CYCLING IN THE AFTERMATH OF COVID-19: AN EMPIRICAL ESTIMATION OF THE SOCIAL DYNAMICS OF BICYCLE ADOPTION IN PARIS

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Cycling in the aftermath of COVID-19: an empirical estimation of the social dynamics of bicycle adoption in Paris

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Abstract

The aim of this paper is to measure the role of social influence in transport mode switch to cycling. We propose an original approach to measure in the context of a natural experiment the influence of social factors on individual intentions within the theory of interpersonal behaviour, by modelling explicitly the diffusion of cycling within the population. We consider the time period following the end of the first COVID-19-lockdown in May 2020 in Paris, France, and estimate a simple model of social imitation based on data from the City of Paris' Open Data initiative, integrating also in our estimation geographical and temporal fixed-effects, as well as controls for the level of precipitation. We find that the increasing adoption of cycling between May and July 2020 can indeed be explained as the result of a new social dynamic tending to increase the switching rate between transport modes.

Keywords: Coronapistes; social imitation; urban design; cycling adoption; COVID-19; theory of interpersonal behaviour

Ethical statement

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1 Introduction

Transport is one of the very few sectors in Europe where greenhouse gas emissions did not decrease between 1990 and 2017 (EEA, 2019). This is the case because of a strong reliance on fossil fuels and the limited impact of electrification as a substitute source of energy (Creutzig et al., 2018). A more promising strategy to cut down emissions seems to be the transition to low-carbon modes of travel, with the promotion of 'active travel' such as cycling and walking (Amelung et al., 2019; Neves and Brand, 2019). Our aim in this paper is to measure the role of social influence in transport mode switch to cycling, by focusing on the effects on bicycle commuting (henceforth, BC) of the various policies implemented in the aftermath of the first COVID-19 lockdowns in 2020. Our analysis contributes to model how social norms influence individual intentions within Triandis (1979) Theory of Interpersonal Behaviour (TIB). Such influences on one's intentions and behaviours may indeed remain significantly underdetected (Nolan et al., 2008), implying that they might be better identified through structural modelling of collective behaviours rather than traditional approaches relying on self-reported individual data. We will thus consider the dynamic evolution of aggregate behaviours and characterise the rate of diffusion of BC within the population, which offers a new approach to effectively *measure* the role of social influence on the choice of transportation mode.[1]

We focus in this paper on the BC rate in Paris, France, based on data from the City of Paris' Open Data initiative. We will estimate the dynamic of BC adoption following the end of the first lockdown (from May 11th, 2020 to July 13th, 2020 – see section 5.2 for more details about the choice of this time window) so as to determine whether (i) there has indeed been an increase in BC compared to the pre-COVID-19 period, and whether (ii) this increase was driven by an emerging social dynamic of imitation, which could last over the COVID-19 crisis, leading potentially to a continuing increase of the BC rate. For sakes of clarity, we will use the labels 'PCP' to designate the pre-COVID-19 period (prior to March 2020), and 'PLP' for the post-lockdown period (from May 11, 2020 onwards). Our analysis highlights that the BC rate did increase during PLP compared to PCP, and furthermore that there

[1] A precise theoretical characterisation of the diffusion dynamic of social influence within the population is out of the scope of the present paper — which remains mostly applied — though we describe in the conclusion along which lines our theoretical model could be refined.

exists a statistically significant effect akin to a form of social influence in the growth of BC during PLP, while this effect did not exist during PCP. This result suggests that the different changes observed during PLP — whether it be the creation of new 'corona' bike lanes, a growing environmental awareness (Severo et al., 2021), or a general aversion to closed spaces such as crowded public transports (Shelat et al., 2022) — contributed to initiate a dynamic of BC adoption that did not exist prior to the COVID-19 crisis. Understanding the precise mechanisms at the origin of such dynamic would provide a significant help to better design future policies aiming to increase BC, which would probably be a more efficient strategy to reduce carbon emissions than technological innovations alone (Brand et al., 2021).

The paper is structured as follows. Section 2 reviews the literature of the effects of the COVID-19 crisis and the different post-lockdown policies implemented in 2020 on the rate of BC. We then present our theoretical framework and state our main hypotheses in section 3. We present the data and our estimation strategy in section 4 and the main results in section 5. Section 6 concludes.

2 Promoting cycling in the aftermath of COVID-19

2.1 Promotion of cycling through urban design

Urban design plays a pivotal role for environmental and health policies, in particular as a means to promote active travel modes such as walking and cycling. The switch from cities built around car-as-default to more sustainable modes might however be very challenging, because notably of a high inertia in individuals' travel habits. When considering the population of would-be cyclists, Cabral and Kim (2020) propose a classification with three types of individuals: (i) 'Uncomfortable or Uninterested', (ii) 'Cautious Majority', and (iii) 'Very Comfortable Cyclists'. Given that individuals belonging to (i) are unlikely to adopt BC and that those from (iii) are already convinced, the core target of policies aiming to promote BC should be (ii), the cautious majority, who would agree to cycle if offered a safe and comfortable environment.

Pucher et al. (2010), in a literature review over 139 studies, confirms that public interventions targeting urban design have a strong effect on the promotion of BC. The main type of policy is to provide separate cycling facilities along roads (Buehler and Dill, 2016;

Götschi et al., 2016; Pucher and Buehler, 2008, 2017; Winters and Teschke, 2010), which contribute to enhance the safety, convenience, and average travel speed of cyclists, as well as reduce car traffic in residential neighbourhoods.[2] Moreover, the development of off-road bike paths may also contribute to a more inclusive practice of cycling, as it seems that such infrastructures are more likely to increase cycling among women (Garrard et al., 2008). In cities with a low level of BC, as in many French cities compared to countries like Denmark, the Netherlands, and Germany, reallocating the road space to the benefit of cyclists might be helpful in converting new riders to overcome the *a priori* perceived risks as well as improving the overall safety of BC (Harms et al., 2016).

Following the COVID-19 crisis, public policies invested in the development of new cycling infrastructures in order to promote BC. Cycling indeed offers a convenient transport mode which may limit the risk of contamination, especially compared to possibly crowded public transports. The World Health Organization explicitly promoted cycling and walking in this perspective,[3] and THE PEP[4] acknowledges in the new draft of the Pan-European Master Plan for Cycling Promotion (May 2021) that the development of cycling infrastructures can contribute to the resilience of cities and urban transport systems to future shocks of a similar nature — in addition to positive effects on health[5] and the environment[6]. Public authorities have thus encouraged cycling by redistributing, temporarily or definitively, the space allocated to different types of vehicles (Nikitas et al., 2021). Reviewing the effects of the creation of such infrastructures in 22 European cities — 11.5km of new cycle paths on average between March and July 2020, with almost 52km for Paris — Kraus and Koch (2021) estimate a large and rapid upsurge in cycling, of a magnitude between 11 and 48% depending on the cities.

[2] A complementary type of policy consists in increasing the costs of using cars, by making it more expensive (through taxes on car ownership, use, parking) and less convenient (Pucher, 1997; Pucher and Buehler, 2008).

[3] See information sheets on ‘Moving around during the COVID-19 outbreak’ `https://www.euro.who.int/en/health-topics/health-emergencies/coronavirus-covid-19/publications-and-technical-guidance/environment-and-food-safety/moving-around-during-the-covid-19-outbreak`

[4] Transport-Health-Environment Pan-European Programme.

[5] E.g. Götschi et al. (2016); Huy et al. (2008); Nieuwenhuijsen (2016); Oja et al. (2011); Pucher and Dijkstra (2003); Pucher and Buehler (2017).

[6] E.g. Handy et al. (2014); Pucher and Buehler (2017).

2.2 Public transports and cycling after the pandemic

In addition to improved infrastructures, a key element in the development of cycling after the end of the first lockdown might have been the perceived health risks of using public transports, leading to a likely mode switch from public transport to cycling. Many studies indeed highlighted that public transport could play an important role in the diffusion of the SARS-CoV-2 virus (e.g. Zheng et al. (2020) on the early diffusion of the virus from Wuhan to other cities in China), because of the air recirculation system in buses (Shen et al., 2020) and the reduced distance at which passengers could get infected in public transports (Hu et al., 2021; Yang et al., 2020). Rahimi et al. (2021) for instance find that 44% of respondents in a SP-RP[7] survey in the Chicago metropolitan area perceive the use of public transit as an “extremely high risk”. Furthermore, Gnerre et al. (2022) find that the perceived risk of using public transports in Turin, Italy, is rated as “extremely risky" both during and after the pandemic. This negative perception, combined with the injunction to social distancing (Hörcher et al., 2022) — which constituted the preferred control strategy to limit the diffusion of the virus before that vaccines became widely available — contributed to an important disaffection of public transport, and inevitably led to a decline in the relative share of public transport users in favour of individual transport modes (cycling but also car – see e.g. Eisenmann et al. (2021) for Germany).

This decline and the change in commuting behaviours has been confirmed by many studies,[8] such as Ciuffini et al. (2021) for Italy, Germany, Canada and USA, based on requests for direction in Apple Maps. Using mobility data of a sample of Berlin residents between January 1st 2019 and September 30th 2021, Kellermann et al. (2022) identify a substitution between public transport and cycling, with a reduction of the number of trips (-49.91%) and distance (-43.16%) for public transports and a significant increase in number of trips (+52.58%) and distance (+116.66%) for cycling. Buehler and Pucher (2021, 2022) also find that cycling increased significantly between 2019 and 2020 in most cities of Europe, North America and Australia and hypothesize that this increase mostly came from former public transport passengers who switched to cycling because of the fear of crowded trains

[7] Stated preference - revealed preference.

[8] A necessary cautionary note is that the pandemic also contributed to the generalisation of remote working, with a direct impact on all modes of travel (Gkiotsalitis and Cats, 2021; Gray, 2020; Nicola et al., 2020), and possibly a relative reduction in bicycle trips (Moulin, 2022)

and buses. Möllers et al. (2022) also find that the switch from public transport to cycling appears to be more pronounced in cities where cycling initially represented a lower modal share. Lastly, we can expect those change to have lasting consequences on travel behaviours. Using a representative sample of 2,800 members from the Netherlands Mobility Panel during the crisis, de Haas et al. (2020) have measured that 20% of people said they would cycle more after the health crisis. Similarly, in the United States, using a representative sample of American adults from the Harris Poll panel, Ehsani et al. (2021) found that respondents anticipated a significant increase in cycling after the pandemic (estimated at 24.54%).

3 Theoretical background and research hypotheses

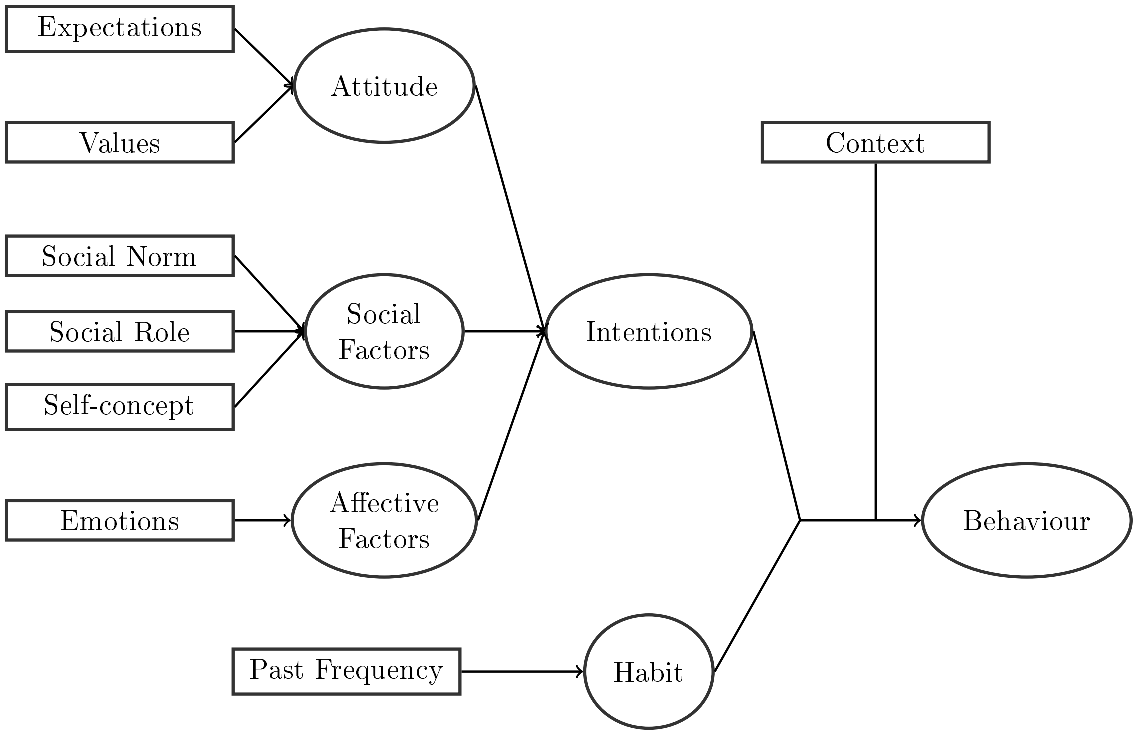
3.1 Theoretical background

We propose to explain transport mode switch by relying on Triandis (1979) Theory of Interpersonal Behaviour (TIB, Figure 1), which constitutes a multidimensional theory explaining behavioural patterns as the result of the combination of internal responses (intentions and habits of the individual) and external conditions (facilitating conditions in the environment). Numerous studies have investigated the role of habits and the socio-psychological determinants of attitudes toward different transport modes such as cycling (Johansson et al., 2006; Galdames et al., 2011; Osman Idris et al., 2015; Gutiérrez et al., 2020; Clark et al., 2021). Lizana et al. (2021) highlight for instance the significant role of attitudes — in addition to facilitating infrastructures — in explaining BC, though the effect is moderated by habit. This suggests that attitudes may contribute to *initiate* the practice of cycling, while the maintenance of the practice is mainly due to habits.

olicies intending to promote BC must therefore first act on fostering the non-cyclists' positive intentions towards cycling, while counting on the reinforcing role of habits to maintain *a posteriori* a sustainable shift to BC. According to the TIB, intentions result from the combination of attitudinal, affective, and social factors, which may produce a certain behaviour (under favourable habitual and contextual aspects), and then possibly lead to the formation of a new habitual conduct (Galdames et al., 2011).

A limitation however of many studies is the lack of a precise *measure* of the effects of social factors on individual behaviours within the TIB. Given the fundamental holistic

Figure 1: Theory of Interpersonal Behaviour



Note: Adapted from Triandis (1979); Galdames et al. (2011).

nature of social influence, it cannot be properly apprehended by solely focusing on individual data — whether it be self-reported answers or the observation of atomistic behaviours — but requires instead investigating the structure of the dynamic of social diffusion within the population. Some recent studies propose to tackle this issue by explicitly integrating elements from network theory to address the dynamic of social influence (Manca et al., 2019, 2020, 2022). Our aim in this paper is to propose a first step in the application of such models to the analysis of data derived from natural experiments. Since this type of analysis requires a heavier statistical treatment than laboratory experiments, we limit ourselves in this paper to a simple model of social imitation with a diffusive logistic model, in line with many classical models of social transmission and innovation diffusion (Giraldeau et al., 1994; Hagerstrand, 1967; Mansfield, 1961). We are aware however that such models require the absence of diffusion irregularity within the network (Raynaud, 2010), meaning that a more elaborated network analysis will be necessary in future research.

3.2 Research hypotheses

We intend to determine whether the various policies implemented in Paris in May 2020 aiming to promote BC [the 'Policies' for short], with in particular the creation of new cycle lanes, initiated a process where more and more members of the cautious majority started to cycle because of a dynamic of social imitation. This process could be driven by the progressive formation of a new social norm, built on the positive signal send to non-cyclists — observing more cyclists on the road constitutes indeed a signal that cycling is becoming safer and more comfortable, which is likely to convince this population to switch, which would then reinforce the signal sent to non-cyclists. Our focus on the post-lockdown period derives from two elements: (i) there has been an exogenous shock with a significant improvement of cycling infrastructures (improving the external conditions, see Table A.1), and (ii) because of the sanitary context, there was an initial exogenous motive to avoid public transport and switch to BC (see section 2.2). What we will measure in this paper is the dynamics of the *diffusion* of BC adoption among the population in the weeks that followed the opening of the networks of *coronapistes* in Paris, and the progressive adaptation to these new infrastructures.

We will use the data of the network of cycling counters in Paris to measure bicycle traffic. M_t denotes the number of bikes counted on day t.[9] We define N as the theoretical maximum value of M_t, i.e. the highest number of bikes that could be counted on day t if BC was at its maximum level.[10] We define the conversion rate μ_t as the share of non-cyclists in t who choose to cycle in $t+1$:

$$\mu_t = \frac{M_{t+1} - M_t}{N - M_t} \tag{1}$$

We also define the rate $\lambda_t = \frac{M_t}{N_t}$ as the variable of interest from the perspective of public policy, measuring the progresses to be made before reaching the maximal level of BC.[11] A high λ_t means than most individuals who can either travel by bike, car, or public

[9] M_t is very likely much higher than the actual number of cyclists: each cyclist is indeed probably counted at several points of passage during one trip. It is however a reasonable proxy for the overall traffic of cyclists and the rate of BC.

[10] We detail in section 5.2 our estimation of N, based on data from Copenhagen that we take as a benchmark for the maximum level of BC

[11] Note that even $\lambda_t = 1$ would not mean that the city would be car-free, since a fraction of urban travels cannot be done by bike — such as large deliveries, and transport of individuals who cannot cycle.

transport choose *in fine* to cycle. In what follows, we will only consider BC and 'other modes of transport', without disentangling between cars and public transport as alternatives to cycling. This is because our focus is explicitly about the adoption of BC, and we will not investigate further whether new riders were former drivers or users of public transport. Although the literature reviewed above suggests a switch from public transports to cycling, this point should of course be investigated, but this is beyond the scope of the current paper.

We propose to model the effect of social influence by hypothesising a direct relationship between μ_t and λ_t, with

$$\mu_t = \phi \lambda_t \tag{2}$$

ϕ captures the effect of the influence of the population of cyclists on non-cyclists, since a higher λ — meaning that more individuals from the population of potential cyclists *do* cycle — implies a higher conversion rate when $\phi > 0$, i.e. a higher share of the remaining non-cyclists will choose to cycle the day after. This simple model suggests that, in the absence of social influence, we would be at a steady state where individuals stick with their preferred transportation mode. Given the restricted time period over which we will estimate the model (two months from mid-May to mid-July in 2019 and 2020), we attribute the causes of the conversion rate μ_t to behavioural imitation solely, meaning that we should observe $\mu_t = 0$ if $\phi = 0$. Clark et al. (2016) indeed suggests that switches to active commuting (cycling and walking) are primarily driven by life events such as changing jobs or moving home, as well as high quality public transport links to employment centres — and we can expect those factors to have remained stable over the two months we consider in our estimation (knowing in particular the general reluctance towards public transports in the period). The only significant changes are indeed the creation of the *coronapistes*, and we expect to measure the progressive conversion of the population to this improved infrastructure. In the absence of social influence, we should merely observe a possible surge in BC right after the end of the lockdown, which would then remain at a stable level.

Given the relationship between μ_t and λ_t described in equation (2), we can check that the diffusion of BC within the population follows a logistic evolution:

$$\lambda_t = \frac{1}{1 + \exp^{-(C+\phi t)}} \tag{3}$$

The constant C adjusts the level of λ, while ϕ can be interpreted as a factor of social influence, describing the rate at which non-cyclists in t starts to cycle in t+1. The hypotheses we will test in our study are the following:

- H1 λ_t is significantly higher during PLP compared to its PCP level
- H2 $\phi > 0$: the conversion rate μ_t depends positively on λ_t during PLP
- H3 $\phi_{PLP} > \phi_{PCP}$: the effect of λ_t on μ_t is significantly higher during PLP compared to PCP

The first hypothesis H1 means that there has been a significant increase in BC after the end of the lockdown, suggesting that the Policies implemented in May 2020 were successful in promoting cycling in Paris. H2 means that the possible increase of BC is driven by a form of social influence: if μ_t depends positively on λ_t, then it means that non-cyclists are more likely to start cycling when cycling is already 'normal' (i.e. λ_t is high). H3 compares the effects of λ_t between the two periods to determine whether the degree of social influence changed over time. We will test H1 with a fixed-effects regression, and H2 and H3 will be tested by estimating equation (3), while controlling for various fixed-effects. In what follows, we confirm H1 and H2, and only offer partial evidence for H3.

4 Data: cycling in Paris

4.1 Cycling infrastructures in Paris

Cycling infrastructure in Paris include bicycle paths, cycle lanes, bus lanes opened to bicycles, and various urban facilities such as pedestrian areas opened to bicycles and contra-flow lanes. While bicycle paths are the most convenient and safest alternative — being clearly separated from the lanes used by motorised vehicles — it is mainly the fourth type of lanes which constitutes the bulk of cycling infrastructure (cf. table A.1 in Appendix). Furthermore, over the past fifteen years the development of the cycling network in Paris mostly favoured (in terms of number of kilometres) other solutions than cycle paths, even though they used to be the most common infrastructure (cf. figure A.1 in appendix). Paris also benefits from an important bike-sharing system called Vélib'. This pioneering large-scale bicycle sharing system (in the words of Nair et al., 2013) installed in 2007 has subsequently inspired a number of cities around the world (El Sibai et al., 2021) and has been a real success in terms of encouraging cycling (Nadal, 2008). Our analysis cannot identify precisely the role of bike-share in the evolution of cycling during PLP, although the literature suggests that the substitution between public transport and cycling also included a higher use of bike-share (Teixeira and Lopes, 2020; Kim and Cho, 2022), which may have contributed to further increase the positive effect on BC.

The main policy in terms of cycling infrastructure implemented by the city of Paris following the lockdown of March-May 2020 has been the creation of new cycle paths, dubbed '*coronapistes*' (corona lanes). In May 2020, 18km of cycle paths were already created, followed by the development of a wider network of 52km of additional lanes by the end of 2020. It is noteworthy that those lanes were also structured alongside major transportation axes, following the main metro lines.[12] This organisation is in line with Buehler and Dill (2016)'s recommendations that the structure of the network matters more than the mere number of kilometres of cycling lanes. The new network created by the *coronapistes* potentially lays out the conditions for a radical transition for Paris to become a bike-friendly city. This policy was accompanied by several financial incentives promoting cycling, such as subsidies for purchasing electric bikes[13] and a nation-wide subsidy for bike repairs (up to 50 euros) until April 2021. This is why, even though we may reasonably assume that the *coronapistes* were the key driver of BC adoption during PLP, we will refer below to the 'Policies' to include the whole package of policies aiming to promote BC.

4.2 Description of the dataset and empirical strategy

Our data comes from the City of Paris' Open Data initiative. The analysis relies on two sets of data, about cycling infrastructure and about bike traffic in Paris. The first set lists for each type of infrastructure (cycle paths, bus lanes open to bicycles, cycle lanes and other

[12] As an illustration, the emblematic *rue de Rivoli*, connecting the *Marais* district to the *place de la Concorde*, has been entirely reconfigured and is now reserved for cabs, buses and bicycles.

[13] E.g. a subsidy granted by the municipality since October 2018 corresponding to 33% of the purchase price, excluding taxes, and capped at 400 euros (600 for a cargo bike); a regional subsidy since December 2019 corresponding to 50% of the price, including taxes, and capped at 500 euros (600 for a cargo bike).

cycle routes), the date of creation and the length of the cycling sections. This set is built from two separate datasets about cycling infrastructure: the *Réseau des itinéraires cyclables* dataset, which records information on the network of cycling infrastructures in Paris (we had to reprocess the data by deleting the observations when the date of infrastructure creation was not provided), and the *Déconfinement - Pistes cyclables temporaires* dataset, which records information on *coronapistes*. The data on bike traffic comes from the *Comptage vélo - Données compteurs* set. These data record bicycle traffic per day thanks to the network of counters in Paris. We reduce our sample to counters that were installed before the period of interest for our estimation strategy and we removed the counters with outliers or missing values. The list of counters used in the estimation strategy is specified in the table A.2 in appendix.

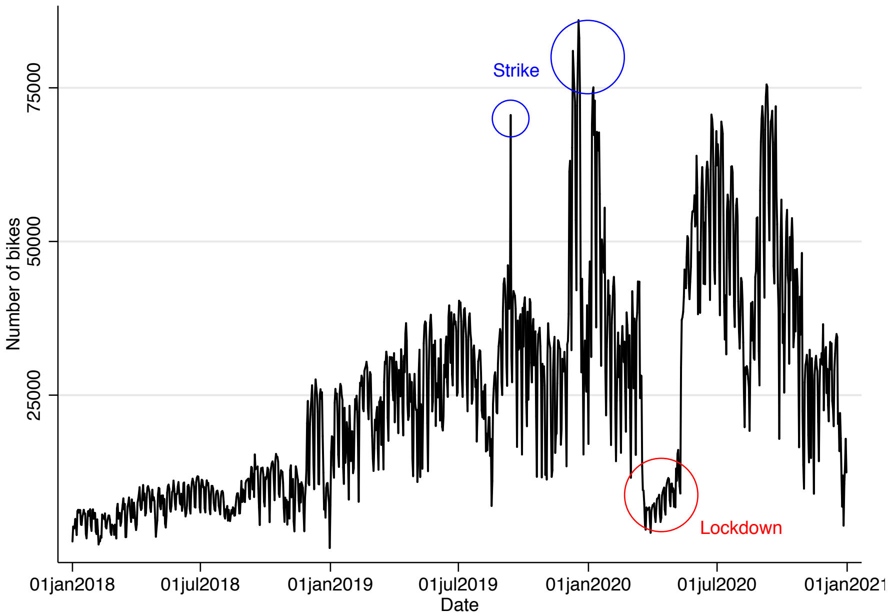
Figure 2 shows the evolution of the traffic per day between 2019 and 2020 in Paris. An increase of the traffic over time seems to appear from the data, with several outliers caused by the major strikes that affected public transport in December 2019-January 2020, as well as one day in September 2019. Those strikes lasted almost two months with significant disruptions in public transports, which led to an upsurge in cycling during the period. The lockdown in March-May 2020 is marked by a logical drop in traffic, as well as the second lockdown in October-December 2020, though to a lesser extent, given that travel restrictions were much lighter, with e.g. schools remaining open during the lockdown.

Our first hypothesis H1 is that the positive trend in the evolution of the traffic during PLP is significantly higher than the PCP trend. We reduce our sample for the statistical estimation to a 100-days period before and after the lockdown.[14] Furthermore, we normalize the measure of traffic by setting the upper bound of the measure to the maximum bicycle traffic per day observed over the period.

We use a fixed-effects regression to test H1. We consider the traffic in 2019 between January 31, 2019 and August 18, 2019, and compare it to the traffic in 2020 between February 1, 2020 and August 18, 2020 — i.e. a 100-days period before and after May 11th (end of the lockdown). Using the same time period allows us to control for the impact of seasonal changes. The measure of bicycle traffic for counter i on day t is denoted $M_{i,t}$, with:

[14]This technical choice reduces the volume of data that we would not take into account because of outliers, while providing sufficiently long support to observe the evolution of traffic that could be attributable to the end of the lockdown and the Policies.

Figure 2: Evolution of the number of bike passages per day between 2018 and 2020



$$M_{i,t} = \alpha T_t \times \tau_t + \beta T_t + \gamma \tau_t + \sum_{j=1}^{3} \delta_j X_{j,t} + \mu_i + \nu_t + \epsilon_{i,t} \quad \text{for } i = 1, ..., n \tag{4}$$

T_t is a dummy that takes value zero before May 11th (end of lockdown) and one from May 11th on. τ_t equals one for 2020 and zero in 2019. The parameter α therefore measures the joint effect of the end of lockdown (May 11th) and the implementation of the Policies (2020 vs 2019) on the circulation of bicycles in Paris on day t. We include fixed-effects for the counter (μ_i) and for the day of the week (ν_t). We also include three covariates. First, X_{1t} takes value one during the lockdown and zero otherwise, so as to capture the drastic reduction in traffic caused by the lockdown restrictions. Second, we add a dummy variable X_{2t} that takes value one for public holidays only, since we can expect a lower traffic caused by the reduction of individuals commuting on such days. Third, X_{3t} captures the effect on traffic of the level of precipitations[15], since we can expect that poor weather conditions can impact the willingness to cycle.

[15]Source of the data: `https://prevision-meteo.ch/climat/journalier/paris-montsouris/`.

5 Results

5.1 Estimation of the effect of the Policies (H1)

Figure 3 show the level of bicycle traffic in Paris before and after the end of the lockdown (Day 0). It seems at first sight that there exists a significant difference in the trends between 2019 and 2020.

Figure 3: Bike passages per day in Paris before and after May 11th, in 2019 and 2020

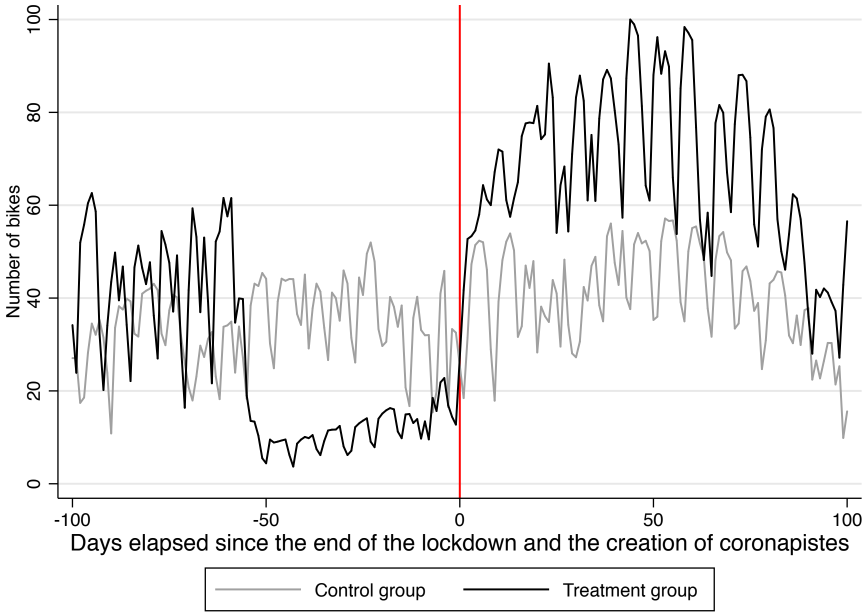


Table 1 presents the results of the estimation for the joint effect of the end of lockdown and the implementation of the Policies. The table reports coefficients using forward stepwise selection. Regardless of the specification used, a significant and positive effect is observed on bicycle traffic during PLP (from May 11th, 2020 onwards). Once the effect of the lockdown (X_{1t}) is taken into account in the model, the results are relatively stable regardless of the specification. Even though it seems that 2019 was characterised by a positive trend in terms of BC, we observe a significant increase in this trend during PLP.

We check the robustness of our estimation by replicating our analysis with an earlier period (without lockdown nor policies equivalent to the ones implemented in May 2020). We run a fixed-effects regression while considering the evolution of traffic in 2018 and 2019. If the effect associated to the period following May 11th is found to be significant, then the trend

Table 1: Results of fixed-effects regression for the joint effect of the end of lockdown and the Policies

	(1)	(2)	(3)	(4)
$T_t \times \tau_t$	0.985^{***}	0.485^{***}	0.494^{***}	0.484^{***}
	(0.022)	(0.020)	(0.020)	(0.020)
Counter fixed-effects	Yes	Yes	Yes	Yes
Day fixed-effects	Yes	Yes	Yes	Yes
Lockdown	No	Yes	Yes	Yes
Public holiday	No	No	Yes	Yes
Precipitation	No	No	No	Yes
Observations	10,000	10,000	10,000	10,000

Note: Coefficients are expressed in terms of standard deviations. Robust standard errors are in parentheses. Standard errors are clustered at the day level.
$^{*}p \leq 0.1;^{**} p \leq 0.05;^{***} p \leq 0.01$.

assumption would not hold, which would invalidate our interpretations. Table 2 summarises the replication of our analysis. The full model specification (column 3) suggests a similar effect of the time window following May 11th in 2018 and 2019 (while this was not the case between 2019 and 2020), which contributes to confirm the robustness of our estimation. Standard errors are quite similar in magnitude than those of our baseline estimates.

Table 2: Robustness checks for fixed-effects estimates

	(1)	(2)	(3)
$T_t \times \tau_t$	-0.124^{***}	-0.114^{***}	-0.036
	(0.030)	(0.030)	(0.029)
Counter fixed-effects	Yes	Yes	Yes
Day fixed-effects	Yes	Yes	Yes
Lockdown	No	No	No
Public holiday	No	Yes	Yes
Precipitation	No	No	Yes
Observations	4,000	4,000	4,000

Note: Coefficients are expressed in terms of standard deviations. Robust standard errors are in parentheses. Standard errors are clustered at the day level.
$^{*}p \leq 0.1;^{**} p \leq 0.05;^{***} p \leq 0.01$.

Over the period considered, we observe an increase of about 50% in bicycle trips, which is similar in intensity to what is observed in Germany following the COVID-19 pandemic by Kellermann et al. (2022). It is also of the same order of magnitude as the effect observed by Kraus and Koch (2021) following the implementation of Provisional COVID-19 infrastructure in several European cities after the first lockdown. Our estimate is in the high range of effects observed in other cities or countries (Buehler and Pucher, 2021, 2022), which is consistent with the fact that the largest effects were observed in cities where cycling initially had a lower modal share (Möllers et al., 2022) – as in Paris. Finally, the effect that we observe is higher than the expectations measured during the crisis, which established a higher post-crisis level of around 20-25% (de Haas et al., 2020; Ehsani et al., 2021). Therefore, our result confirms the literature discussed in section 2.2 on the increase in cycling observed in many cities following the pandemic, while providing a high degree of control with the introduction of counter and day fixed-effects, as in Kraus and Koch (2021); Möllers et al. (2022).[16]

5.2 Parametrization of ϕ

We now turn to the estimation of ϕ so as to test H2 (ϕ_{PLP} is positive) and H3 (ϕ_{PLP} is higher than ϕ_{PCP}). Estimating ϕ during PCP and PLP requires two preliminary steps: (i) the estimation of N, the theoretical maximum value for M_t, and (ii) the specification of the time period over which we could compare ϕ during PCP and PLP. This second step is critical because of the various events that affected public transports in Paris in 2019 and 2020, with important strikes in December 2019 and January 2020 (which already led to an upsurge in cycling because of the lack of public transport), the lockdowns in 2020 (from March to May, and then October to December), and the summer holidays in 2020 characterised by a significant decrease of international tourism. Furthermore, Parisian households are characterised by high departure rates during the summer, meaning that the population commuting in Paris during the summer (after mid-July) is different from the usual population. We therefore take the period between May 11 (end of the lockdown) and July 13 (last day before French National Holiday, which is traditionally followed by departures for the summer) to estimate our model in 2019 and 2020.

Regarding N, we have to estimate what could be the highest possible value for N. We can note that an overestimation of N will lead — everything else being equal — to an underestimation of ϕ: we therefore voluntarily choose a relatively high value for N, implying that the effect we could find from ϕ are probably underestimated. The rate of BC in Paris is estimated to 5% during PCP, compared to 49% in Copenhagen, which is the

[16] A significant difference with Kraus and Koch (2021) is however that their analysis is based on a between-cities analysis (taking for control cities without new lanes) while we propose a within-city analysis by comparing the evolution in the same city over two different time periods.

self-proclaimed 'city of cyclists'.[17] We therefore take 49% as the highest possible BC rate that could be attained in Paris, and derive N as the theoretical value of M_t if traffic was 49/5 more important.[18]

5.3 Social influence as a determinant of cycling (H2, H3)

Now that we have identified the time periods in 2019 and 2020 to compare the evolution of λ_t, and specified the value of N, we will estimate the following function (equivalent to (3)) to derive the value of ϕ, while also controlling for public holidays and levels of precipitation:

$$ln\left(\frac{\lambda_t}{1-\lambda_t}\right) = C + \phi t \tag{5}$$

The estimation results are summarized in table 3.

Table 3: Simulation

	2019 (PCP)	2020 (PLP)
ϕ	0.002	0.004**
	(0.001)	(0.002)
C	-2.810***	-2.662***
	(0.194)	(0.232)
Number of counters	25	25

Note: The models include controls for public holidays and the level of precipitation. They include day-of-the-week fixed-effects. Robust standard errors are in parentheses. Standard errors are clustered at the day level.
$^{*}p \leq 0.1;^{**}p \leq 0.05;^{***}p \leq 0.01$.

First, C does not have a genuine qualitative interpretation, since it merely defines the level of λ (here, negative values typically mean that $\lambda < 1/2$, and therefore that much can still be done to increase BC in Paris — as mentioned above, this might be the consequence of our high estimation of N, which likely underestimate both C and ϕ). Even though we observe a higher value for C in 2020, the difference with 2019 is not statistically significant.

Second, and more interestingly, we can check that ϕ_{PLP} is strictly positive (with a p-value of 0.023), which supports our hypothesis H2, according to which the conversion rate

[17] See `https://ecf.com/resources/cycling-facts-and-figures` and `https://copenhagenizeindex.eu/` for data.

[18] In more details: on the period of 64 days from May 11 to July 13 2019, we have 1960213 counts on the restricted sample of counters defined above. If this corresponds to a BC rate of 5% a rate of 49% would be $1960213 \times \frac{49}{5} = 19210087$, and then $N = 300158$ per day on average.

μ_t depends positively on λ_t during PLP. This suggests that the increase in BC during PLP can be driven by the growing influence of the population of cyclists over non-cyclists, who are progressively tempted to switch transportation mode. Furthermore, we find that there is no such effect during PCP (p-value of 0.205 for ϕ in 2019), which would *a priori* support our hypothesis H3. However, we cannot reject the hypothesis that $\phi_{PCP} = \phi_{PLP}$ and have therefore only a limited support for H3.

We run an additional estimation comparing the evolution of λ_t over the same time period in 2018, 2019, and 2020. This however forces us to restrict the set of counters used in our calibration for 25 to 10, i.e. the counters that were in place over the three years. The results are given in the table 4.

Table 4: Robustness checks for simulation

	2018 (PCP)	2019 (PCP)	2020 (PLP)
ϕ	0.001	0.001	0.004***
	(0.001)	(0.001)	(0.001)
C	-2.841***	-2.408***	-2.514***
	(0.182)	(0.183)	(0.228)
Number of counters	10	10	10

Note: The models include controls for public holidays 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. The list of counters used in the estimation strategy is specified in the table A.3.
$^{*}p \leq 0.1;^{**} p \leq 0.05;^{***} p \leq 0.01$.

With this restricted dataset, we find values for ϕ and C of a similar magnitude than above for 2019 and 2020, although the value of ϕ in 2020 is now higher and statistically significant at the 1% level (giving additional support for H2). What appears from these results confirms our theoretical predictions: we indeed observe a higher C in 2019 compared to 2018, both time without influence of ϕ, suggesting that λ_t might be higher in 2019 compared to 2018, but without an underlying dynamic of social imitation. The fact that ϕ is significantly higher in 2020 compared to both 2018 and 2019 suggests that — at least in the short term following the end of the lockdown — the general context as well as the creation of the *coronapistes* and the various policies promoting BC might have trigger the progressive conversion of the 'cautious majority' to cycling. We cannot conclude whether this is only due to the implementation of the Policies or also of the sanitary context, though our results suggest that policies aiming to increase BC should incorporate measures targeting such behavioural mechanisms — with e.g. communication campaign on the relative safety and convenience of those infrastructures to trigger an initial adoption (which could possibly lead over time to a progressive conversion of the cautious majority). From a methodological perspective, our analysis suggests that a dynamic of social influence might be measured through an adequate modelling (while being well aware that it remains simplistic in the present work) and applied to data derived from a natural experiment. As noted by Manca et al. (2019), who also propose an analytical framework to quantify different social influence processes, it remains difficult to gather experimental data where participants form a genuine social network, meaning that an alternative road might be to develop estimation strategies relying on natural experiments with existing social networks.

6 Concluding remarks

Our aims in this paper were twofold. First we measured the evolution of the BC rate following the end of the COVID-19-lockdown in Paris in May 2020, and second we determined whether this effect, if confirmed, could be driven by a dynamic of social influence. We confirm H1, i.e. that the BC rate is significantly higher during PLP compared to PCP, by offering a within-city analysis including geographical (counters) and temporal (day of the week) fixed-effects. Furthermore, it seems that the conversion to BC during PLP is driven by an imitation effect (H2), since the rate of conversion μ_t depends positively on the share of cyclists λ_t, implying that a growing population of cyclists is likely to accelerate the adoption of BC among the remaining non-cyclists. Lastly, we can offer a limited support for H3, i.e. that the imitation effect is strictly higher during PLP compared to its PCP level, which could suggest that the implementation of the policies contributed to create a dynamic which could lead *in fine* to a greater adoption of BC. In line with the literature on the promotion of BC, we confirm that improving infrastructures is a key strategy if public authorities want to increase the rate of BC. We moreover suggest that a mechanism which could drive the success of such policies is the positive spillovers they could generate by triggering a social adoption of BC. A simple back-of-the-envelope calculation suggests that within the 64 days from May 11th to July 13th, 2020, this social effect alone contributed to increase λ_t by 0.0175, i.e. an increase of more than 3 percentage points of the BC rate. While shifting from car-as-default to active travel seems *a priori* very challenging, because of the absence of a bike culture in many cities and a strong attachment to cars, our result suggest policies consisting of developing better infrastructures — possibly accompanied by additional financial incentives lowering the cost of mode shift — could be sufficient on their own, in the long run, to generate bike-friendly dispositions among the population through the initiation of a dynamic of social adoption of BC.

To the best of our knowledge, our work is the first to explicitly model and measure social imitation within the TIB while relying on data derived from a natural experiment. Several extensions must however be considered for future research. First, we need to work on a longer time period to better estimate the dynamics of social imitation and offer a definitive confirmation to H3. This might however be very challenging given that the pandemic is not over (as of 2022-23), and recurrent transport restrictions over the last years (especially in 2021, with a prolonged curfew and changing rules for remote working depending on the periods and sectors of activity) seriously limit our ability to measure properly long-run tendencies and a more global acceptance of BC. Second, we can offer a more elaborated analysis of the diffusion of social influence, by explicitly considering the typology of the social networks connecting cyclists to non-cyclists (either geographically speaking, or by modelling the social relationships between those different populations). A possible next step, from a theoretical perspective, would be to propose an analysis of norms *à la* Ross et al. (2021) and to model the diffusion of social influence using the tools of conditional game theory (Stirling, 2012; Stirling et al., 2016). This formalism would give us the flexibility to model structural utility functions incorporating the various dimensions of the TIB while allowing for the individuals' utilities to be defined conditionally on others, depending on the network within which individuals are embedded. This would give more precise information about the mechanisms through which individual intentions are shaped by various social influences.

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A Appendix

Table A.1: Cycling infrastructures before and after the lockdown in km

Type of infrastructure	Distance (km)
A. PCP (before the lockdown)	
Cycle paths	233.51
Bus lanes open to bicycles	56.97
Cycle lanes	83.42
Other cycle routes (e.g. pedestrian areas)	364.86
B. PLP	
Cycle paths at the end of 2020	51.93
Additional km in May	18.15
Additional km in June	14.66
Additional km in July	3.74
Additional km in August	4.38
Additional km in September	4.29
Additional km in October	0.82
Additional km in November	3.99
Additional km in December	1.91

Note: The table reports the length of cycling infrastructures by type before and after the lockdown. The data is only reported when an infrastructure creation date has been indicated.

Table A.2: List of counters used in the estimation strategy

Counter number	Counter location
100003096-SC	97 avenue Denfert Rochereau SO-NE
100003097-SC	105 rue La Fayette E-O
100003098-SC	106 avenue Denfert Rochereau NE-SO
100003099-SC	100 rue La Fayette O-E
100006300-SC	135 avenue Daumesnil SE-NO
100007049-101007049	28 boulevard Diderot O-E
100007049-102007049	28 boulevard Diderot E-O
100036718-103036718	39 quai François Mauriac SE-NO
100036718-104036718	39 quai François Mauriac NO-SE
100041488-SC	27 boulevard Diderot E-O
100042374-109042374	Voie Georges Pompidou SO-NE
100042374-110042374	Voie Georges Pompidou NE-SO
100044495-SC	7 avenue de la Grande Armée NO-SE
100047533-SC	89 boulevard de Magenta NO-SE
100047535-SC	Pont du Garigliano NO-SE
100047536-SC	102 boulevard de Magenta SE-NO
100047537-SC	26 boulevard de Ménilmontant SE-NO
100047539-SC	21 boulevard Auguste Blanqui SO-NE
100047542-103047542	Face au 48 quai de la marne NE-SO
100047542-104047542	Face au 48 quai de la marne SO-NE
100047547-103047547	6 rue Julia Bartet SO-NE
100047547-104047547	6 rue Julia Bartet NE-SO
100047550-SC	35 boulevard de Ménilmontant NO-SE
100047551-102047551	Pont du Garigliano SE-NO SE-NO
100049408-SC	10 boulevard Auguste Blanqui NE-SO

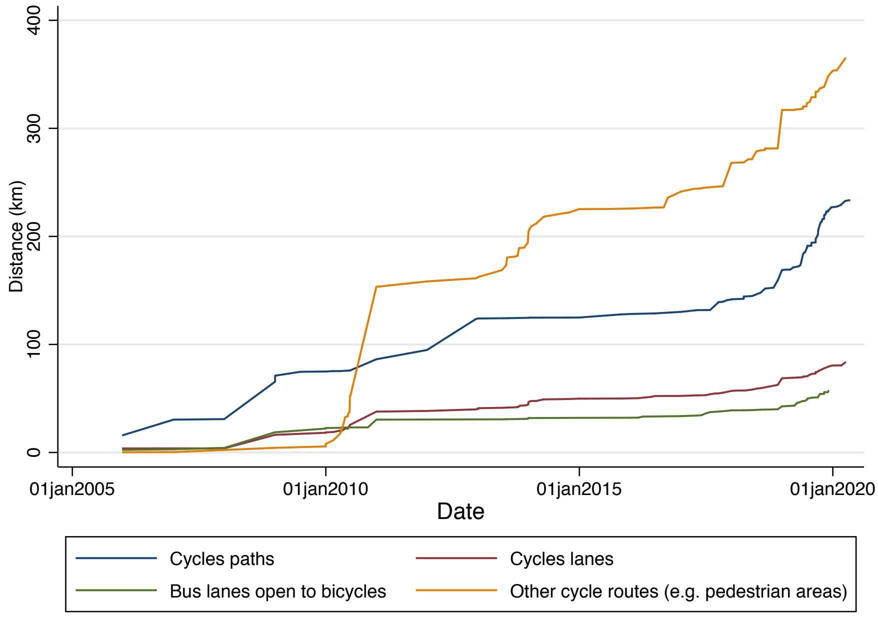
Note: The table reports the list of counters used in the estimation strategy.

Table A.3: List of counters used in the robustness check

Counter number	Counter location
100003096-SC	97 avenue Denfert Rochereau SO-NE
100003097-SC	105 rue La Fayette E-O
100003098-SC	106 avenue Denfert Rochereau NE-SO
100003099-SC	100 rue La Fayette O-E
100006300-SC	135 avenue Daumesnil SE-NO
100007049-101007049	28 boulevard Diderot O-E
100007049-102007049	28 boulevard Diderot E-O
100036718-103036718	39 quai François Mauriac SE-NO
100036718-104036718	39 quai François Mauriac NO-SE
100041488-SC	27 boulevard Diderot E-O

Note: The table reports the list of counters used in the robustness check.

Figure A.1: Evolution of the length of cycling infrastructures before the lockdown and the creation of *coronapistes*



Note: The table reports the size of cycling infrastructures by type before the lockdown and the creation of *coronapistes*. The data is only used when an infrastructure creation date has been entered.

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