End of lockdown, *coronapistes* and circulation of bicycles in Paris

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1 Introduction

Beyond its effects on health, the COVID-19 pandemic and the successive lockdowns that resulted from it had major economic consequences in various areas (Brodeur, Gray, Islam and Bhuiyan, 2021), including mobility. At the end of lockdown, the municipality of Paris has decided to develop cycling exponentially through the creation of new bike-lanes, called *coronapistes*. This ambitious project created 52 km of cycle lanes at the end of 2020. This new cycle lanes were created on major development routes for cycling in Paris, following the metro lines. In addition to the development of new bike-lanes networks, the end of the lockdown may have impacted the number of bicycle users in Paris due to social distancing by avoiding public transport.

The aim of this paper is to estimate the joint effect of the end of the lockdown and the creation of *coronapistes*. To answer this question we use three sets of data[1] from the City of Paris' Open Data initiative. Using DiD (difference-in-differences) and a RDD-DiD (regression discontinuity design), we find a significant increase in the practice of cycling before and after the lockdown. The validity of our results is confirmed through a robustness test.

2 Empirical strategy

2.1 Difference-in-differences estimator

To estimate the effect of the end of lockdown and the development of new bike-lanes networks on the use of bicycles, we rely on differences-in-differences method. We compare the use of bicycles before and after the end of lockdown and the creation of *coronapistes* in 2020 to the use of bicycles before and after the same date in 2019. Since we consider the same analysis periods in the treatment group and the control group, this method allows us to control for the impact of seasonal changes on our results.

This differences-in-differences strategy assumes that the circulation of bicycles in Paris Y_i on day i can be written as:

$$Y_i = \alpha T_i \times t_i + \beta T_i + \gamma t_i + \sum_{j=1}^{4} \delta_j X_{ji} + \mu_i + \epsilon_i \tag{1}$$

where α is the joint effect of the end of lockdown and the development of new bike-lanes networks on the circulation of bicycles in Paris on day i. T_i is a dummy that takes value zero before the end of lockdown and one after the end of lockdown and the creation of *coronapistes*. t_i is equal to one for 2020 and zero in 2019. The models include day of the week fixed effects (μ_i).

We also include three covariates in the model. Firstly, because the use of bicycles was drastically reduced during the lockdown which constrained most of daily travel, we include a binary variable taking into account this effect. X_{1i} is equal to one during the lockdown and zero outside of this period. Secondly, there is a decrease in cycling during public holidays. We therefore create a binary variable X_{2i} equal to one on public holidays and zero on other days. Thirdly, the practice of the bicycle being able to be conditioned to the weather conditions, we take into account the temperature (X_{3i}) and the level of precipitation[2] (X_{4i}) on the use of bicycle.

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[1] *Réseau des itinéraires cyclables*, *Déconfinement - Pistes cyclables temporaires* and *Comptage vélo - Données compteurs.*

[2] The measurements of these two variables are taken in the Paris region, at Orly. We use the precipitation level during the last hour in millimeter and the temperature K at 6 am each day.

In this estimation strategy we assume common trend assumption. Then, in the absence of the end of lockdown and the creation of new bike-lanes networks, the use of bicycles in Paris would have evolved similarly in control and treatment groups.

2.2 RDD-DiD estimator

We also perform a regression discontinuity design to test for the immediate structural break caused by the end of the lockdown and the creation of *coronapistes*. We follow the strategy used in (Brodeur, Clark, Fleche and Powdthavee, 2021). Our RDD-DiD estimator compare potential breaks before and after the end of lockdown and the creation of new bike-lanes networks over the same period in 2020 and 2019 (figure 2). The RDD-DiD estimator can be written as follow:

$$\begin{aligned} Y_i &= \alpha' T_i \times t_i + \psi f(D_i) \times T_i \times t_i + \theta f(D_i)(1-T_i) \times t_i + \phi f(D_i) \times T_i \\ &\quad + \lambda f(D_i)(1-T_i) + \beta' T_i + \gamma' t_i + \sum_{j=1}^{4} \delta'_j X_{ji} + \mu'_i + \epsilon'_i \end{aligned} \tag{2}$$

where D is the distance in days from the end of the lockdown and the creation of *coronapistes*. This distance is negative before the cut-off and positive after. α' is the joint effect of the end of lockdown and the development of new bike-lanes networks on the circulation of bicycles in Paris on day i. $f(D_i)$ is a polynomial function of the distance in days from the end of the lockdown and the implementation of *coronapistes*. T_i and t_i are interacted with $f(D_i)$ in the RDD-DiD strategy and ψ, θ, ϕ and λ capture these effects. As in the DiD model, we include covariates for the lockdown effect, public holiday, the temperature and the level of precipitation. Our estimation are fitted using a polynomial of order one.

3 Results

3.1 Main estimates

Figure 1 show the circulation of bicycles in Paris before and after the the end of lockdown and the development of new bike-lanes networks for control and treatment groups. A difference in trend can be observed[3].

Table 1 presents the differences-in-differences estimates for the joint effect of the end of lockdown and the creation of *coronapistes*. The table reports coefficients using forward stepwise selection. Regardless of the specification used, a significant and positive effect is observed for the circulation of bicycles in Paris before and after the end of lockdown and the development of new bike-lanes networks. Once the effect of the lockdown on cycling in Paris is taken into account in the model, the results are relatively stable regardless the specification implemented.

3.2 RDD-DiD estimation results

In the RDD-DiD model we test the immediate structural break caused by the end of lockdown and the development of new bike-lanes networks. Our RDD-DiD estimator compare potential breaks before and after the end of the lockdown and the creation of *coronapistes* over the same period in 2020 and 2019. These estimated breaks are shown in figure 2.

As in the DiD estimation, the joint effect of the end of lockdown and the creation of *coronapistes* on the circulation of bicycles in Paris is significant and positive whereas the specification used (table 2).

3.3 Robustness check

To assess the validity of the results of our main estimates, we replicated our analysis in period before the creation of *coronapistes* and without lockdown. Then we assign placebo treatments. We run DiD with the period of 2018 like a control group and the period of 2019 as treatment group. If the ATT is significant it means that the common trend assumption does not hold (Lechner, 2010).

In table 3 we replicate our analysis in period before the treatment occurred. Full model specifications (columns 3 and 4) show that control and treatment groups have similar changes in the circulation of bicycles in Paris per day between 2019 and 2018. Standard errors are quite similar in magnitude than those of our baseline estimates. Our robustness check indicates that common trend assumption hold. In

[3]We have chosen to normalize our outcome to the maximum volume of bicycles traffic per day observed over the period.

other words, it means that the observed positive joint effect of the end of the lockdown and the creation of *coronapistes* on bicycles circulation in Paris is only valid for the period after the lockdown and the development of new bike-lanes networks.

Table 1: DiD estimates for the joint effect of the end of lockdown and the creation of *coronapistes*

	(1)	(2)	(3)	(4)	(5)
$T_i \times t_i$	35.22***	17.39***	17.69***	17.73***	17.36***
	(2.62)	(2.19)	(2.16)	(2.18)	(2.15)
Day fixed effects	Yes	Yes	Yes	Yes	Yes
Lockdown	No	Yes	Yes	Yes	Yes
Public holiday	No	No	Yes	Yes	Yes
Temperature	No	No	No	Yes	Yes
Precipitation	No	No	No	No	Yes
Observations	400	400	400	399	399

Note: The table reports the coefficient for the joint effect of the end of lockdown and the creation of *coronapistes*. Each column corresponds to a specification of the differences-in-differences estimation. The models include controls for the year and for the pré- and post- period of the end of lockdown and the creation of *coronapistes*. We also include controls for the lockdown period, public holidays, the temperature and the level of precipitation. The models include day of the week fixed effects. Robust standard errors are in parentheses. Standard errors are clustered at the day level.
$^*p \leq 0.1$;$^{**}\ p \leq 0.05$;$^{***}\ p \leq 0.01$.

Table 2: RDD-DiD estimates for the joint effect of the end of lockdown and the creation of *coronapistes*

	(1)	(2)	(3)	(4)	(5)
$T_i \times t_i$	63.59***	12.43**	11.90**	13.25**	12.44**
	(4.42)	(5.38)	(5.37)	(5.39)	(5.32)
Day fixed effects	Yes	Yes	Yes	Yes	Yes
Lockdown	No	Yes	Yes	Yes	Yes
Public holiday	No	No	Yes	Yes	Yes
Temperature	No	No	No	Yes	Yes
Precipitation	No	No	No	No	Yes
Observations	400	400	400	399	399

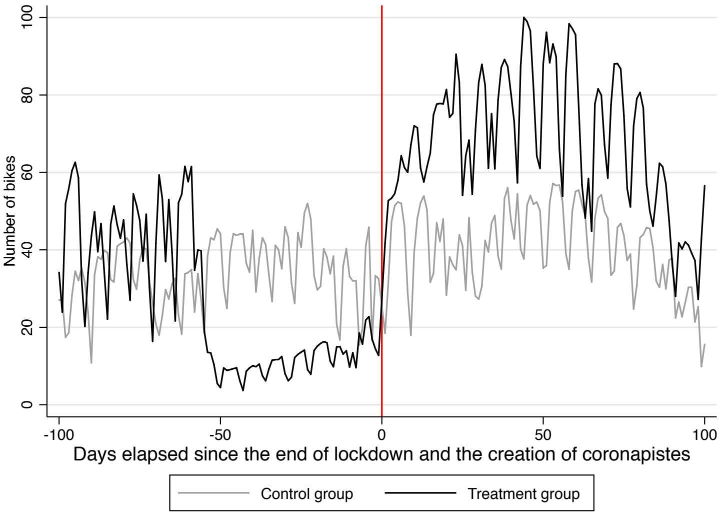
Note: The table reports the coefficient for the joint effect of the end of lockdown and the creation of *coronapistes*. Each column corresponds to a specification of the RDD-DiD estimation. The models include separate linear trends for the days elapsed before and after the end of the lockdown and the creation of *coronapistes* and are also fully interacted with the year 2020. The models include controls for the year and for the pré- and post- period of the end of the lockdown and the creation of *coronapistes*. We also include controls for the lockdown period, public holidays, the temperature and the level of precipitation. The models include day of the week fixed effects. Robust standard errors are in parentheses. Standard errors are clustered at the day level.
$^*p \leq 0.1$;$^{**}\ p \leq 0.05$;$^{***}\ p \leq 0.01$.

Table 3: Robustness checks for DiD estimates

	(1)	(2)	(3)	(4)
$T_i \times t_i$	-4.90*	-4.54*	-3.73	-3.73
	(2.73)	(2.71)	(2.74)	(2.75)
Day fixed effects	Yes	Yes	Yes	Yes
Lockdown	No	No	No	No
Public holiday	No	Yes	Yes	Yes
Temperature	No	No	Yes	Yes
Precipitation	No	No	No	Yes
Observations	400	400	398	394

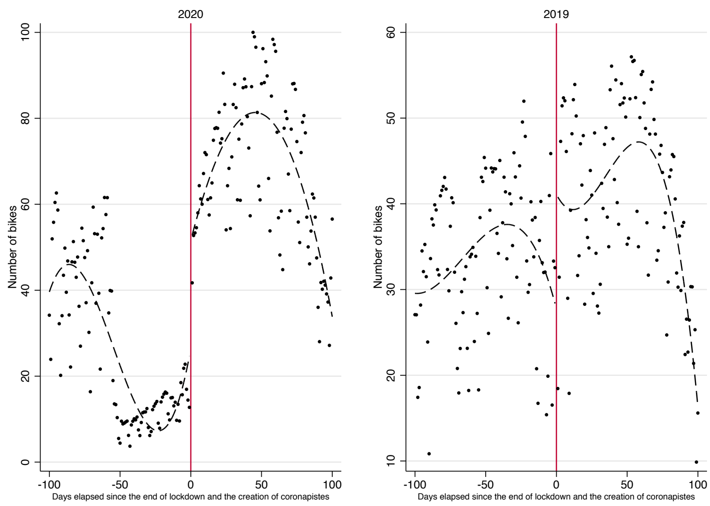
Note: he table reports the coefficient for the joint effect of the end of lockdown and the creation of *coronapistes*. Each column corresponds to a specification of the differences-in-differences estimation. The models include controls for the year and for the pré- and post- period of the end of the lockdown and the creation of *coronapistes*. We also include controls for public holidays, the temperature and the level of precipitation. The models include day of the week fixed effects. Robust standard errors are in parentheses. Standard errors are clustered at the day level.
$^*p \leq 0.1$;$^{**}\ p \leq 0.05$;$^{***}\ p \leq 0.01$.

Figure 1: Circulation of bicycles in Paris before and after the end of lockdown and the creation of *coronapistes*



Note: This figure displays the scalled number of bicycles per day (y axis) each day before and after the end of lockdown and the creation of *coronapistes* (y axis) for the control (grey line) and the treatment group (black line).

Figure 2: Circulation of bicycles in Paris before and after the end of lockdown and the creation of *coronapistes* (RDD-DiD strategy)



Note: This figure displays the scalled number of bicycles per day (y axis) each day before and after the end of lockdown and the creation of *coronapistes* (y axis) for the control (2019) and the treatment group (2020). Estimations are fitted using a polynomial of order 3.

References

Brodeur, A., Clark, A. E., Fleche, S. and Powdthavee, N. (2021), 'COVID-19, lockdowns and well-being: Evidence from Google Trends', *Journal of Public Economics* **193**, 104346.

Brodeur, A., Gray, D., Islam, A. and Bhuiyan, S. (2021), 'A literature review of the economics of COVID-19', *Journal of Economic Surveys* p. joes.12423.

Lechner, M. (2010), 'The Estimation of Causal Effects by Difference-in-Difference MethodsEstimation of Spatial Panels', *Foundations and Trends in Econometrics* **4**(3), 165–224.