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Race against time to save human lives during the COVID-19 with vaccines: Global evidence

Phuc V. Nguyen¹ Toan L.D. Huynh² Vu M. Ngo³ Huan H. Nguyen⁴

Abstract

Voluminous vaccine campaigns are used globally since the COVID-19 pandemic owes devastating mortality and destructively unprecedented consequences on different aspects of economies. Notwithstanding different approaches to measure the effectiveness of COVID-19 vaccines in clinical medicines, this paper sheds new light on the efficacy of COVID-19 vaccines by using the difference-in-differences (DiD) design of 127 countries in the daily frequency from February 2020 till the end of August 2021. We show that the number of new deaths per million significantly decreases after half of the population is vaccinated, but the number of new cases witnesses an insignificant change. We found that the effects are more pronounced in Europe and North America by offering insights about different continents. Our results remain robust after using other proxies and testing the sensitivity of the vaccinated proportion, providing causality and evidence that expanding and expediting COVID-19 vaccination can save human lives.

Keywords: COVID-19; global scope; effectiveness; vaccines.

JEL Classification: I10; I18.

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1. Introduction

The COVID-19 pandemic is not the worst pandemic in human history, but it has been one of the deadliest pandemics since the Spanish flu in the early 20th century (Feehan & Apostolopoulos, 2021). Since the initial outbreak in January 2020, after nearly two years, the pandemic has killed more than 4.5 million people globally (WHO, 2021a). Herd immunity is one of the key strategies in controlling epidemic (Fontanet & Cauchemez, 2020), and mass vaccination program has been widely accepted as one of the optimal ways to achieve herd immunity (Anderson & May, 1985; Jeyanathan et al., 2020; Matrajt et al., 2021). However, vaccine hesitancy has become a huge challenge to achieve global COVID-19 immunity (Machingaidze & Wiysonge, 2021). Social factors such as social norms and herding behaviors were found to dominate individual free-riding will in vaccine uptake decisions (Agranov, Elliott & Ortoleva, 2021). Thus, intensive media coverage about the COVID-19 vaccine side effects, instead of real effects in controlling the pandemic, could be a reason for low vaccine uptake rates (Machingaidze & Wiysonge, 2021). Even herd immunity without a vaccine path has been voiced by both governments and scientists (Aschwanden, 2020; de Vlas & Coffeng, 2021). In contrast, very little research has been conducted to provide empirical evidence on the immunity impacts of vaccination programs until now (Fontanet & Cauchemez, 2020; Rossman et al., 2021) partly either because of limitation of data or lack of interest. This study aims to fill this gap by providing real-world evidence on the effects of vaccination programs on controlling the COVID-19 pandemic before and after achieving a relatively high vaccinated population rate.

The percentage of vaccinated people to achieve herd immunity varied with different epidemics (i.e., 95% for measles, 80% for polio) (WHO, 2021b). Using simulated data and mathematical models, many studies have found that a vaccine with an acceptable level of effectiveness (i.e., $\geq 50\%$) or efficacy (i.e., $\geq 70\%$) would be sufficient to significantly contain the COVID-19 pandemic (i.e., reduce severe symptoms and mortality rate) if a major proportion of the population is vaccinated (MacIntyre, Costantino, & Trent, 2021; Swan et al., 2021; Deplanque & Launay, 2021). The thresholds from 60% to 90% of the vaccinated population have been usually referred to as the herd immunity for the COVID-19 pandemic (Matrajt et al., 2021; Aschwanden, 2021). When adding a proportion of the population immune because they've been infected to the 50% of the vaccinated population, we might approach the proposed COVID-19 herd immunity in some countries (see Figure A1.1). Then, using a Difference-in-Differences (DiD) imputation estimator following Borusyak and Jaravel (2018), this study attempts to explore the causal effect relationship between pandemic infection rates, mortality rates, and the event of 50% of the population vaccinated against the COVID-19 virus. The evidence provided in this study about the real-world herd immunity impacts of mass vaccination programs could help to mitigate the vaccine hesitancy, achieve higher vaccine uptake rate faster which could alleviate the pressure for healthcare systems globally.

The rest of the study is structured as follows. The next section summarizes our research design. Section 3 shows the results. The last section summarizes and concludes.

2. Research design

We examine the changes of new deaths and new cases per million when half of the population has been vaccinated by drawing the data of 127 countries⁵ from February 2020 till the end of August 2021. In this study, we applied a Difference-in-Differences (DiD) imputation estimator when 50% population got vaccinated at different times across countries following Borusyak and Jaravel (2018).

The heterogeneous treatment effects happening when units in the panel receive treatment effects at differential timings is a limitation when examining event studies using conventional two-way fixed effect regression (Goodman-Bacon 2021). The imputation estimator developed by Borusyak and Jaravel

⁵ China is not in our sample due to data unavailability.

(2018) is a finite-sample efficient and unbiased estimator among some emerging DiD estimators robust to unrestricted heterogeneous treatment effects (Callaway and Sant’Anna 2020; de Chaisemartin and D’Haultfœuille 2020). The imputation estimation process follows three steps. First, we estimate a model for untreated (i.e., never-treated and not-yet-treated) potential outcomes using untreated observations only in a two-way fixed effects regression:

$$Y_{it} = \alpha_i + \beta_t + X_{it} + \varepsilon_{it} \quad (1)$$

While Y_{it} are outcome variables including new deaths per million and new cases per million, α_i and β_t are country and year fixed effects accordingly. The standard error is clustered at the unit (country) level following Abadie et al. (2017). X_{it} stands for covariates including lag outcome variables, mobility variables (changes in retail and recreation, parks, workplaces, residential mobility), government policies (economic support and containment health), and a dummy variable standing for delta variants. The summary statistic, variables description, selection, and sources are in Appendix 1. Next, we extrapolate the equation (1) to treated observations, imputing untreated potential outcomes $Y_{it}(0)$ ⁶, and calculate treatment effects τ_{it} .

$$\tau_{it} = Y_{it} - Y_{it}(0) \quad (2)$$

Finally, we take the averages of these individually imputation-based treatment effects, called τ_w , which shows how the new deaths or new cases change after a specific event date. We also test the parallel trend assumption for DiD as discussed in Appendix 2.1. In other words, we test if there is an insignificant difference between the treatment and control group before the event dates before conducting any DiD regressions. Apart from that, we also discuss the “no anticipation effects” assumption in Appendix 2.2.

3. Results and findings

3.1. Half of the population vaccinated, and its causal effects on COVID-19 infected and mortality rates

In Table 1, we test the changes of COVID-19 new deaths per million and new cases per million based on different specifications. The variable of interest here is τ_w . In specification (1), we control the lag outcome variables, country and year fixed effects, and cluster by country. In column (2), we further control government policies. In column (3), we control for mobility variables and delta variants. Given the satisfied parallel trend and “no anticipation effect” assumptions (Tables A2.1 and A2.3 in Appendix 2), we examine how new deaths and new cases change when half of the population gets vaccinated. From Table 1, the number of new deaths per million decreases by 0.445 people after 50% of the population is vaccinated, while there is an insignificant change in new cases averagely. The changes of the two outcome variables are visualized in Figures 1 and 2, supporting our statistical results.

⁶ The period-t potential outcome of unit i if it is never treated

Table 1: The treatment effects on new deaths and new cases per million when half of the population vaccinated

	<i>Panel A: New deaths per million</i>			<i>Panel B: New case per million</i>		
	(1)	(2)	(3)	(1)	(2)	(3)
τ_w	-0.618*** (0.003)	-0.559*** (0.004)	-0.445** (0.025)	-7.037 (0.406)	-2.234 (0.802)	2.168 (0.819)
Lag	0.545*** (0.000)	0.539*** (0.000)	0.514*** (0.000)	0.671*** (0.000)	0.647*** (0.000)	0.629*** (0.000)
Containment		0.0372*** (0.000)	0.0177*** (0.000)		1.223*** (0.000)	0.686*** (0.000)
Economic		-0.0022*** (0.001)	-0.0014** (0.039)		-0.0836*** (0.001)	-0.0749*** (0.003)
Recreation			-0.0097*** (0.000)			0.0324 (0.497)
Park			-0.0064*** (0.000)			-0.247*** (0.000)
Workplaces			-0.0004 (0.759)			0.0447 (0.346)
Residential			0.0208*** (0.000)			1.246*** (0.000)
Delta dummy			-0.0502 (0.475)			0.549 (0.842)
N	61,536	60,452	59,359	65,489	64,373	63,207
Adj. R-sq	0.483	0.517	0.526	0.612	0.613	0.616

*Note: New deaths per million and New cases per million are the daily recorded COVID-19 new deaths and new cases per million, while Lag is their one-period lag variables accordingly. Mobility indices include Recreation, Park, Workplaces, and Residential, collected from Google about the mobility of people to retail and recreation, parks, workplaces, and residential areas. The government policies include Containment and Economic, which are about the policies of governments regarding containment and economic supports. The Delta dummy receives the value of 0 before the first delta-variant case recorded in each country and 1 otherwise. p-values in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.*

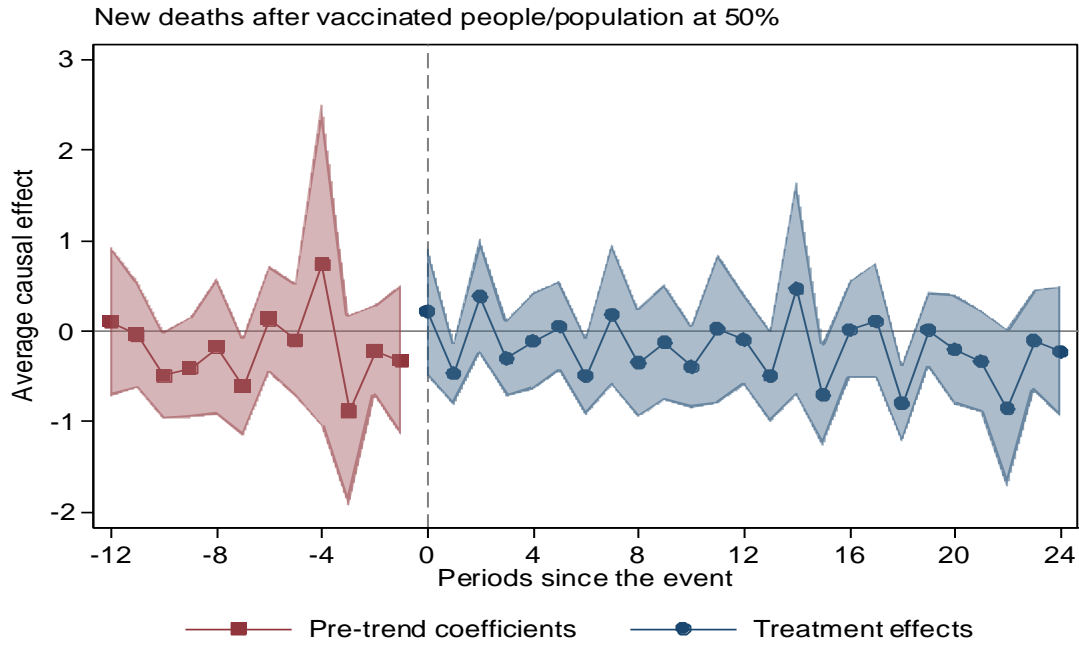


Figure 1: New deaths before and after vaccinated people/ population reaches 50%
 Note: The dots show the average treatment effects for each day around the event date. That blue dots primarily lie under the x-axis implies the decrease in new deaths after vaccinated people/population reaches 50%.

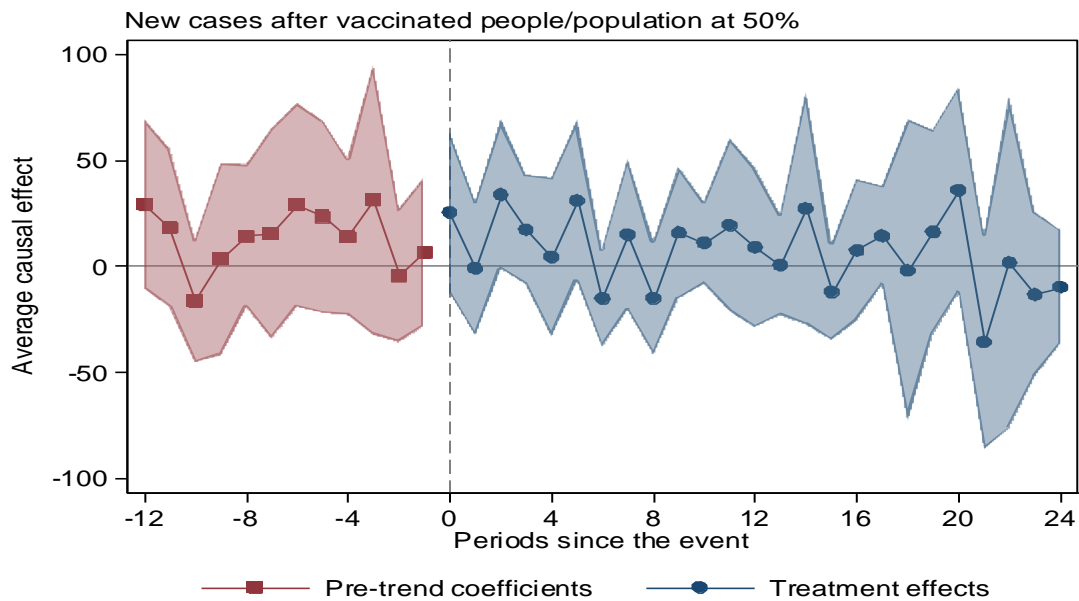


Figure 2: New cases before and after vaccinated people/ population reaches 50%.
 Note: The dots show the average treatment effects for each day around the event date. The blue dots fluctuating around the x-axis implies the indecisive movement of new cases after vaccinated people/population reaches 50%.

3.2. Does vaccine origin matter?

We further classify the data into two subsamples based on vaccine origins. One subsample includes European and North American countries, where most globally accepted vaccines come from, while another includes countries from four continents: Africa, Asia, Oceania, and South America.

Due to the data limitation, we are only able to conduct the test in these subsamples until the level of people vaccinated/population reaches 30% for Africa, Asia, Oceania, and South America countries (see Table A4.3 and A4.4 in Appendix 4). However, because the parallel trend assumption is violated at this level (30%), we conduct the imputation estimator for both outcomes in these two subsamples when people vaccinated/population reaches 20% level (see Table A2.2 in Appendix 2). The statistical results show that when vaccinated people comprise one-fifth of the population, new deaths decrease in Europe and North America. There is also no anticipation assumption violation in new deaths and new cases in these two continents (see Table A2.4 in Appendix 2). In contrast, there is an insignificant change in both new deaths and new cases in the other four continents. It is a caveat in our study that the followed-up research can have a broader vision with more data available for higher percentages of vaccinated people/population in these subsamples.

We also visualize the changes in new deaths of these two subsamples when people/population reaches 20% in Figures 3 and 4. These two figures also support our conclusion.

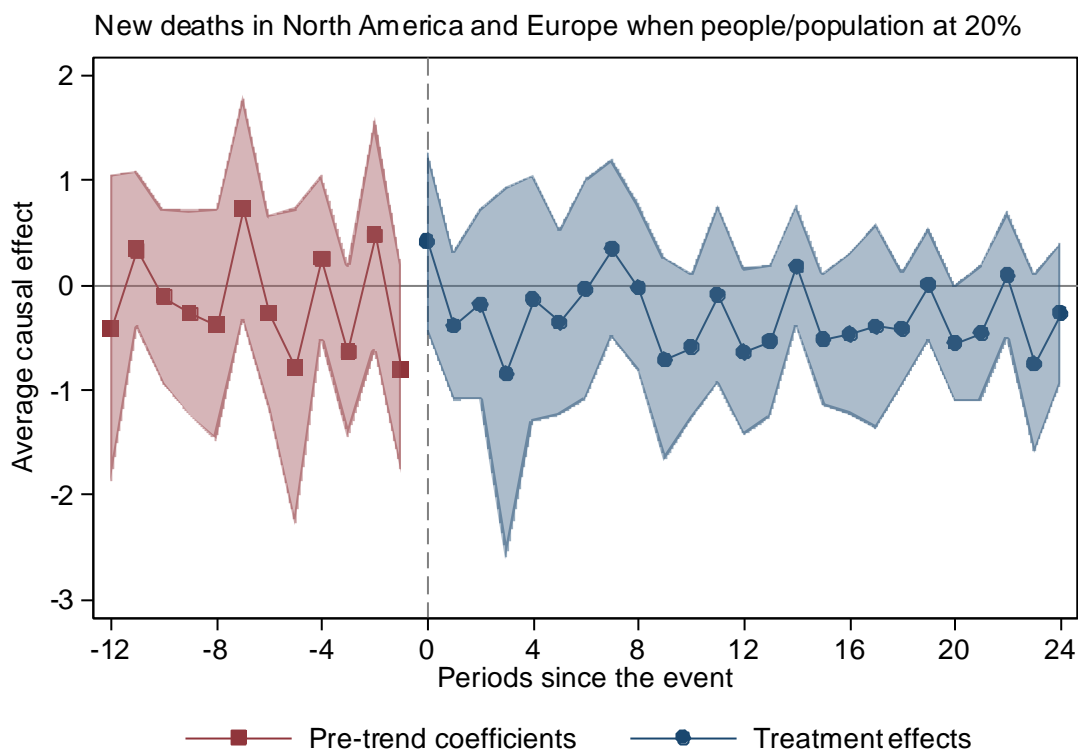


Figure 3: New deaths in Europe and North America before and after vaccinated people/population is at 20%

Note: The dots show the average treatment effects for each day around the event date in North America and Europe. That blue dots mainly lie under the x-axis implies the decrease in new deaths in these two continents after vaccinated people/population reaches 20%.

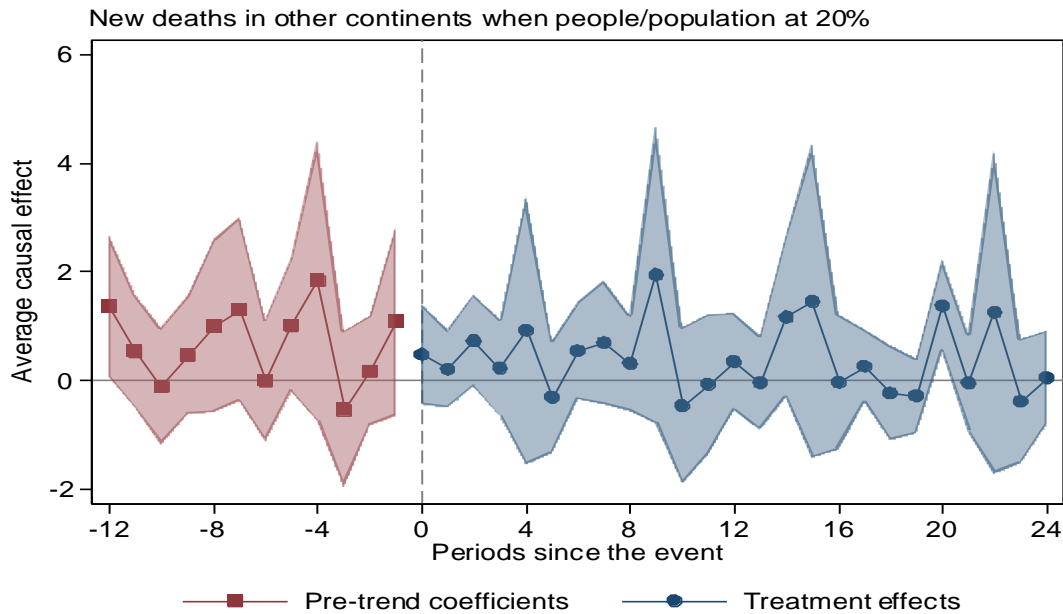


Figure 4: New deaths in Asia, Oceania, South America, and Africa before and after vaccinated people/population is at 20%

Note: The dots show the average treatment effects for each day around the event date in four continents: Asia, Oceania, South America, and Africa. That the blue dots mostly fluctuating around the x-axis implies the indecisive movement of new cases after vaccinated people/population is at 20%.

3.3. Robustness tests

We also use total vaccination doses per hundred capita (doses/population) as another measure of vaccination uptake rate for each country. Regarding the requirements of the parallel trend test (see Table A4.2 in Appendix 4), the level of 70% doses/population is used to robustly test the main result. Our results when using this alternative benchmark are still robust to the main results (see Tables 3A.1 in Appendix 3). In an additional analysis, we also report the statistical and visualized sensitivity tests on the causal effects of different levels of vaccinated people/population and doses/population (see Figure 5 and Appendix 4 and 5).

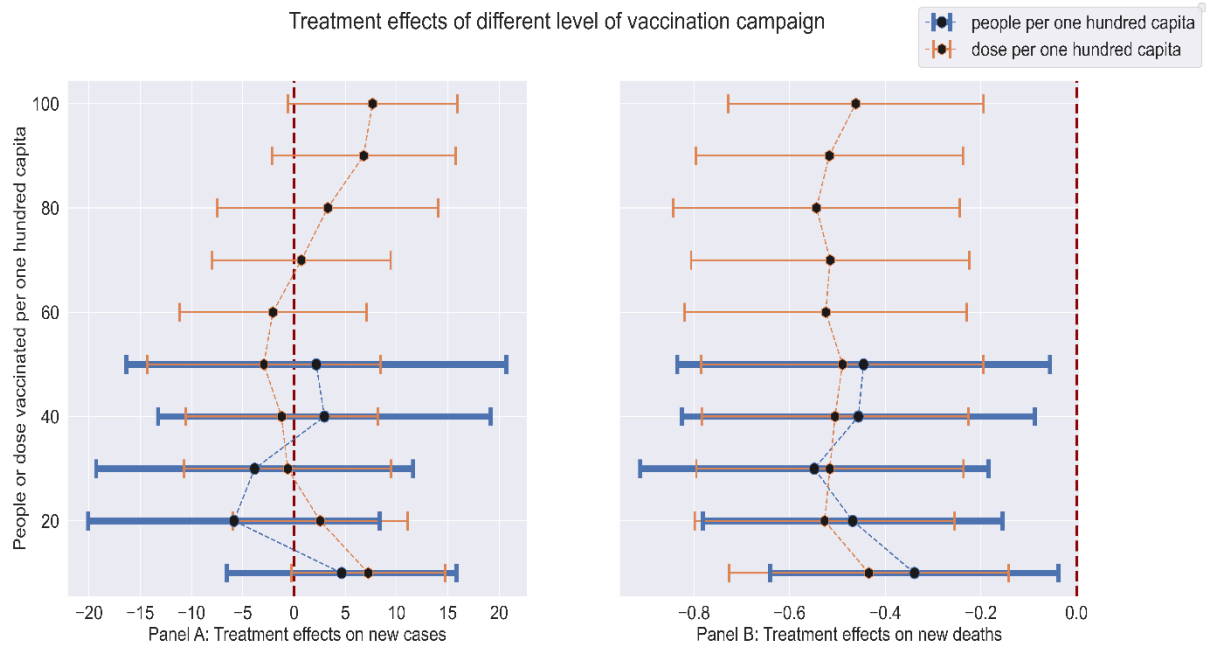


Figure 5: Mean and 95% confidence interval of treatment effects at different vaccination uptake rates.

Panel A shows that the treatment effects on new cases per million is not significant at all levels of vaccination campaign for both people vaccinated/population or dose vaccinated/population rates. In contrast, Panel B shows that at all levels of vaccination uptake rates, the difference in differences treatment effects on new death per million is significant and negative with mean treatment effects are approximately -0.451 and -0.503 for people vaccinated/population and dose /population, respectively.

4. Conclusion

Our paper provides causal evidence of significantly lower death rates (but the insignificant change in new cases) after achieving the high vaccination rate in the global scope. Our main finding is to estimate the lives saved by expanding and expediting the vaccination campaign. Our results have important implications for policymakers. Given the faster spread and evolution of different variants, vaccines exhibit the effective pharmaceutical intervention to save human lives during the COVID-19 pandemic. This refers to herd immunity. Therefore, it is possible to generalize the causal evidence to using vaccines to release the burden on the health system when the number of deaths increases. However, our results only focus on adult immunization while the children have no vaccines access. Concomitantly, the pronounced effects of Europe and North American could initially raise the vaccination inequality. This point sounds the alarm by equally distributing vaccines from advanced countries to developing economies to contain the spread and evolution of more dangerous variants.

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Appendix 1: Variable description, sources and descriptive statistics

Table A1.1: Variables description, correlation, and sources

Panel A: Correlation matrix of the main sample

	New cases	New deaths	Recreation	Park	Workplaces	Residential	Containment	Economic
New cases	1							
New deaths	0.5886	1						
Recreation	-0.1545	-0.2295	1					
Park	-0.0446	-0.1206	0.523	1				
Workplaces	-0.1285	-0.1521	0.6433	0.1608	1			
Residential	0.0794	0.1349	-0.7367	-0.465	-0.6695	1		
Containment	0.2346	0.2288	-0.4971	-0.2242	-0.388	0.4653	1	
Economic	0.1552	0.1029	-0.2396	0.056	-0.1961	0.172	0.3436	1

Note: This is the correlation matrix of the main sample

Panel B: Variables description

Variables	Description	Sources
New deaths per million	New daily confirm COVID-19 death per million population	Ritchie et al. (2020)
New cases per million	New daily confirm COVID-19 infected cases per million population	Ritchie et al. (2020)
Population_density (1,000 people/km2)	Population density index	World Bank national accounts data
Containment	Containment and Health index collected from the project of Covid-19 Government Response Tracker of Blavatnik School of Government, University of Oxford. The index combines ‘lockdown’ restrictions and closures with measures such as testing policy and contact tracing, short-term investment in healthcare, as well investments in vaccines.	Hale et al. (2021)
Economic	Economic support index collected from the project of Covid-19 Government Response Tracker of Blavatnik School of Government, University of Oxford. The index records measures such as income support and debt relief from governments during the COVID-19 pandemic	Hale et al. (2021)
Recreation Park Workplaces Residential	Daily change in mobility index in categories of Recreation/Parks and public/Workplaces/Residential according to baseline days from 3 Jan to 6 Feb 2020 collected from COVID-19 Google community mobility dataset. These data are calculated using aggregated, anonymized sets of data from users who have turned on the Location History setting	COVID-19 Google community mobility (2021)
Delta dummy	The variable receives the value of 0 before the first delta-variant case recorded in each country and 1 otherwise.	GISAID (2021). https://www.gisaid.org/hcov19-variants/

Table A1.2: Summary statistics

Variable	Obs	Mean	Std. dev.	Min	Max
Lag (cases)	67,889	88.357	174.691	0	3558.259
Lag (deaths)	63,958	1.727	3.939	0	215.334
New deaths per million	64,083	1.727	3.938	0	215.334
New cases per million	68,015	88.471	174.791	0	3558.259
Recreation	67,761	-18.734	26.184	-100	142
Park	67,432	5.001	55.218	-100	670
Workplaces	68,340	-20.551	19.213	-99	88
Residential	67,918	7.791	9.029	-35	55
Containment	67,339	57.307	15.739	0	92.02
Economic	67,362	48.904	30.627	0	100
Delta dummy	67,997	0.115	0.319	0	1

COVID-19 vaccination uptake rates by continents*

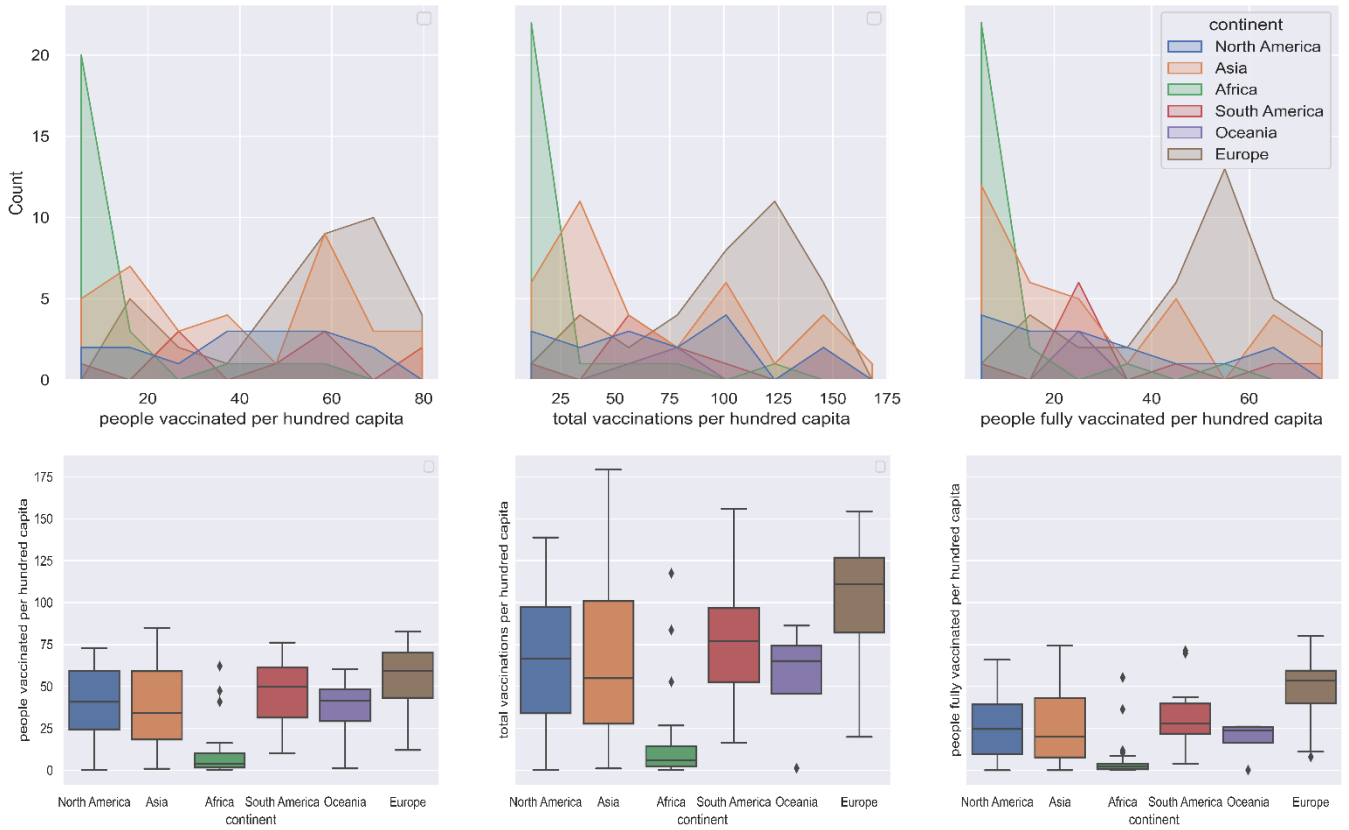


Figure A1.1: COVID-19 vaccination uptake rates distribution by continents until 26 August 2021. African countries have got the lowest COVID-19 vaccine uptake rate with the average number of vaccinated people per one hundred capita is only 5.4. European countries and North America have got the highest and second highest COVID-19 vaccine uptake rates with the average number of vaccinated people per one hundred are 25.63 and 24.06, respectively. The statistics for South American, Asian, and Oceanian countries are 22.24, 20.83, and 14.59, accordingly. *China is not included in the sample due to data unavailability.

Appendix 2: Assumption of Difference-in-Differences estimator

Appendix 2.1: Parallel trend test for the main results

We run the regression below on untreated sample to falsify the parallel trend violation:

$$Y_{it} = \alpha_i + \beta_t + X_{it} + D_{it} * \mu + \varepsilon_{it} \quad (3)$$

where D_{it} is the sets of indicators for observations during some periods before treatment ($t < 0$), with the periods before t serving as the reference group. For example, observations at t^{th} periods before the treatment date will receive the value of $D_{it} = 0$ and 1 otherwise.

We estimate μ by using OLS on untreated observations only, followed by a joint null test that $\mu = 0$ by using the Chi-squared test.

That the $\text{Prob} > \text{chi}^2$ of the joint null test is higher than 0.1 supports the parallel trend assumption. In other words, it means that there is an insignificant difference between treatment and control groups before the event date. Although there is no universal optimal choice of t (Borusyak and Jaravel 2018), we follow Dasgupta and Žaldokas (2019) to choose $k = 3$. Apart from that, we also go further to test the parallel trend assumption at $k = 5$ to solidify our results.

Table A2.1: Parallel trend test for people/population at 50% level

	New deaths		New cases	
t	5 days	3 days	5 days	3 days
Prob > chi2	0.429	0.334	0.768	0.816

Note: In this table, t is the number of periods before the event date used for the parallel trend test. Prob>chi2 is the p-value of the joint null test that $\mu = 0$. That Prob>chi2 is higher than 0.1 supports the parallel trend assumption. The results show that parallel is satisfied in both new deaths and new cases when vaccinated people/population reaches 50%.

Table A2.2: Parallel trend test for people/population by continents at 20% level

Panel A: Europe and North America

	New deaths		New cases	
t	5 days	3 days	5 days	3 days
Prob > chi2	0.2549	0.1808	0.197	0.0954

Panel B: Asia*, Africa, Oceania, and South America

	New deaths		New cases	
t	5 days	3 days	5 days	3 days
Prob > chi2	0.2485	0.5054	0.1938	0.3321

*Note: In this table, t is the number of periods before the event date used for the parallel trend test. Prob>chi2 is the p-value of the joint null test that $\mu = 0$. That Prob>chi2 is higher than 0.1 supports the parallel trend assumption. The results show that parallel is satisfied in both new deaths and new cases when vaccinated people/population reaches 20%. *China is not in the sample of Asian countries because of a lack of data.*

Appendix 2.2: Anticipation effects for the main results

“No anticipation effect” is another assumption in the Difference-in-Differences estimator apart from parallel trend satisfaction. This assumption is mainly focused on when examining how a law affects an outcome variable. For example, Dasgupta and Žaldokas (2019) examine anticollusion laws' impact on firms' asset growth. In this case, the anticipation effect should be tested because firms may receive the information about the anticollusion implementation through the government discussion, media, leading to that they adjust their assets expansion extents. Therefore, the “no anticipation effect” should be tested to support that the implementation of anticollusion laws is unpredicted or the prediction level is insignificant. In our case, we examine the changes of new deaths and new cases when the vaccinated population reaches specific levels, which is random and hardly predicted, meaning that the “no anticipation effect” should be a little concern in this situation. However, we also perform an anticipation investigation for main results as a comprehensive purpose-based test.

We investigate the existence of the anticipation effect following Borusyak and Jaravel (2018) by shifting the event dates in each country to three or five days before the actual ones. There is no universal rule to choose the number of periods to be shifted; we choose three and five days to be consistent with our parallel trend test. After having a series of τ_t by using equation (2), the relative effects of events on outcome variable in each date from the shifted date to the actual event date, we perform a joint null test on that $\tau_t = 0$ by using the Chi-squared test. That the Prob > chi2 of the joint null test is higher than 0.1, 0.05 means that the “no anticipation effect” assumption is supported at 1%, 5% significance levels in that order, advocating that the significant change of outcome variables is contributed to the actual dates that the vaccinated population reach specific levels.

Table A2.3: Anticipation test for people/population at 50% level

t	New deaths		New cases	
	5 days	3 days	5 days	3 days
τ_0	-0.074 (0.759)	-0.887* (0.066)	23.515 0.204	30.556 0.294
τ_1	0.733 (0.346)	-0.245 (0.222)	13.429 (0.426)	-4.752 (0.733)
τ_2	-0.779** (0.049)	-0.308 (0.405)	32.620 (0.267)	6.456 (0.657)
τ_3	-0.245 (0.228)		-4.427 (0.753)	
τ_4	-0.304 (0.413)		6.724 (0.646)	
	Joint null test			
Prob > chi2	0.248	0.238	0.663	0.772

Note: In this table, t is the number of periods shifted before the actual event date used for the anticipation investigation. τ_t ($t=0,1,2,3,4$) represents the corresponding estimates for 5th, 4th, 3rd, 2nd, 1st days before the actual event date. Prob>chi2 is the p-value of the joint null test that $\tau_t = 0$. The results show that the “no anticipation effect” assumption is satisfied in both new deaths and new cases when vaccinated people/population reaches 50%.

Table A2.4: Anticipation test for people/population by continents at 20% level

Panel A: Europe and North America

t	New deaths		New cases	
	5 days	3 days	5 days	3 days
τ_0	-1.146 (0.159)	-0.514 (0.148)	-2.071 (0.956)	-30.633 (0.100)
τ_1	0.285 (0.5)	0.270 (0.505)	-11.696 (0.697)	-13.273 (0.698)
τ_2	-0.519 (0.146)	-0.876** (0.038)	-30.703* (0.099)	-38.600** (0.023)
τ_3	0.266 (0.513)		-13.336 (0.697)	
τ_4	-0.891** (0.037)		-38.126** (0.023)	
	Joint null test			
Prob > chi2	0.2069	0.1543	0.1649	0.0849

Note: In this panel A, t is the number of periods shifted before the actual event date used for the anticipation investigation. τ_t ($t=0,1,2,3,4$) represents the corresponding estimates for 5th, 4th, 3rd, 2nd, 1st days before the actual event date. Prob>chi2 is the p -value of the joint null test that $\tau_t = 0$. The results show that the “no anticipation effect” assumption is satisfied in both new deaths and new cases when vaccinated people/population reaches 20% in Europe and North America.

Panel B: Asia*, Africa, Oceania, and South America

t	New deaths		New cases	
	5 days	3 days	5 days	3 days
τ_0	0.834* (0.090)	-0.832 (0.221)	62.131** (0.011)	1.572 (0.919)
τ_1	1.621 (0.153)	-0.044 (0.912)	50.833** (0.039)	38.918 (0.156)
τ_2	-0.549 (0.324)	0.894** (0.021)	7.973 (0.627)	33.795* (0.063)
τ_3	-0.025 (0.951)		40.312 (0.148)	
τ_4	0.918** (0.019)		35.003 (0.058)	
	Joint null test			
Prob > chi2	0.0002	0.0003	0.0307	0.1192

*Note: In this panel B, t is the number of periods shifted before the actual event date used for the anticipation investigation. τ_t ($t=0,1,2,3,4$) represents the corresponding estimates for 5th, 4th, 3rd, 2nd, 1st days before the actual event date. Prob>chi2 is the p-value of the joint null test that $\tau_t = 0$. The results show that the “no anticipation effect” assumption is violated in both new deaths and new cases when vaccinated people/population reaches 20% in Asia, Africa, Oceania, and South America. *China is not in the sample of Asian countries because of a lack of data.*

Appendix 3. Robustness test with 70% dose/population uptake rate *

Table A3.1: Parallel trend test and treatments effects on new deaths and new cases at 70% dose/population uptake rate

<i>t</i>	New deaths		New cases	
	5 days	3 days	5 days	3 days
Prob > chi2	0.461	0.2697	0.8406	0.6019
τ_w	-0.515*** (0.001)		0.721 (0.871)	
N	61,519		65,390	

*Note: In this table, t is the number of periods before the event date used for the parallel trend test. Prob>chi2 is the p-value of the joint null test that $\mu = 0$. That Prob>chi2 is higher than 0.1 supports the parallel trend assumption. The results show that parallel is satisfied in both new deaths and new cases when the dose/population reaches 70%. We control for country and year fixed effects, cluster standard error by countries. We also control for lag outcome variables, government policies, mobility variables, and a dummy variable standing for delta variants. The variable of interest here is tau_w. This table shows that new deaths per million significantly decrease while there is an insignificant or marginal change in new cases per million when vaccinated doses/population reach the 70% level. The numbers in parentheses are p-value. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively*

**The parallel trend test for vaccinated dose/population rates that larger than 70% are not satisfied (see Table A4.2 in Appendix 4). Thus, for comparison purposes, 70% dose/population uptake rate of the vaccination campaign is used as the benchmark for robustness test.*

Appendix 4. Sensitivity test for different vaccination uptake rates

Table A4.1: Parallel trend test and treatment effects for different levels of people vaccinated /population on new deaths and new cases per million

Panel A: New deaths per million

Levels	10% ^(v)		20%		30%		40%		50%	
t	5 days	3 days	5 days	3 days	5 days	3 days	5 days	3 days	5 days	3 days
Prob > chi2	0.077	0.041	0.616	0.339	0.666	0.559	0.104	0.335	0.429	0.334
τ_w	-0.338**		-0.468***		-0.548***		-0.456**		-0.445**	
	(0.027)		(0.003)		(0.003)		(0.016)		(0.025)	
N	61,519		61,519		61,519		61,519		61,519	

Panel B: New cases per million

Levels	10% ^(v)		20% ^(v)		30%		40%		50%	
t	5 days	3 days	5 days	3 days	5 days	3 days	5 days	3 days	5 days	3 days
Prob > chi2	0.001	0.0003	0.071	0.672	0.289	0.909	0.658	0.975	0.768	0.816
τ_w	4.645		-5.860		-3.841		2.966		2.168	
	(0.415)		(0.419)		(0.626)		(0.720)		(0.819)	
N	65,390		65,390		65,390		65,390		65,390	

Note: In this table, levels are different ratios of vaccinated people compared to the population. t is the number of periods before the event date used for the parallel trend test. Prob>chi2 is the p-value of the joint null test that $\mu = 0$ in Appendix 1. That Prob>chi2 is higher than 0.1 supports the parallel trend assumption. The asymptotic properties (consistency and efficiency) will hold approximately for sufficiently large enough samples (30 observations for OLS regression (Verbeek 2017)). There are less than 30 countries where vaccinated people/population reaches 60%; therefore, we examine the sensitivity from 50% and smaller levels. From panel A, we see that the parallel trend assumption is satisfied at all levels, leaving an exception for 10%. From panel B, the parallel trend assumption is satisfied at 30%/40%/50% levels. For the results of vaccination levels where the parallel assumption is violated, the (v) is put next to the associated levels. For testing the treatment effects, we control the lag outcome variable, government policy, mobility variables, and a dummy variable standing for delta variants. The variable of interest here is τ_w . The result from this table shows that new deaths significantly decrease while there is an insignificant change in new cases in any levels of vaccinated people/population when the parallel assumption is satisfied. The numbers in parentheses are p-value. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively

Table A4.2: Parallel trend tests and difference in differences treatment effects for new deaths per million and new cases per million in each level of vaccinated doses/population

Panel A: New deaths per million

Levels	10%		20%		30%		40%		50%		60%		70%		80% ^(v)		90% ^(v)		100% ^(v)	
t	5 days	3 days	5 days	3 days	5 days	3 days	5 days	3 days	5 days	3 days	5 days	3 days	5 days	3 days	5 days	3 days	5 days	3 days	5 days	3 days
Prob > chi2	0.6443	0.6097	0.2226	0.3644	0.7279	0.5275	0.0331	0.0671	0.0313	0.0084	0.220	0.1021	0.461	0.2697	0.0663	0.017	0.0552	0.1599	0.0028	0.0069
τ_w	-0.434***		-0.526***		-0.515**		-0.504***		-0.489***		-0.524***		-0.515***		-0.543***		-0.516***		-0.461***	
	(0.004)		(0.000)		(0.000)		(0.000)		(0.001)		(0.000)		(0.001)		(0.000)		(0.000)		(0.001)	
N	61,519		61,519		61,519		61,519		61,519		61,519		61,519		61,519		61,519		61,519	

Panel B: New cases per million

Levels	10%		20%		30%		40%		50% ^(v)		60%		70%		80% ^(v)		90%		100%	
t	5 days	3 days	5 days	3 days	5 days	3 days	5 days	3 days	5 days	3 days	5 days	3 days	5 days	3 days	5 days	3 days	5 days	3 days	5 days	3 days
Prob > chi2	0.4975	0.2405	0.2528	0.6058	0.3255	0.4107	0.7482	0.4496	0.0739	0.3211	0.4165	0.8343	0.8406	0.6019	0.0497	0.0157	0.1243	0.4754	0.348	0.2079
τ_w	7.2322*		2.5426		-0.6151		-1.2194		-2.9427		-2.063		0.721		3.2882		6.7789		7.6529*	
	(0.059)		(0.559)		(0.905)		(0.799)		(0.612)		(0.658)		(0.871)		(0.549)		(0.137)		(0.069)	
N	65,390		65,390		65,390		65,390		65,390		65,390		65,390		65,390		65,390		65,390	

Note: In this table, levels are different ratios of vaccinated people compared to the population. t is the number of periods before the event date used for the parallel trend test. Prob>chi2 is the p-value of the joint null test that $\mu = 0$ in Appendix 1. That Prob>chi2 is higher than 0.1 supports the parallel trend assumption. The asymptotic properties (consistency and efficiency) will hold approximately for sufficiently large enough samples (30 observations for OLS regression (Verbeek 2017)). There are less than 30 countries where vaccinated doses/population reaches 110%; therefore, we perform the sensitivity test when doses/population is at 100% and smaller levels. From panel A, we see that the parallel trend assumption is satisfied at 10%/20%/30%/60%/70% levels. From panel B, the parallel trend assumption is satisfied at almost all levels, leaving exceptions for 50% and 80%. For the results of vaccination levels where the parallel assumption is violated, the (v) is put next to the associated levels. For testing the treatment effects, we control the lag outcome variable, government policy, mobility variables, and a dummy variable standing for delta variants. The variable of interest here is τ_w . This table shows that new deaths significantly decrease while there is an insignificant or marginal change in new cases in any levels of vaccinated doses/population. The numbers in parentheses are p-value. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively

Table A4.3: Parallel trend test and difference in differences treatment effects for different levels of people/population in Europe and North America for new death and new cases

Panel A: New deaths per million

Levels	10%		20%		30% ^(v)		40% ^(v)		50% ^(v)	
t	5 days	3 days	5 days	3 days	5 days	3 days	5 days	3 days	5 days	3 days
Prob>chi2	0.2789	0.1567	0.2549	0.1808	0.0503	0.2262	0.034	0.2142	0.0267	0.0055
τ_w	-0.6779***		-0.5160***		-0.6906***		-0.5972***		-0.5431***	
	(0.001)		(0.001)		(0.000)		(0.000)		(0.000)	
N	25,785		25,785		25,785		25,785		25,785	

Panel B: New cases per million

Levels	10% ^(v)		20% ^(v)		30% ^(v)		40% ^(v)		50%	
t	5 days	3 days	5 days	3 days	5 days	3 days	5 days	3 days	5 days	3 days
Prob>chi2	0.1904	0.0805	0.197	0.0954	0.0018	0.0064	0.0177	0.0356	0.3195	0.3103
τ_w	-22.7756**		-22.6485**		-24.0563***		-8.7037		3.26	
	(0.018)		(0.017)		(0.009)		(0.272)		(0.717)	
N	26,711		26,711		26,711		26,711		26,711	

Note: In this table, levels are different ratios of vaccinated people compared to the population in Europe and North America. t is the number of periods before the event date used for the parallel trend test. Prob>chi2 is the p-value of the joint null test that $\mu = 0$ in Appendix 1. That Prob>chi2 higher than 0.1 supports the parallel trend assumption. The asymptotic properties (consistency and efficiency) will hold approximately for sufficiently large enough samples (30 observations for OLS regression (Verbeek 2017)). There are less than 30 countries where the vaccinated people/population in these two continents reaches 60%; therefore, we examine the sensitivity from 50% and smaller levels. From panel A, we see that the parallel trend assumption is satisfied at 10% and 20% levels. From panel B, the parallel trend assumption is satisfied only when 50% population gets vaccinated. For the results of vaccination levels where the parallel assumption is violated, the (v) is put next to the associated levels. For testing the treatment effects, we control for country and year fixed effects, cluster standard error by countries. We also control for lag outcome variables, government policies, mobility variables, and a dummy variable standing for delta variants. The variable of interest here is τ_w . The results from this table show that new deaths significantly decrease while there is an insignificant or marginal change in new cases in any levels of vaccinated people/population satisfying parallel trend assumption. We also report the results for levels where the parallel assumption is violated with the (v) next to the associated levels. The numbers in parentheses are p-value. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table A4.4: Parallel trend test and difference in differences treatment effects for different levels of people/population in Asia, Africa, Oceania, and South America for new death and new cases

Panel A: New deaths per million

Levels	10%		20%		30%	
t	5 days	3 days	5 days	3 days	5 days	3 days
Prob>chi2	0.2355	0.1425	0.2485	0.5054	0.5619	0.3867
τ_w	0.4942		0.2389		0.2871	
	(0.143)		(0.334)		(0.302)	
N	35,734		35,734		35,734	

Panel B: New cases per million

Levels	10% ^(v)		20%		30% ^(v)	
	5 days	3 days	5 days	3 days	5 days	3 days
t	5 days	3 days	5 days	3 days	5 days	3 days
Prob>chi2	0.0929	0.0503	0.1938	0.3321	0.087	0.0709
τ_w	31.455**		18.159*		22.461*	
	(0.038)		(0.087)		(0.077)	
N	38,679		38,679		38,679	

Note: In this table, levels are different ratios of vaccinated people compared to the population in four continents: Asia, Oceania, South America, and Africa. t is the number of periods before the event date used for the parallel trend test. Prob>chi2 is the p-value of the joint null test that $\mu=0$ in Appendix 1. That Prob>chi2 higher than 0.1 supports the parallel trend assumption. The asymptotic properties (consistency and efficiency) will hold approximately for sufficiently large enough samples (30 observations for OLS regression (Verbeek 2017)). There are less than 30 countries where the vaccinated people/population in these four continents reaches 40%. We see that the parallel trend assumption is satisfied at 10%, 20%, and 30% levels from panel A. From panel B, the parallel trend assumption is satisfied only when 20% population gets vaccinated. For the results where the parallel trend assumption is violated, the (v) is put next to the associated levels. For testing the treatment effects, we control for lag outcome variables, government policies, mobility variables, and a dummy variable standing for delta variants. The variable of interest here is τ_w . The results from this table show an insignificant or marginal change in new cases and new deaths in any levels of vaccinated people/population, satisfying the parallel trend assumption. The numbers in parentheses are p-value. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

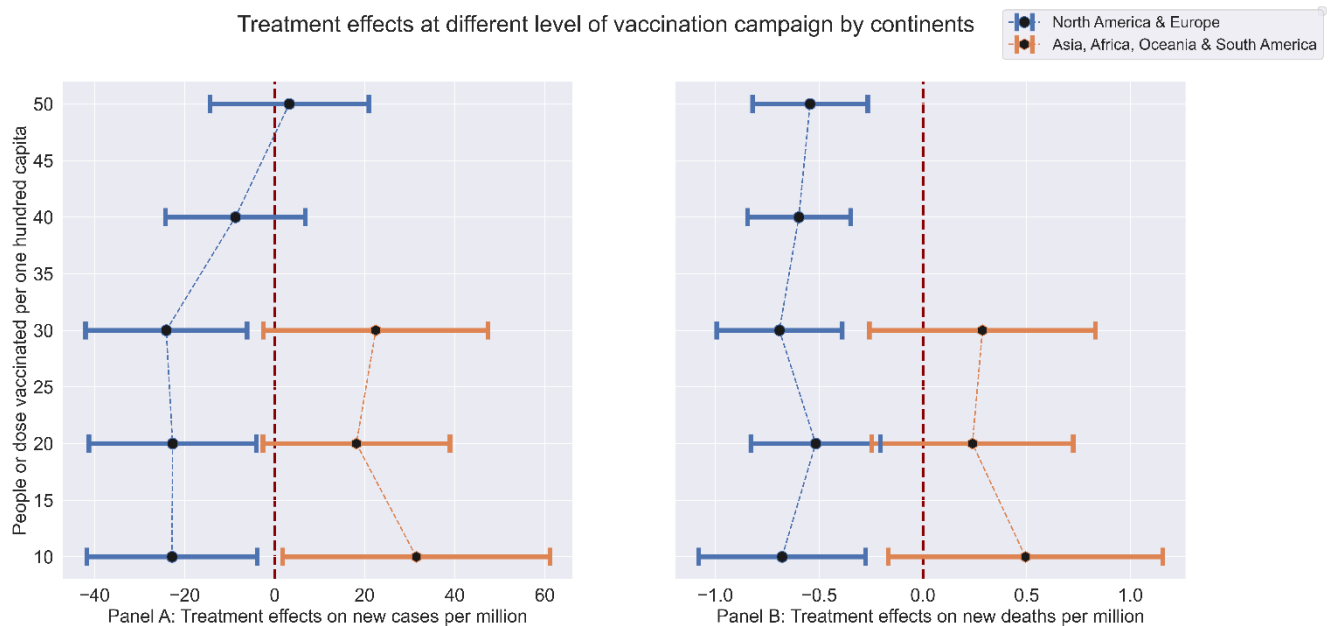


Figure A4.1: Mean treatment effects of different uptake rates of vaccination campaign and their 95% confidence interval by continents.

Panel A shows that for European and North American countries, the treatment effects on new cases per million is significant at 10%, 20%, 30% levels of vaccination campaign. Panel B shows that at all levels of vaccination campaign, the treatments effects on new death per million for European and North American countries are significant and negative at all levels. However, because of the violation of parallel trend test at most of the levels, the difference in differences treatment effects on new cases can only be concluded at 10% and 20%. For countries in Asia, Africa, Oceania and South America, the treatment effects are insignificant on both new death per million and new cases per million at all level of vaccination campaign.

Appendix 5. Visualizing the effects before and after the event dates of achieving different vaccination uptake rates satisfying parallel trend test

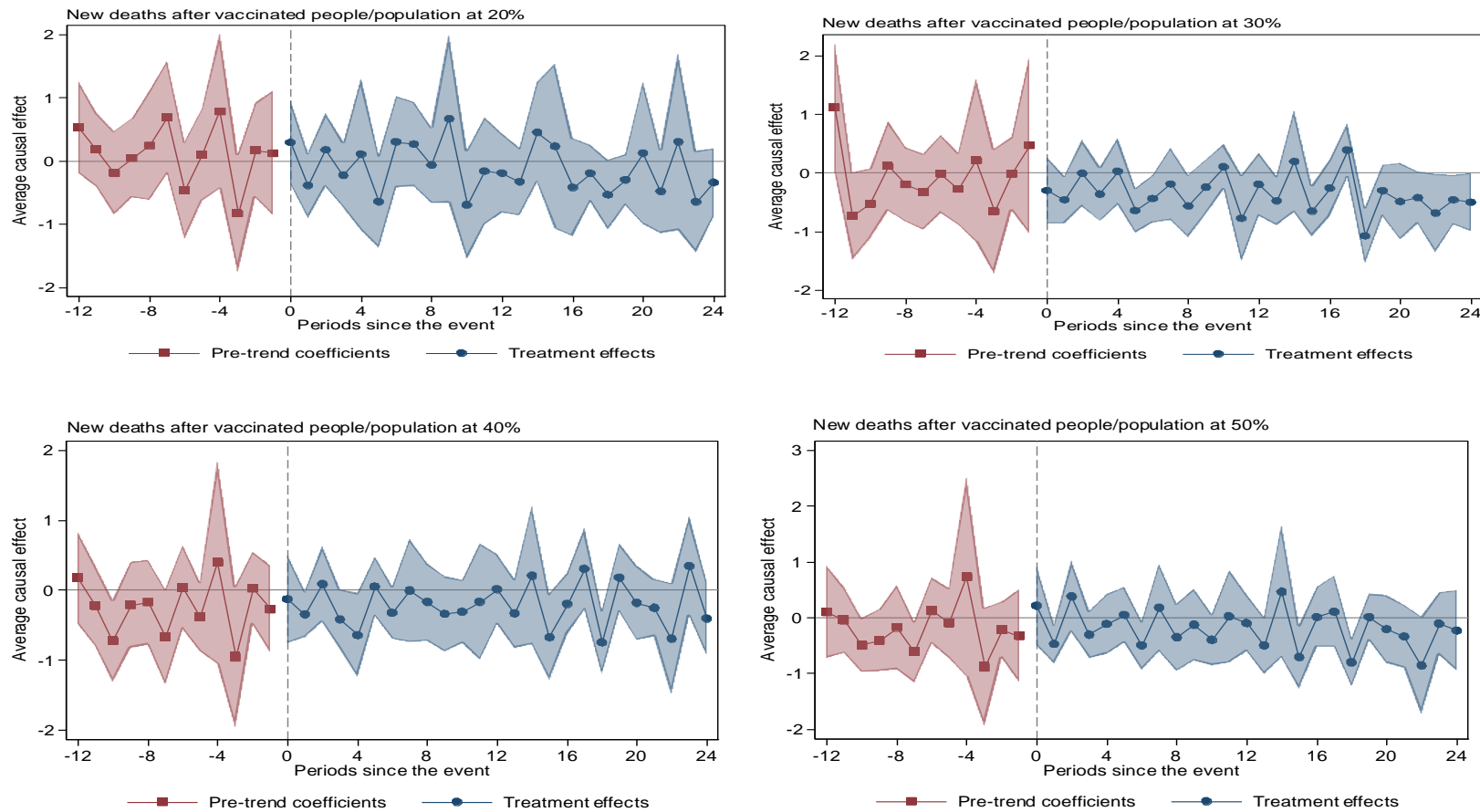


Figure A5.1: Visualizing the effects on new deaths per million before and after the event dates of achieving different vaccination uptake rates measured in people/population

Note: The dots show the average treatment effects for each day around the event date. That blue dots mainly lie under the x-axis implies the decrease in new deaths at any vaccinated people/population levels where the parallel trend assumption is satisfied.

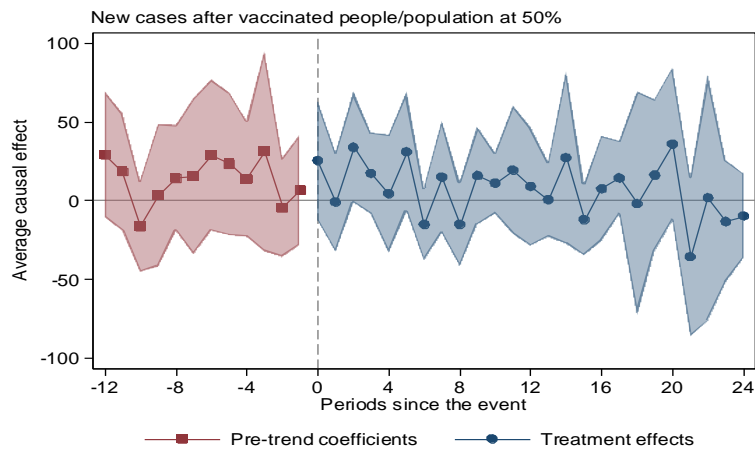
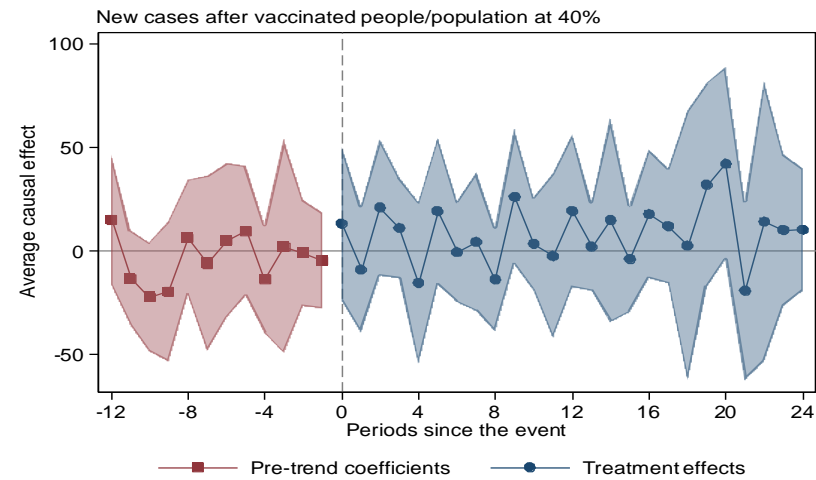
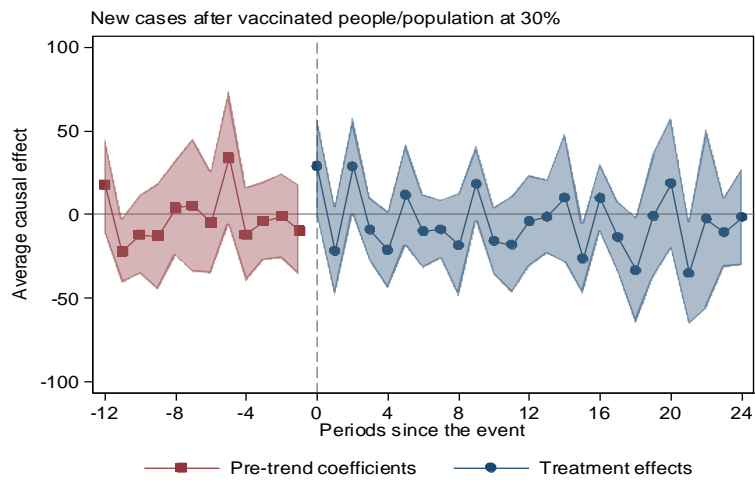


Figure 5A.2: Visualizing the effects on new cases per million before and after the event dates of achieving different vaccination uptake rates measured in people/population

Note: The dots show the average treatment effects for each day around the event date. That the blue dots mostly fluctuating around the x-axis implies the indecisive movement of new cases at any vaccinated people/population levels where the parallel trend assumption is satisfied.

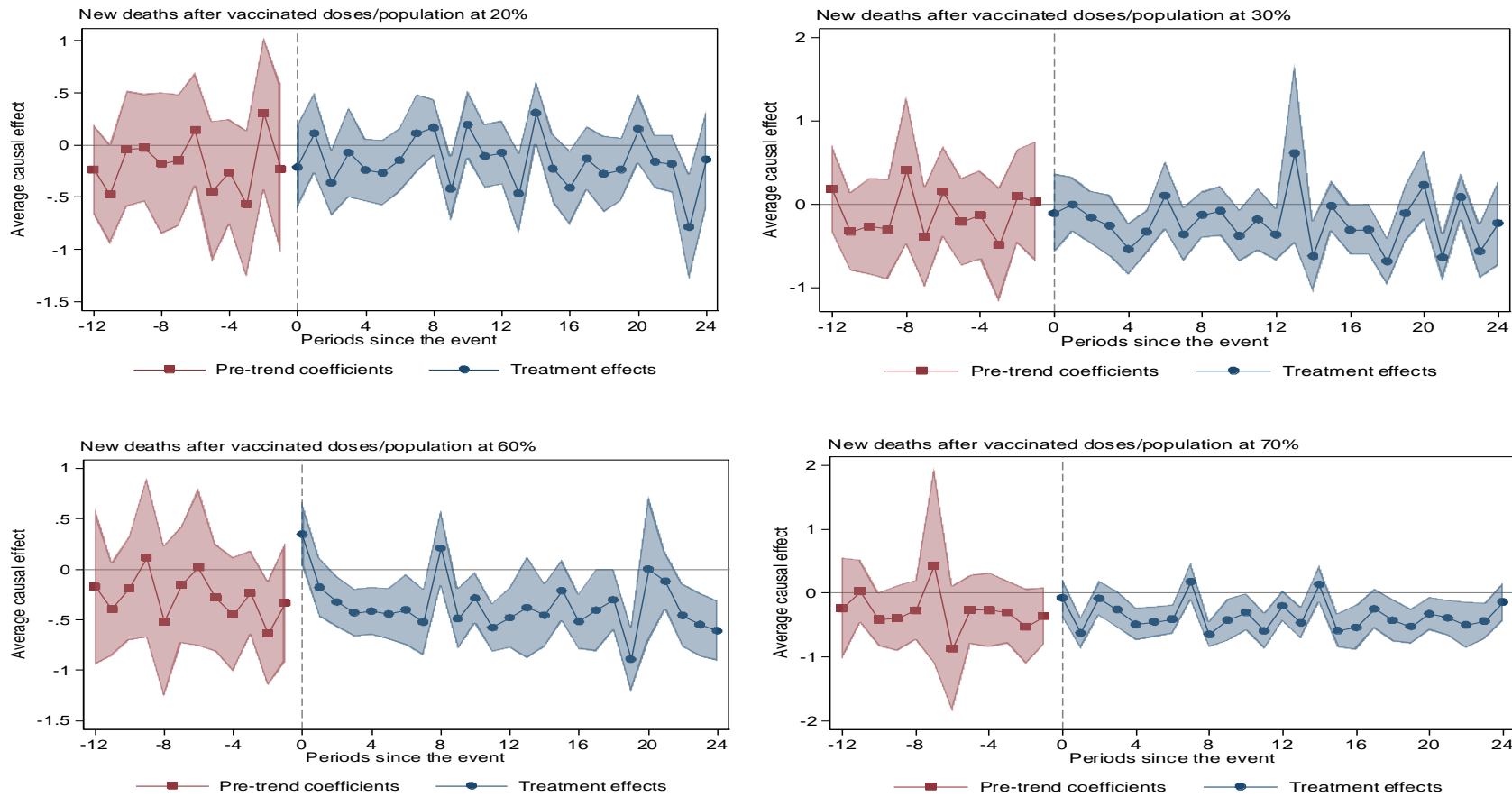
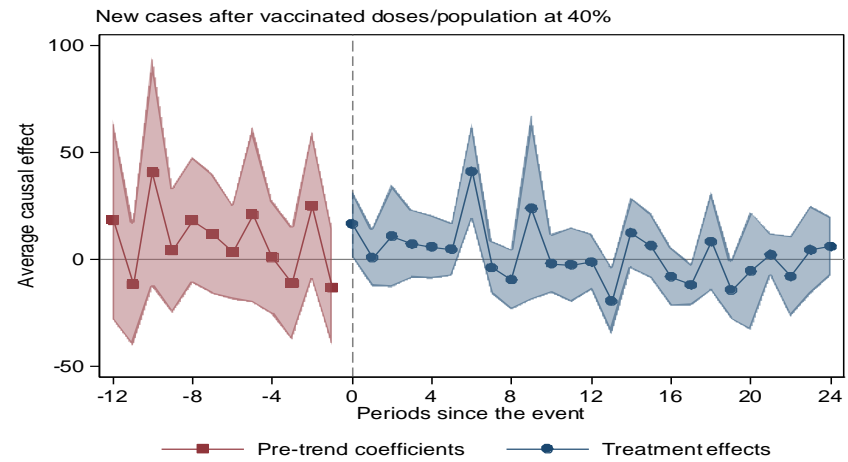
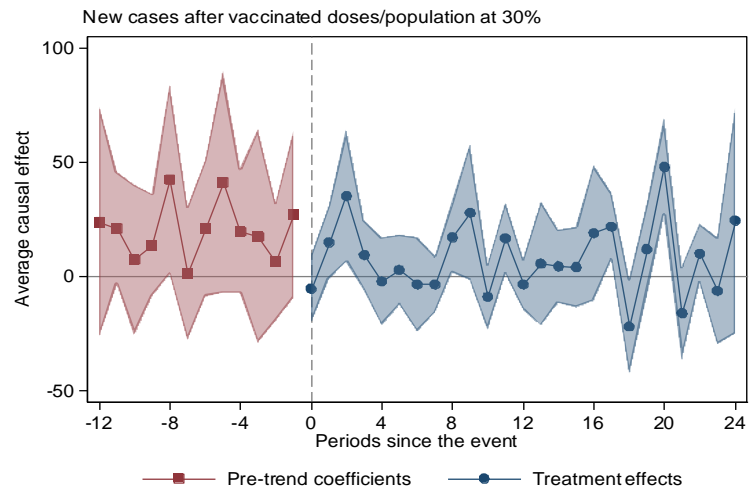
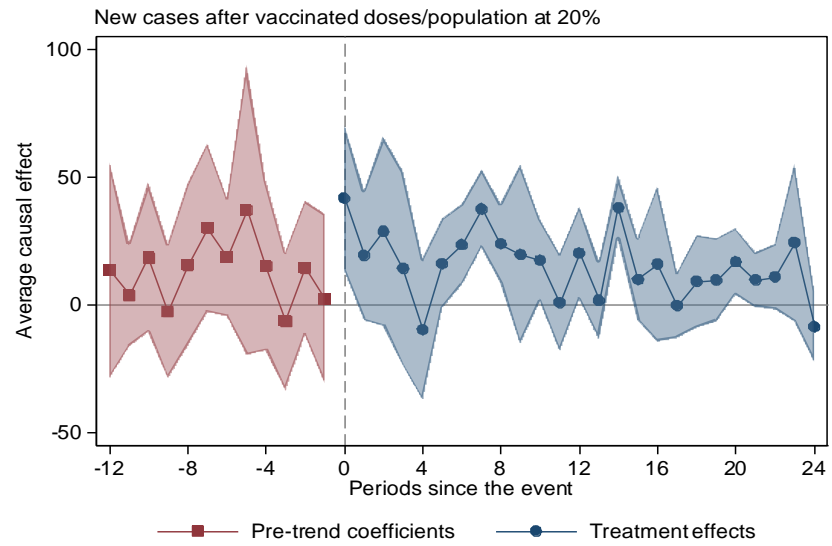
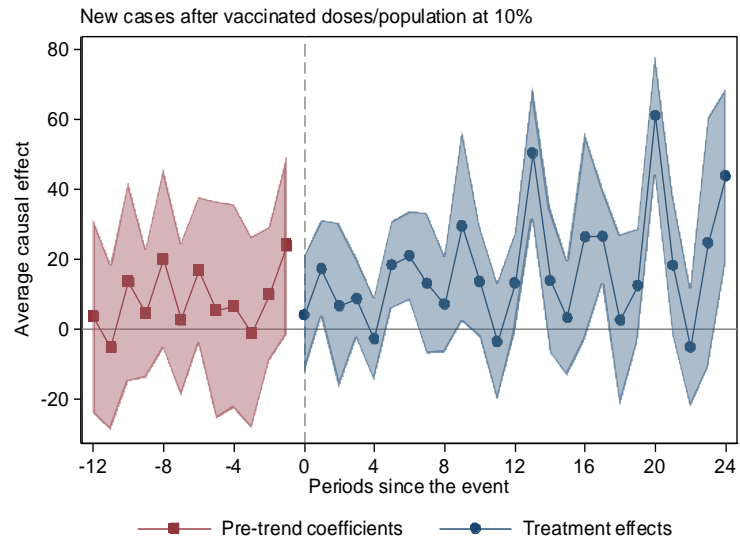


Figure 5A.3: Visualizing the effects on new death per million before and after the event dates of achieving different vaccination uptake rates measured in doses/population

Note: The dots show the average treatment effects for each day around the event date. That blue dots mainly lie under the x-axis implies the decrease in new deaths at any vaccinated doses/population levels where the parallel trend assumption is satisfied.



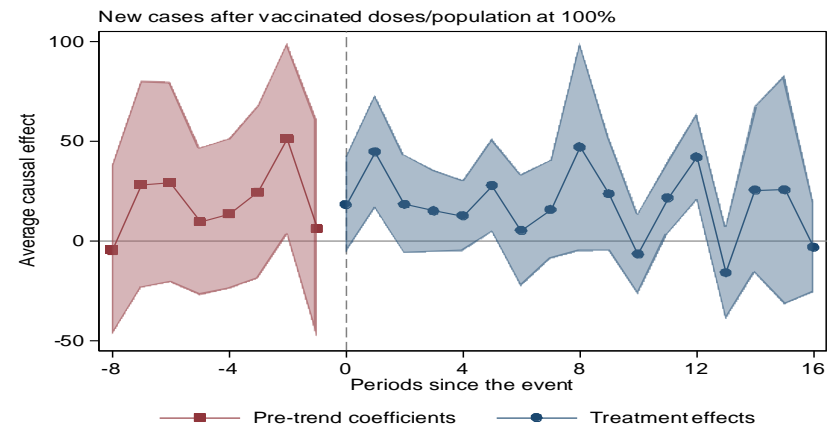
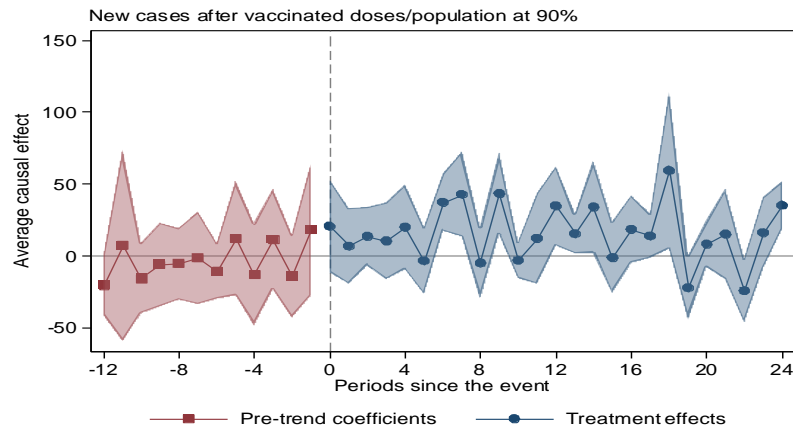
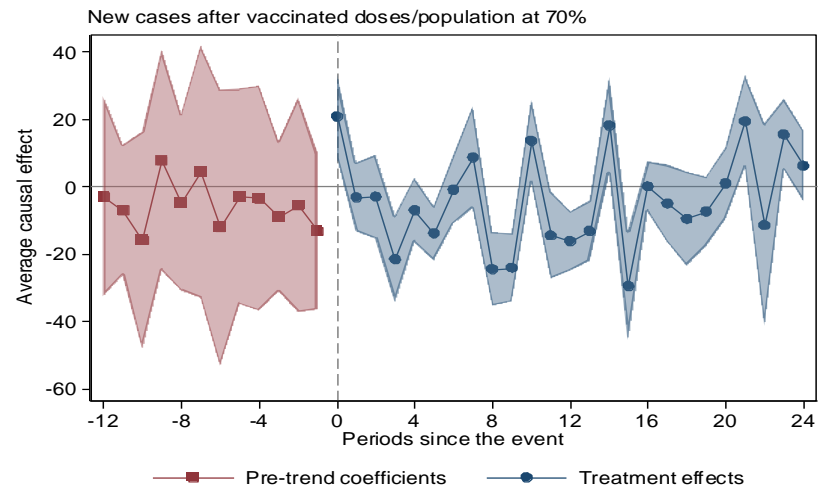
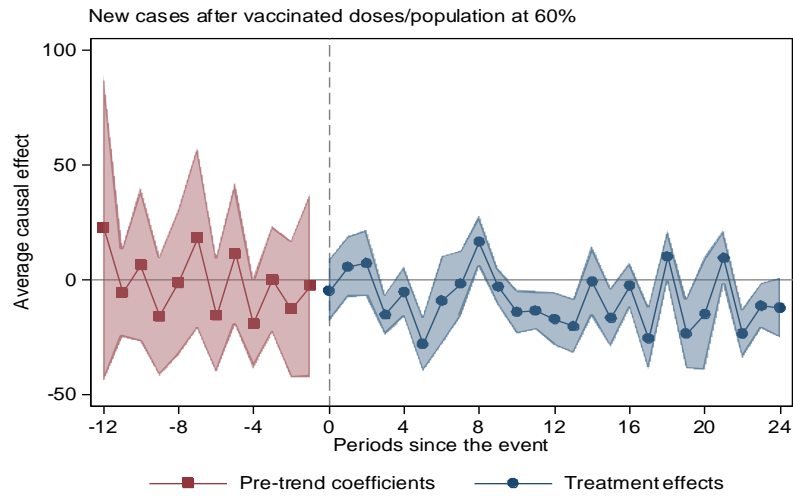


Figure 5A.4: Visualizing the effects on new cases per million before and after the event dates of achieving different vaccination uptake rates measured in doses/population

Note: The dots show the average treatment effects for each day around the event date. That blue dots mostly fluctuating around the x-axis implies the indecisive movement of new cases at any vaccinated doses/population levels where the parallel trend assumption is satisfied.

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