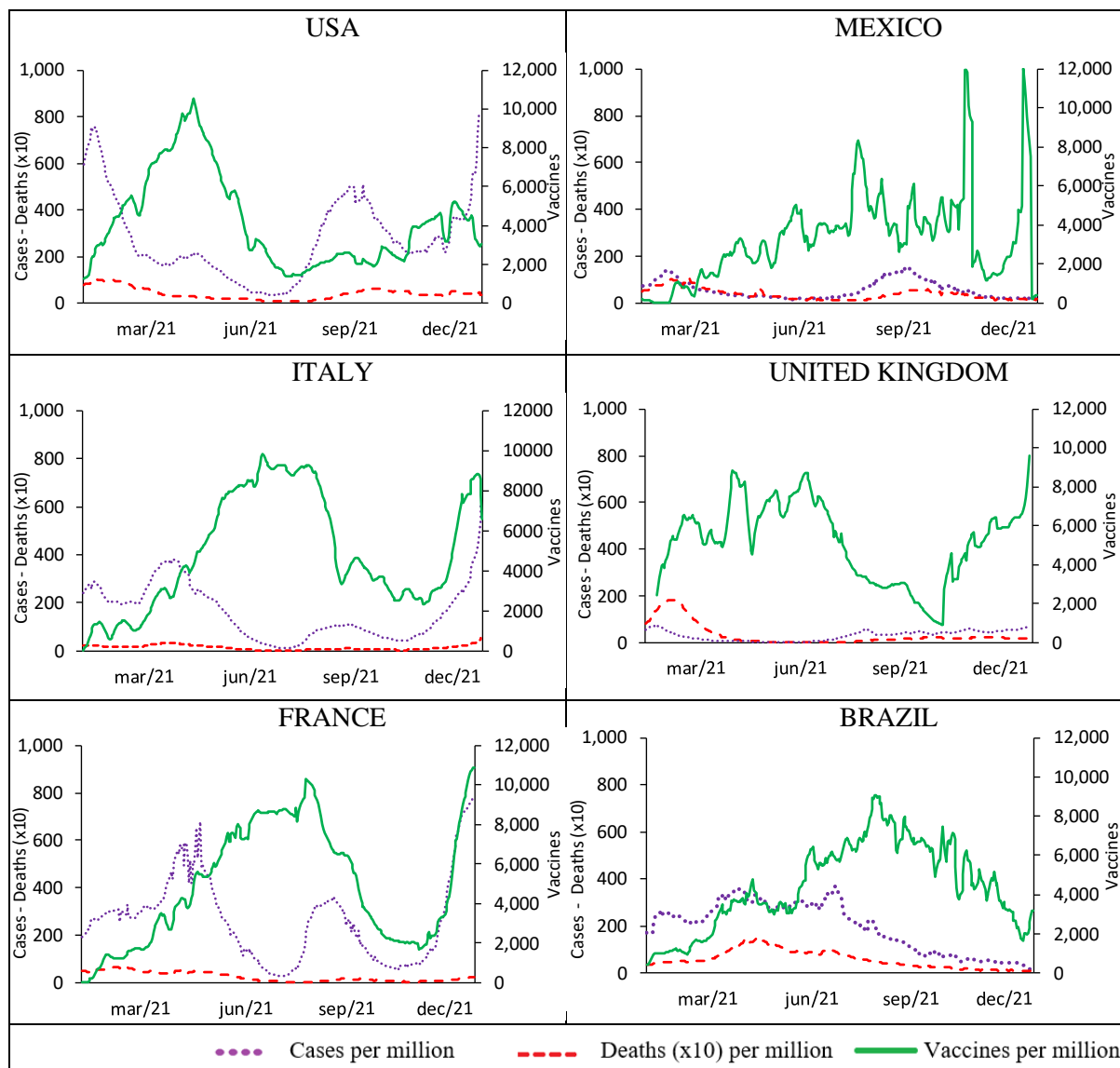
Note: As the immunization effect of the vaccination takes around 3 weeks, this variable was delayed by 21 days

Figure 2: Cases x Deaths*10 x Vaccines 7-day moving average from Jan 2021 to Dec 2021

An important point in the study is the incorporation of adequate control variables. These are described below.

2.4   Climate

Some studies indicate that the incidence of the H3N2 and H1N1 viruses and other influenza variants would be greater in regions and/or periods of lower temperature

and humidity (see Fredericks (2020), Wang et al. (2021), Chen et al. (2020), Shi et al. (2020) and Carleton and Meng (2020)[11]). Then, it is important to investigate whether a similar pattern is observed for the transmission of COVID-19, by incorporating these variables in the modeling.

The data were taken from the National Centers for Environmental Information (NOAA NCEI)[12], by using the Global Summary of the Day dataset. Daily average temperature, daily dew point temperature[13] and total precipitation for each weather station of each country were collected. Then, the daily average temperature, average dew point temperature and total precipitation for each country were calculated by taking the simple average of these weather stations. The relative humidity was calculated following Chen et al. (2020).

2.5   Elderly People

Many references indicate the greater effect of the disease in the elderly people. Countries with a large elderly population had a high incidence of COVID-19 (Singhal, 2020). A control variable was used for the proportion of elderly people (over 65, in relation to the population) in each country from World Bank data[14].

2.6   Months Since First Case

This variable refers to the number of months counting from the first month COVID-19 recorded case in each country until the month of the sample[15]. The objective of incorporating this variable into the model is to control the effect of the natural advance of the disease over time, despite the other variables` values.

2.7   Capacity of the Healthcare system

The more capable a country's healthcare system, the better that country will probably be able to isolate and treat contaminated people and, thus, reduce transmission. As a proxy for capacity of the healthcare system, we used the number of hospital beds[16], based on the World Bank website[17]. Moreover, to compare countries with different populations, we incorporated in the model the number of beds per thousand inhabitants in the model.

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[11] Carleton and Meng (2020) and Shi et al. (2020) do not find evidence that the humidity will have an effect on the growth rate of COVID-19.
[12] https://www.ncdc.noaa.gov/cdo-web/datatools/selectlocation.
[13] The dew point temperature is the one at which air is saturated with water vapor. In other words, relative humidity is 100% when the dew point temperature is equal to the actual temperature.
[14] https://data.worldbank.org/indicator/SP.POP.65UP.TO.ZS.
[15] https://ourworldindata.org/grapher/daily-cases-covid-19?tab=map&year=2020-05-11.
[16] Beds for admission into hospitals and public, private, general and specialized rehabilitation centers.
[17] https://data.worldbank.org/indicator/SH.MED.BEDS.ZS

3. Methodology

We use panel regression model to estimate the relationship between number of new COVID-19 cases and deaths, social distancing, vaccination and control variables. Considering as the dependent variable, Y_{it}, the logarithmic monthly variation rate of both the number of new cases C_{it} and deaths D_{it} caused by COVID-19, per million inhabitants, in the country i on day t^{18}: $Y_{it} = \ln\left(\frac{C_{it}}{C_{i,t-1}}\right)$ and $\ln\left(\frac{D_{it}}{D_{i,t-1}}\right)$. Similar dependent variables were considered by Siedner et al. (2020), Baumgartner et al. (2020), Sevi et al. (2020).

Formally, we estimate the following model for Y_{it}:

$$Y_{it} = \gamma_i + \gamma_i t + \phi_t + \underline{\theta}'\underline{X} + \varepsilon_{it} \qquad\qquad (2)$$

where $i = 1$ to 131; $t = 1$ to 640, where $t = 1$ corresponds the March 01, 2020, $t = 640$ corresponds to December 31, 2021; γ_i, ϕ_t and $\gamma_i t$ represent the effects between countries (intercept and trend) and over time, respectively[19]; $\underline{X}$ and $\underline{\theta}$ contain, respectively, all the variables described in data sub-section and their coefficients.

A procedure for the selection of variables was implemented via F tests, using backwise methodology (general to specific), applying the usual correction for heteroscedasticity and serial autocorrelation errors. The following variables resulted significant at the 0.05 level: SD_{it} = binary variable that indicates whether or not there is strict social distancing, as previously described[20]; $Vacc_{it}$ = number of daily vaccines ($\times 1,000$) doses per million administered; $Temp_{it}$ = average temperature; FC_{it} = number of months since the first case of COVID-19 was registered in the country i; EP_i = proportion of elderly people (aged 65 or greater) in country i; HM_{it} = average humidity (10^3 hPA Kg/Kg); HB_i = number of ICU (intensive care units) beds per thousand people. We also incorporated both interaction and non-linear terms, some of them were significant at the considered 0.05 level.

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[18] The logarithmic rate is a proxy for: $Y_{it} = (C_{it} - C_{i,t-1})/C_{i,t-1}$.

[19] The effects γ_i, invariant over time, allow for capturing differences between countries that have not been explicitly incorporated in the modeling (for example, because they are not possible to observe or difficult to measure). Examples include habits related to hygiene and social interaction. The fixed effects ϕ_t, which do not vary among countries, allow for capturing global changes over time, such as information about the disease and meteorological conditions.

[20] Remember that $SD_{it} = 1$, if the people circulating on streets in relation to the level prior to the pandemic is less than 40%, in country i and t-21 days before; and $SD_{it} = 0$, otherwise.

4. Results[21]

Sub-sample 1 (From March 2020 to December 2020)

The final estimated model for new cases (Model 1), was:

$Y_{it} = 0.01096 - 0.06024\,SD_{it} + 0.0081FC_{it} + 0.00008\,FC_{it}SD_{it} - 0.000093Temp_{it} + 0.00002Temp_{it}^2 + 0.00024Temp_{it}SD_{it} + 0.03541EP_i - 0.00007HM_{it} - 0.000102HB_i$ (3)

The final estimated model for deaths (Model 2), was:

$Y_{it} = -0.01513 - 0.05484\,SD_{it} + 0.0053FC_{it} - 0.000027\,Temp_{it} + 0.09866EP_i - 0.000111HM_{it} - 0.000871HB_i$ (4)

Sub-sample 2 (From January 2021 to December 2021)

The final estimated model for new cases (Model 3), was:

$Y_{it} = 0.041207 - 0.022471Vacc_I - 0.046521SD_{it} - 0.000289SD_{it}Vacc_{it} + 0.000148FC_{it} + 0.071844EP_i - 0.000152Temp_{it} - 0.000323\,HM_{it} - 0.000288HB_i$ (5)

The final estimated model for deaths (Model 4), was:

$Y_{it} = 0.01957 - 0.029811Vacc_i - 0.027003SD_{it} - 0.000332SD_{it}Vacc_{it} + 0.000355FC_{it} + 0.0231844EP_i + 0.01462EP_{it}Vacc_{it} - 0.000058Temp_{it} - 0.000004HM_{it} - 0.001567HB_i$ (6)

5. Discussion

5.1   Model 1

From equation (3), we found, as expected, a negative coefficient for strict social isolation. However, the interpretation of this coefficient is not trivial, because the statistical significance of the interaction terms from $Temp_{it}SD_{it}$, $FC_{it}SD_{it}$ shows that the effect is not direct, but also depends on the values of some control variables. Concerning the final effects of social distancing policies, Tables 1 and 2 compare the estimated monthly variation rates of new cases per million - with and without strict social distancing - under different scenarios[22].

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[21] For all models, in addition to the fixed effects, a weekend dummy (non-reported) was also used to correct the effects of underreporting on these dates.

[22] A similar exercise can be done with the other variables in the model.

Table 1: Estimated Growth Rates (Cases) - Countries/Periods without Strict Distancing

	Scenarios (Possible Values for the Explanatory Variables)							
$Temp_{it}$	25	20	15	10	5	0	-5	-10
EP_i	0.02	0.06	0.1	0.14	0.18	0.22	0.26	0.3
FC_{it}	1	2	3	4	5	6	7	8
HM_{it}	8	7	6	5	4	3	2	1
HB_i	8	7	6	5	4	3	2	1
Estimated Logarithmic Variation Rates (Cases per million):								
1.81%	2.75%	3.71%	4.68%	5.69%	6.69%	7.70%	8.71%

Table 2: Estimated Growth Rates (Cases) - Countries/Periods with Strict Distancing

	Scenarios (Possible Values for the Explanatory Variables)							
$Temp_{it}$	25	20	15	10	5	0	-5	-10
EP_i	0.02	0.06	0.10	0.14	0.18	0.22	0.26	0.30
FC_{it}	1	2	3	4	5	6	7	8
HM_{it}	8	7	6	5	4	3	2	1
HB_i	8	7	6	5	4	3	2	1
Estimated Logarithmic Variation Rates (Cases per million):								
-3.61%	-2.78%	-1.93%	-1.07%	-0.18%	0.72%	1.61%	2.51%

We observed a stronger reduction in the variation rates in Table 2, as compared to Table 1, suggesting a potential effect. Specifically, considering the average values in sample, a strict social distancing may be associated with a reduction of a little more than 5.5 percentage points in the monthly growth rate of new cases per million.

5.2 Model 2

From equation (4), we see again a negative sign for the coefficient of strict social isolation. Moreover, unlike Model 1, the interpretation of this coefficient is direct here, because no interaction terms were statistically significant. Therefore, we can conclude that a strict social distancing may be associated with a reduction of almost 5.5 percentage points in the monthly growth rate of new deaths per million. Tables 3 and 4 compare the estimated variation rates of new deaths per million - with and without strict social distancing - under different scenarios.

Table 3: Estimated Growth Rates (Deaths) - Countries/Periods without Strict Distancing

	Scenarios (Possible Values for the Explanatory Variables)							
$Temp_{it}$	25	20	15	10	5	0	-5	-10
EP_i	0.02	0.06	0.1	0.14	0.18	0.22	0.26	0.3
FC_{it}	1	2	3	4	5	6	7	8
HM_{it}	8	7	6	5	4	3	2	1
HB_i	8	7	6	5	4	3	2	1
Estimated Logarithmic Variation Rates (Deaths per million):								
-1.64%	-0.60%	0.43%	1.47%	2.51%	3.54%	4.58%	5.62%

Table 4: Estimated Growth Rates (Deaths) - Countries/Periods with Strict Distancing

	Scenarios (Possible Values for the Explanatory Variables)							
$Temp_{it}$	25	20	15	10	5	0	-5	-10
EP_i	0.02	0.06	0.10	0.14	0.18	0.22	0.26	0.30
FC_{it}	1	2	3	4	5	6	7	8
HM_{it}	8	7	6	5	4	3	2	1
HB_i	8	7	6	5	4	3	2	1
Estimated Logarithmic Variation Rates (Deaths per million):								
-7.12%	-6.09%	-5.05%	-4.01%	-2.98%	-1.94%	-0.90%	0.13%

One can note that strict social distancing has a similar impact on either the growth rate of cases or deaths, both around 5.5% compared with the previous month. As we will see below, the magnitude of the vaccination effects on cases and deaths was stronger.

5.3   Model 3

From equation (5), we verify, a negative sign for the coefficient of vaccination. However, the interpretation of this coefficient is not direct, because the statistical significance of the interaction term $SD_{it}Vacc_{it}$ shows that the effect is not direct, but also depends on whether there is a strict distancing or not. Moreover, the negative sign of the mentioned interaction term also shows that these variables jointly contribute to control the pandemic.

Concerning the final effects of vaccination, Tables 5 and 6 compare the estimated variation rates for countries without vaccination and with $Vacc_{it} = 4$, according to equation (5) - under some scenarios.

Table 5: Estimated Growth Rates (Cases) - no Vaccination

	Scenarios (Possible Values for the Explanatory Variables)							
$Temp_{it}$	25	20	15	10	5	0	-5	-10
EP_i	0.02	0.06	0.1	0.14	0.18	0.22	0.26	0.3
FC_{it}	10	11	12	14	16	18	20	22
HM_{it}	8	7	6	5	4	3	2	1
HB_i	8	7	6	5	4	3	2	1
	Estimated Logarithmic Variation Rates (Cases per million):							
	3.54%	3.98%	4.42%	4.88%	5.33%	5.78%	6.24%	6.69%

Table 6: Estimated Growth Rates (Cases) – with Vaccination (4.000 daily)

	Scenarios (Possible Values for the Explanatory Variables)							
$Temp_{it}$	25	20	15	10	5	0	-5	-10
EP_i	0.02	0.06	0.1	0.14	0.18	0.22	0.26	0.3
FC_{it}	10	11	12	14	16	18	20	22
HM_{it}	8	7	6	5	4	3	2	1
HB_i	8	7	6	5	4	3	2	1
	Estimated Logarithmic Variation Rates (Cases per million):							
	-5.44%	-5.01%	-4.57%	-4.11%	-3.66%	-3.20%	-2.75%	-2.30%

Again, we observe not only a strong reduction, but also an inverse sign of the variation rates in Table 6, compared to Table 5. This suggests that vaccinations may have led to a reduction in new registered cases. The average variation rate of cases in the sample, possibly associated with 4.000 daily vaccination, was -3.37%. The average effect of the 4.000 daily vaccination is a reduction of around 9 percentage points in the growth of cases.

5.4   Model 4

From equation (6), the coefficient of vaccination was negative as expected. Here again, nevertheless, the interpretation of this coefficient is not direct, due to the statistical significance of both interaction terms $SD_{it}Vacc_{it}$ and $EP_{it}Vacc_{it}$ (the latter was non-significant in Model 3). Therefore, the final vaccination effect depends both on strict distancing measures and the percentage of elderly people. Tables 7 and 8 compare the estimated variation rates for countries without vaccination and with $Vacc_{it} = 4$, under some different scenarios.

Table 7: Estimated Growth Rates (Deaths) - no Vaccination

	Scenarios (Possible Values for the Explanatory Variables)							
$Temp_{it}$	25	20	15	10	5	0	-5	-10
EP_i	0.02	0.06	0.1	0.14	0.18	0.22	0.26	0.3
FC_{it}	10	11	12	14	16	18	20	22
HM_{it}	8	7	6	5	4	3	2	1
HB_i	8	7	6	5	4	3	2	1
	Estimated Logarithmic Variation Rates (Deaths Per million):							
	0.96%	1.27%	1.59%	1.94%	2.28%	2.63%	2.98%	3.33%

Table 8: Estimated Growth Rates (Deaths) – with Vaccination (4.000 daily)

	Scenarios (Possible Values for the Explanatory Variables)							
$Temp_{it}$	25	20	15	10	5	0	-5	-10
EP_i	0.02	0.06	0.10	0.14	0.18	0.22	0.26	0.30
FC_{it}	10	11	12	14	16	18	20	22
HM_{it}	8	7	6	5	4	3	2	1
HB_i	8	7	6	5	4	3	2	1
	Estimated Logarithmic Variation Rates (Deaths Per million):							
	-10.85%	-10.30%	-9.75%	-9.17%	-8.59%	-8.00%	-7.42%	-6.84%

Just as in model 3, we observe a strong reduction and an inverse sign of the variation rates from Table 7 to 8. The average monthly variation rate of deaths in the sample, possibly associated with 4.000 daily vaccination, was -8.24%. Moreover, the calculated average impact of the 4.000 daily vaccination on deaths caused by COVID-19 was much stronger than the 9 percentage points estimated for new cases, reaching here around 12 percentage points.

5.5   Control Factors

In relation to control factors, the coefficient of EP_i indicates that, the greater the elderly population, the greater the growth rate of both COVID-19 cases and deaths. Although a greater number of registered cases was expected for elderly people, the presence of this variable in the model is essential for correctly estimate other impacts. For example, the significance of $EP_{it}Vacc_{it}$ in Model 4 shows that the vaccination impact on deaths is higher for older populations. FC_{it} also plays a very important role in the model: control the natural evolution, that is, the fact that different countries in sample may be in distinct phases of the pandemic[23]. Other significant variables were HM_{it} and HB_i, both with negative sign. It is worth mentioning that HB_i is correlated with income (GDP), which may explain the exclusion of this variable - that could be supposed relevant - in the final model[24].

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[23] The omission of relevant control variables leads to inconsistent estimators for the model coefficients, so that the respective estimates would not have a practical application. A quadratic term was also considered to capture the drop in the growth rate in some countries at the end of the sample, but it was not statistically significant at the usual levels.

[24] Another explanation is that the model's fixed effects (invariant over time) capture the effect of income.

Another point is the stronger impact of both EP_{it} and HB_i on deaths than on cases over 2020, evidenced by the comparison their coefficients. The Model 2 coefficient was 8 times higher than that of Model 1.

6. Conclusion

This work had two main results. The first one is the potential association between strict social distancing (defined here as a people circulation less than 40%) and the reduction in the evolution of COVID-19 cases, in the first part of the sample. We estimate that strict social distancing may be associated with a reduction of around 5.5 percentage points both in the monthly variation rate of COVID-19 cases and deaths per millions of people over 2020.This result lead us not to reject the hypothesis that the social distancing may have been one of the most important measures to control the pandemic before the advent of vaccines. The second important result of this work was based on the data from 2021, when the vaccination progress enabled us to evaluate its impact on the transmission of COVID-19. We found a decrease of 9 percentage points on the monthly variation rate of cases, as a possible consequence of 4.000 daily vaccines per million. The vaccination effect was stronger on deaths, impacting them by around 12 percentage points, under the considered vaccination level. The specific effects depend also on the observed values of other control variables for each country and period.

In summary, the data and the method adopted do not allow to exclude the hypothesis that the reduction of the growth of both cases and deaths of COVID-19 may be related with strict social distancing over 2020, and with higher rates of vaccination over 2021, reinforcing the role of these variables to control the evolution of the pandemic. It is important to highlight the use of suitable control factors to correctly estimate these effects.

It is important to mention that the results reported here only reflect the use of statistical techniques, and there is no underlying model of an epidemiological nature to allow more specific conclusions. In the absence of this type of complementary information, these results are insufficient for the formulation of public policies.

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