Identifying the influences of Early-Policies to the COVID-19 transmission and Deaths

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March 18, 2022

Abstract

The transmission of COVID-19 led to a series of damages to the world, hence the countries around the world implemented their policies against the damages that COVID-19 may bring to them. However, the different strategies led to varieties of results. In this essay, I estimated the early policies' effects on COVID-19 transmission through 4 dependent variables: Daily new cases, cumulative cases, daily deaths, cumulative deaths. The data is provided by World Health Organization and Our World in Data. I implemented two different Difference-in-Difference models to estimate the effects of Mandatory policies, Optional policies, and no-control policies with 3 groups of analysis. I found that mandatory policy has the most significant impact on limiting and decreasing COVID-19 transmission and damages, then followed by optional-policy and no-control policies are the least effective. I also found that the optional policies will somehow increase the cumulative deaths compared with no-control policy.

1 Introduction

Should government officials take responsibility for those infected or killed by COVID-19? COVID-19, an infectious disease, the first case was discovered in China in 2019 December. Although the Chinese government's and World Health Organization(hereinafter referred to as WHO)'s attentions were drawn, it did not cause a general concern among the world society. Soon, With the widespread of COVID-19, the administrations of different countries eventually implement their early policies to limit the transmission, including mandatory or optional keeping social distance, wearing medical masks, clean hands with sanitizer. However, the results of such policies vary due to the adaptive restrictions and coercive measures, which such "adaptive policies" were made based on the dilemma between Economy and citizens' lives.

The essay will focus on the effects of the early COVID-19 policies implemented by these countries. Using WHO COVID-19 data, I will analyze the infected cases and death within six countries over time, Canada, China, Japan, India, the United Kingdom, and the United States of America. To analyze the effects, I implemented two Difference in Differences methods to the data to examine the impact of policies on four measurements: new cases, cumulative cases, new deaths, and cumulative deaths (All in terms of Per million people). Furthermore, [RMRG+20] data provides the policies' stringency at the early stage of transmission. Therefore, I can categorize these countries' policies into three classes: 1. Mandatory Countries, where the policy strictly restricted travel, enforced citizens to wear medical masks, mandatory keep social distance, etc; 2. Optional Countries, where the policy restricted travel, advised citizens to wear masks, keep social distance, etc.; 3. No-control Countries, where the policy restricted the travels but did not provide other suggestions. By investigating the data, I designed two different DID research, where first model utilizes standard DID model and second model includes *Country* variables instead of *treatment* variable in standard DID model. I found that mandatory policy has the most significant effect of limiting COVID-19, then followed by optional policies; the no-control policy does not affect limiting COVID-19 from the large transmission. I also discussed the possible reasons that optional policy increases cumulative deaths and the importance of promptly implementing effective policies.

2 Literature Review

The impacts of the policies toward infectious disease are wide discussed by various scholars, from political aspects to economic aspects. Nonetheless, the results maintain huge differences based on their different starting points and goals to achieve, but in the limiting transmission aspect, scientists familiar believe that restrictions are needed to avoid further loss. [TLL+20] implemented a general linear model (adjusted by Akaike Information Criterion) estimation, which indicates that the Chinese government's early restrictions decreased at least 74,400(±15,6000) possible infections in 15 days, which is approximately "96% reduction on the total number of cases expected in the absence of interventions." (Huaiyu Tian et al. 2020, Page 5), considering the lingering effects of the reinfection, the effects of the policy exceeded the estimation. Furthermore, [LW20] estimated the impact of the policy that the fifteen states plus Washington, D.C. published on April 1 about mandatory wearing masks, the paper indicates that "because of these mandates, 230,000–450,000 cases may have been averted by May 22" (Lyu and Wenhby 2020, page 1422). Additionally, Imad A. Moosa[Moo20] also provided an empirical statistical analysis about the social lockdown and keeping social distance. She concludes that "The results show that social distancing is effective, even though it is difficult to separate the effect of government measures from that of social distancing triggered by personal initiatives" (Moosa 2020, Page 6292) and "First, countries that have not imposed lockdown and social distancing have performed poorly... Second, countries that have imposed lockdown either late or without stringency have performed poorly. Third, countries that have imposed social distancing at lower levels of cases have done better than countries that have imposed social distancing at higher levels of cases. It seems, therefore, that social distancing does matter." (Moosa 2020, Page 6300); she pointed out that keeping social distance and social lockdowns maintain positive effects on decreasing the active cases within the country.

The estimations above are consistent with the primary goal of COVID-19 early policies, limiting the infection cases and avoiding further disease outbreaks, especially due to the lingering reinfection effects. Also, their estimations are consistent with my estimation, the mandatory policies and optional policies indeed limit the COVID-19 transmission to a large extent, and no control policies have no effect on controlling COVID-19.

3 Data

3.1 WHO Data

WHO is a non-profit global organization that intend to promote global health and respond to health emergencies. Due to its responsibility of responding to health emergencies, they collected the COVID-19 data [WHO20] of different countries in time series, which provides a basic data set to analyze. The data is divided into eight sections: Date Reported, Country Code, Country, WHO region, New cases, Cumulative cases, New deaths, and Cumulative deaths. Also, the data contains 1511 observations of 6 countries: Canada, China, India, Japan, the United Kingdom, and the United States of America. The data is well-organized, but there are bias in it, which is that most of the countries can not afford the medical pressures that COVID-19 bring to them hence it led to the late-record and late calculation due to short of hands, the late-record brings bias to the data set yet I can not ignore the

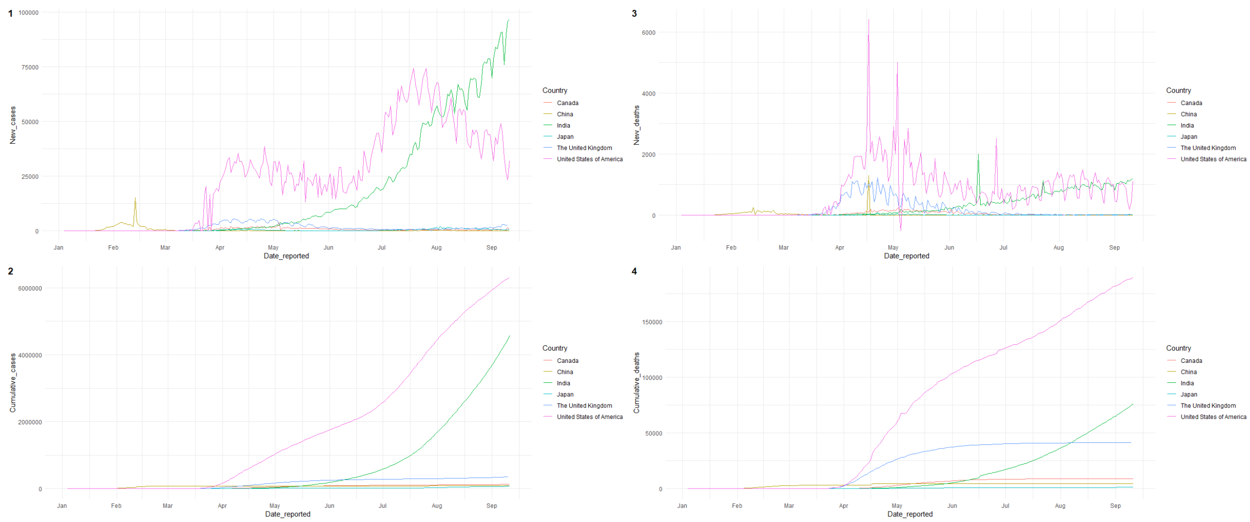

Figure 1: Line graph of cases and deaths

extreme value since it is correlated with other variables, which indicates that the ignoring will result in a larger error for the regression. 1 1 is a more intuitive view of the situations. (There is a negative number in U.S. daily deaths, CDC [CDC22] announced that this is due to the mis-record of the actual death reasons.) As we can see in the figures, the United States of America and India maintain relatively high COVID-19 cases and deaths; China, India, Japan, and the U.K. experienced relatively low pressure instead. Furthermore, to limit the influences of population, figure 2 measured the above graphs in terms of case/deaths per million people through the formula $\left(\frac{cases}{population}\right) \times 1000000$. After conducting the graph, we can see the data of the U.K. and Canada increased exponentially, this is due to the large populations in other countries enlarged the scale of the recorded variables.

3.2 Our World in Data

Our World in Data is an individual non-profit organization that intends to "Against the world's largest problems" by researching data. The organization provides a set of data

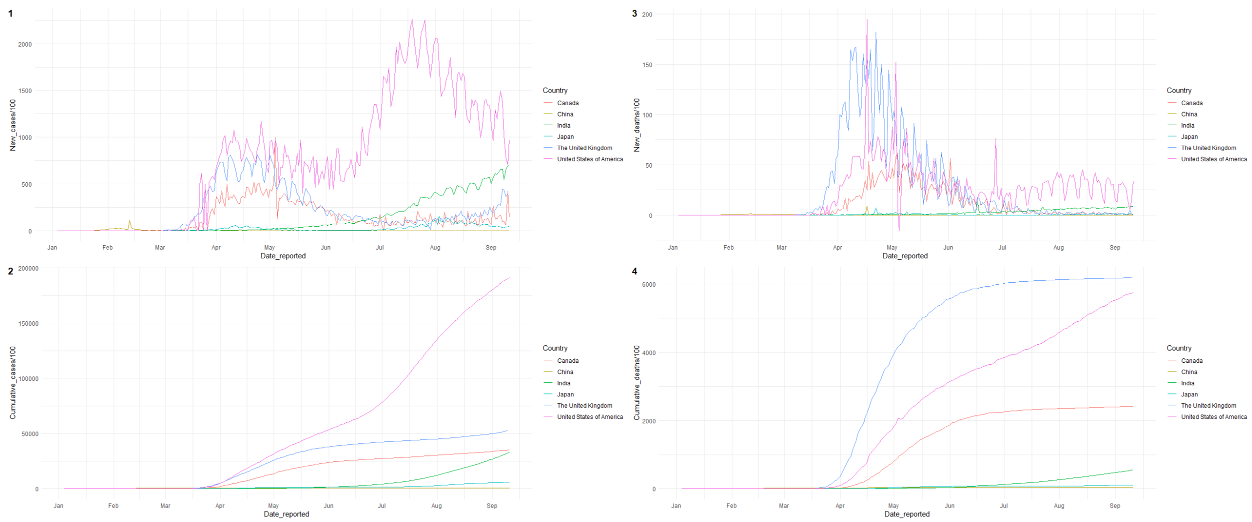

Figure 2: Line graph of cases and deaths in terms of per 1 million people

[iD22] that indicates the policy stringency of each country from 2020/01/02 to present; the stringency index is based on nine metrics from school closures to stay at home requirements, [HAG+21] states that the data is being spot-checked, which means that the data maintains "high degree of accuracy in the initial data collection," which we don't need to consider the inaccuracy of it. Using their data, I am able to allocate the treatment group, control group, before treatment time, and after treatment time for each country that I estimate.

4 Method

I implement two Difference in Differences research designs to estimate early policies effects on decreasing further COVID-19 transmissions, where daily new cases, daily deaths, cumulative cases, and cumulative deaths are used as the dependent variables to estimate the effects. The analysis's motivation is that multiple literature works indicate that early policies have huge impacts on the COVID-19 situation. I don't need to consider the effects of other policies since the stringency indexes suggest that the policy contains numerous aspects so these policies are considered an aggregate policy, which means that no other same-objective policies are excluded, resulting in inaccuracy to our estimation. Furthermore, since the dependent variables should have no huge differences before the treatment for both treatment group and control group for implementing DID, I use per 1 million people as the unit to estimate the regression so that I can ignore the influences that population brings to the estimation.

4.1 Regular DID approach

$$y_{g1it} = \lambda_0 + \lambda_1 After_t + \lambda_2 Mandatory_{1i} + \lambda_3 (After_t * Mandatory_{1i}) + \eta_{it} \tag{1}$$

$$y_{g2it} = \rho_0 + \rho_1 After_t + \rho_2 Mandatory_{2i} + \rho_3 (After_t * Mandatory_{2i}) + \nu_{it} \tag{2}$$

$$y_{g3it} = \psi_0 + \psi_1 After_t + \psi_2 Optional_i + \psi_3 (After_t * Optional_i) + \phi_{it} \tag{3}$$

The first DID research is based on the standard DID estimation model, where I set three different groups. The first group utilizes Mandatory countries as the treatment group, other-policy countries as the control group; the Second group utilizes the mandatory countries as treatment groups, optional countries as the control group; the Third group utilizes optional countries as the treatment group, no-control country as the control group.

Equation (1) represents the estimation model for group 1, where y_{g1it} represents four indicators: New cases per million people, cumulative cases per million people, new deaths per million people, and cumulative deaths per million people. $After_t$ is a dummy variable that indicates whether the country had released its policy, $Mandatory_i$ indicates the country's policy is strict or not, eta_it is the error term. My interest focuses on λ_3, which estimates the mandatory policy's effect on COVID-19 further transmission and deaths. Equation (2) represents the estimation model for group 2, same with equation (1), the interest is focused on ρ_3, where it estimates the effects of the mandatory policy on COVID-19 further transmission and deaths, note that in equation (2), the data of the country that implements no-control policy will be excluded. Equation (3) represents the estimation model for group 3, ψ is my estimation interest, in this estimation, the data of the country that implements mandatory policy will be excluded.

4.2 Modified DID approach

$$y_{it} = \alpha_0 + \alpha_{Country}Country + \alpha_1 After_t + \alpha_2 Mandatory_i * After_t + \alpha_3 Optional_i * After_t + \mu_{it} \tag{4}$$

The second DID research is modified based on the basic DID estimation model, where I imposed Country dummy variables to estimate the effects of different policies. The benefit of using such regressions is that I am able to control the time-invariant country-specific factors, so the results will be less biased than the basic DID model.

Equation(3) represents the estimations model. $Country$ are six dummy variables that indicate each country, $After_t$ is a dummy variable that indicates whether the country had released its policy, $mu_i t$ is the error term. The estimates of interests here are α_2 and α_3, they estimates the effects of the mandatory policy and optional policy on four dependent variables.

5 Results

5.1 Regular DID Approach

Table 1: Normal Difference in Difference model for first group

	Dependent variable:			
	‘New_cases/100‘	‘Cumulative_cases/100‘	‘New_deaths/100‘	‘Cumulative_deaths/100‘
	(1)	(2)	(3)	(4)
after	350.497*** (21.972)	28,285.040*** (1,859.727)	16.704*** (1.351)	1,895.201*** (104.553)
mandatory	−3.902 (77.714)	−174.852 (6,577.587)	−0.068 (4.777)	−17.452 (369.787)
mandatory:after	−348.148*** (82.004)	−27,720.010*** (6,940.734)	−16.572*** (5.041)	−1,867.701*** (390.203)
Constant	4.324 (18.505)	176.212 (1,566.254)	0.081 (1.138)	17.489 (88.054)
Observations	1,511	1,511	1,511	1,511
R^2	0.193	0.176	0.125	0.234
Adjusted R^2	0.191	0.175	0.123	0.233
Residual Std. Error (df = 1507)	354.024	29,964.190	21.764	1,684.565
F Statistic (df = 3; 1507)	119.822***	107.429***	71.535***	153.591***

Note: *p<0.1; **p<0.05; ***p<0.01

Table 1 indicates the estimates for running equation (1). the $\lambda 1$ which estimates the effects of $After$ on dependent variables, the reason that coefficients of $after_t$ turn out to be influential to the dependent variables is that COVID-19 is an infectious disease that has an incubation period, this leads to a phenomenon that most of the cases were recorded and out-breaked after the policy is implemented, in other words, the $after_i$ is overestimated. However, it does not influence the estimation since our interest of estimation is focused on λ_3, which attached $Mandatory : After$ variables, as we can see in table 1, the mandatory policy is highly correlated with the dependent variables after it was posted, same with the λ_1, the effects of the mandatory policy is also lagged due to the characteristic of incubation, which indicates that the effects of λ_3 will cancel out the overestimation part of λ_1. In this estimation, the interpretation is that the mandatory policy limits and decreased about 348 daily new cases (Robust SE = 15.46), 27720 cumulative cases (Robust SE = 1310.81), 16 daily deaths (Robust SE = 0.948), and 1867 cumulative deaths(Robust SE = 74.925) (all in per million people) compare with two other policies.

Table 2: Normal Difference in Difference model for second group

	Dependent variable:			
	‘New_cases/100‘	‘Cumulative_cases/100‘	‘New_deaths/100‘	‘Cumulative_deaths/100‘
	(1)	(2)	(3)	(4)
after	165.315*** (11.274)	18,573.560*** (1,009.235)	15.955*** (1.859)	2,053.680*** (136.971)
mandatory	−5.902 (31.339)	−294.082 (2,805.470)	−0.109 (5.168)	−29.531 (380.753)
mandatory:after	−162.966*** (33.222)	−18,008.530*** (2,974.043)	−15.823*** (5.478)	−2,026.181*** (403.631)
Constant	6.324 (9.528)	295.441 (852.960)	0.123 (1.571)	29.569 (115.762)
Observations	1,008	1,008	1,008	1,008
R^2	0.263	0.351	0.106	0.267
Adjusted R^2	0.261	0.349	0.104	0.265
Residual Std. Error (df = 1004)	140.033	12,535.890	23.092	1,701.347
F Statistic (df = 3; 1004)	119.370***	181.134***	39.865***	122.054***
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 2 indicates the DID estimation for group 2, without the data of no-control country. For group 2 estimation, the coefficients of $after_i$ and $mandatory : after$ become smaller, which verified that the optional policies are more effective than no-control policies. An interpretation of the estimation is that the country that implements mandatory policy will limit and decrease about 163 daily new cases (Robust SE = 8.49); 18008 cumulative cases

(Robust SE = 770.89); 16 daily deaths (Robust SE = 1.35); 2026 cumulative cases (Robust SE = 103) (per million people) compare with the country that implements only optional policies after it was posted.

Table 3: Normal Difference in Difference for third group

	Dependent variable:			
	‘New_cases/100‘	‘Cumulative_cases/100‘	‘New_deaths/100‘	‘Cumulative_deaths/100‘
	(1)	(2)	(3)	(4)
after	633.598*** (32.902)	43,130.440*** (3,048.001)	17.847*** (2.323)	1,651.683*** (179.078)
optional	4.880 (35.879)	290.920 (3,323.779)	0.102 (2.533)	29.474 (195.280)
optional:after	−468.284*** (42.675)	−24,556.880*** (3,953.358)	−1.892 (3.013)	401.997* (232.270)
Constant	1.444 (27.563)	4.522 (2,553.398)	0.020 (1.946)	0.095 (150.018)
Observations	1,259	1,259	1,259	1,259
R^2	0.352	0.214	0.093	0.187
Adjusted R^2	0.351	0.212	0.091	0.185
Residual Std. Error (df = 1255)	337.577	31,272.610	23.836	1,837.344
F Statistic (df = 3; 1255)	227.372***	113.634***	42.901***	96.001***

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3 indicates the DID estimation for group 3. Our interest of estimation is *optional* : $after$, which indicates that the country that implements optional policies will decrease and limit approximately 468 daily new cases (Robust SE = 32.67); 24557 cumulative cases (Robust SE = 3037.5); 2 daily deaths (Robust SE = 1.81) (All in per million people). However, it will increase about 402 cumulative deaths (Robust SE = 2.74) per million people compared with no-control policies. A possible explanation is that there are some factors that did not captured by the estimations, such as medical resources or universal health care. Note that the ψ_3 is statistically insignificant for daily deaths per million people with 70% confidence

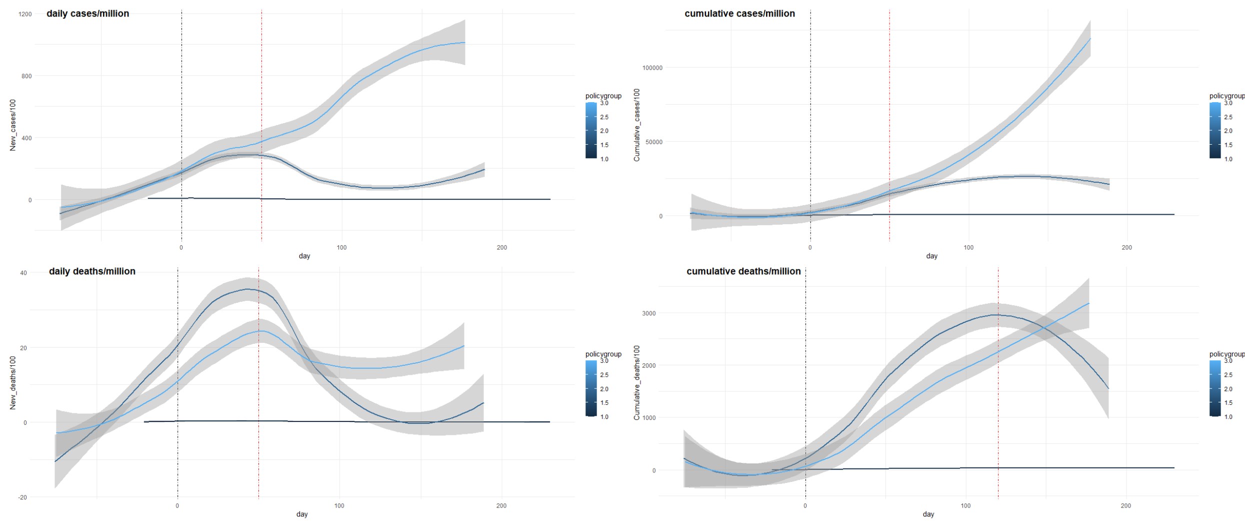

Figure 3: DID Line trends

and only 90% confidence for cumulative deaths per million people.

Figure 3 indicates the line trends graph of the comparison between different policy groups (1 = mandatory policy country, 2 = optional policy country, 3 = no-control policy country) for four dependent variables. The grey area represents the fluctuation of the data. Day 0 represents the last day of the pre-treatment and represents the boundaries of $After_t$. However, since the COVID-19 has an incubation period, I manually adjusted the vertical line, which indicates the pre-treatment time and treatment time, to the day it took effect. For daily cases, daily deaths, and cumulative cases, I adjusted it to the Day 50 by considering the incubation period and lingering effects. For cumulative deaths, I adjusted it to the Day 120 since the medical help is able to extend the death period. Also, note that since its dependent variables are too small and stable for the mandatory-policy country, they were displayed on the area near X-axis, although it is hard to capture. As we can see in the figure 3 that mandatory-policy country's trends are quite stable, which they nearly all lies on the x-axis with little fluctuations. We see that they had little differences with no-control countries for optional-policy countries before treatments took effects. However, there are a large number of decreases in four dependent variables for optional-policy countries after their policies took effects. This indicates that compared with no-control policy, the optional policy can indeed limit the transmission and deaths within the countries. In contrast, in the figure 3, the dependent variables for no-control countries rise along with the time, indicating that the COVID-19 transmission and damages keep increasing through time. From the above interpretation, it is reasonable to conclude that under the COVID-19 situation, mandatory policies are highly effective in controlling and limiting the COVID-19 transmission and damages. Then, followed by optional policies, the no-control policies work least effectively.

5.2 Modified DID approach

Table 4: Modified Difference in Difference

	Dependent variable:			
	‘New_cases/100‘	‘Cumulative_cases/100‘	‘New_deaths/100‘	‘Cumulative_deaths/100‘
	(1)	(2)	(3)	(4)
China	107.397* (55.991)	13,277.330** (5,432.582)	12.326*** (4.522)	1,603.966*** (277.581)
India	−202.285*** (30.919)	−11,744.130*** (2,999.966)	2.109 (2.497)	559.312*** (153.285)
Canada	123.129*** (21.668)	14,607.960*** (2,102.315)	9.723*** (1.750)	1,175.959*** (107.419)
UK	197.143*** (21.706)	23,740.620*** (2,106.086)	25.178*** (1.753)	3,402.390*** (107.612)
US	423.247*** (30.969)	38,638.720*** (3,004.835)	22.693*** (2.501)	2,662.663*** (153.534)
Japan				
mandatory:after	−628.302*** (59.175)	−42,327.240*** (5,741.547)	−17.617*** (4.779)	−1,614.241*** (293.368)
optional:after	−456.011*** (30.726)	−23,195.360*** (2,981.205)	−0.649 (2.481)	565.603*** (152.327)
after	630.651*** (23.638)	42,892.270*** (2,293.502)	17.750*** (1.909)	1,641.740*** (117.188)
Constant	−106.975*** (21.188)	−13,275.970*** (2,055.832)	−12.312*** (1.711)	−1,603.928*** (105.044)
Observations	1,511	1,511	1,511	1,511
R^2	0.621	0.491	0.290	0.609
Adjusted R^2	0.619	0.489	0.286	0.607
Residual Std. Error (df = 1502)	243.090	23,586.080	19.632	1,205.146
F Statistic (df = 8; 1502)	307.087***	181.300***	76.735***	292.847***
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 4 indicates the estimation results for the modified DID model. The model utilizes the *Country* factors to replace the treatment factor, which allows me to control the time in-variant country-specific factor so that the result will be less biased than the standard DID model. As we can see in 4, one of the estimation interests, $mandatory * after$, has more significant impacts on new cases, new deaths, and cumulative cases than the standard DID model (group 1). However, the cumulative deaths coefficients became higher than the standard DID model. A possible interpretation of such results is that the *Country* variables contain time in-variant factors such as medical resources, universal health care, or infrastructure capabilities. Comparing the standard DID model and modified DID model, we can see that the differences are quite minor with the $optional * after$ coefficients, but $Country$ variables contain factors that the standard DID model did not capture. Note that although Japan's estimation is fully blanked, the $constant$ coefficients contain the estimations of Japan's data. One of the estimation interests, $Mandatory : After$, indicates that there will be approximately 628 daily new cases reduced (Robust SE: 33.6), 42327 cumulative cases reduced (Robust SE: 3084), 17 daily deaths decrease (Robust SE: 1.25), and 1614 cumulative deaths reduce (Robust SE: 110.938) after a country implement mandatory policy to control COVID-19. For another estimation interest, $Optional * After$, it indicates that there will be approximately 456 daily new cases reduced (Robust SE: 34.8562), 23195 cumulative cases reduce (Robust SE: 3200.93), 0.649 daily deaths decrease (Robust SE: 1.95), and 565 cumulative deaths increase (Robust SE: 160.879) after a country implement optional policy to control COVID-19. The interpretations of the estimation are that Nearly all the estimations are statistically significant, but the $newdeaths$ estimations are statistically insignificant for variable $India$ and $optional * after$. This may be due to the omitted variables not being captured by the dataset.

5.3 An interpretation to optional policy

In both the regular DID and modified DID models, the optional policy somehow increases cumulative deaths. Besides the situation of omitted variables, this is may also due to the phenomenon that Moosa [Moo20] mentioned in her paper. She concludes that ”Countries that have imposed social distancing at lower levels of cases have done better than countries that have imposed social distancing at higher levels of cases."(Moosa 2020, Page 6292). From her conclusion, it is possible that most of the optional countries implemented their policies at a higher level of cases, their strategies indeed successfully prevent COVID-19 from the large transmission, but the level of cases is too high that their medical resources can not afford the pressures, which lead to extra deaths. Furthermore, people within the optional policy countries are more inclined to think that they are safe compared to the no-control policy, which such thinking increases the infectious rate. According to 3, we can see in the daily deaths section and cumulative deaths section that optional countries' data is downward sloping after the policies took effect, this means that optional countries' indeed controlled and limited COVID-19, which proved Moosa's conclusion, at the first half of the data, they act terrible, but with enough time, they can control it

6 Conclusion

Early policies should intend to decrease and limit the transmission of COVID-19. By observing and analyzing the data, it is reasonable to conclude that mandatory policy is highly correlated with improving the COVID-19 situation. Optional policies, compared with no-control policies, somehow improved the COVID-19 situation. Despite the estimation that it decreases 468 daily new cases and 24557 cumulative cases, its effects on daily deaths is statistically insignificant as well as it will also increase the 402 cumulative deaths, this may due to the omitted variables such as medical resources or universal health cares. Figure 3 also proved the above estimations. In conclusion, mandatory policies are the best way to stop and limit the transmission and damages of COVID-19, it decreases 348 daily new cases (Robust SE = 15.46), 27720 cumulative cases (Robust SE = 1310.81), 16 daily deaths (Robust SE = 0.948), and 1867 cumulative deaths(Robust SE = 74.925). Then followed by optional policies, where it decreases 468 daily new cases (Robust SE = 32.67); 24557 cumulative cases (Robust SE = 3037.5). Lastly, no-control policies do nothing to the COVID-19. Also, the 3 indicates that the optional policy in the countries that already have a relatively high level of cases may not work efficiently in limiting transmission sides, but such policies will, eventually, control and limit the transmission. However, due to the different aspects and points of view, some people may argue from the economic aspect or human rights aspect that mandatory policy, or even optional policies, are highly impossible to achieve. The truth is that COVID-19 damages are larger with less control, I found in my past analysis that the economic issues raised by COVID-19 are due to the ripple effects that led by COVID-19 transmission to a large extent, such as liquidity trap and bankruptcy of small and medium-sized enterprises. Back to the question, should government officials take responsibility for those infected or killed by COVID-19? Yes, and this is based on the data.

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