Bike-friendly cities: an opportunity for local businesses? Evidence from the city of Paris

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Workshop Micro-mobility in cities

Introduction

Infrastructure investment $\Rightarrow \uparrow$ market access $\Rightarrow \uparrow$ local revenues.

Does this mechanism apply to investments in cycling infrastructure as well?

Anecdotal evidence and existing theory suggests it might...

- $(-)$ business owners' fear a sales decline due to constrained parking
- $(+) \uparrow$ uptake of active mobility $\Rightarrow$ businesses more salient, "footfall" externalities, etc. $\Rightarrow$ stimulus to consumption (even if the uptake is at the expenses of other transport modes)

Answer this question by exploiting a large-scale cycling infrastructure investment $\Rightarrow$ Plan Vélo in Paris.

Literature review

1. Infrastructure investment within cities:
   - Empirical evaluation of infrastructure investments:
     - Gibbons and Machin (2005); Billings (2011); Cervero and Kang (2011); Pogonyi et al. (2019)
   - Market access approach to infrastructure investments:
     - Ahlfeldt et al. (2015); Heblich et al. (2020); Tsivanidis (2019); Gorback (2020)
2. Consumption in cities
   - Consumption benefits of agglomeration (Glaeser et al., 2001; Handbury and Weinstein, 2014; Couture, 2016)
   - Consumption patterns with large-scale spatial data: online review data (Davis et al., 2019), mobile phone data (Athey et al., 2018) and credit card transaction (Relihan, 2017; Allen et al., 2020; Diamond and Moretti, 2021)
3. *Cycling Economics*:
   - Pucher and Buehler (2008); Klingen and van Ommeren (2020) soon: Viladecans et al. , Bernanrd; Thorne

This paper

- We *estimate* the elasticity of **non-tradables sector revenues** to **bike market access** by exploiting the **development of a large-scale bicycle network in Paris**
  $\rightarrow$ *bike market access = the demand that can "sufficiently easily" reach a given business location by bike*

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  $\rightarrow$ *bike market access = the demand that can "sufficiently easily" reach a given business location by bike*
- We *identify* the elasticity by relying on changes in bike market access triggered by bike lanes development in **more distant parts of the network**/focusing **only on locations with some planned development**

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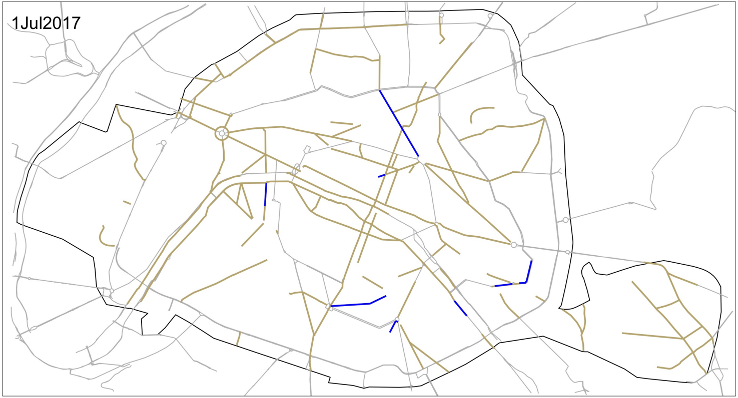
- We *identify* the elasticity by relying on changes in bike market access triggered by bike lanes development in **more distant parts of the network**/focusing **only on locations with some planned development**

- We *estimate* a **0.45 elasticity of monthly revenues to bike market access** - equivalent to 3pp increase in revenues p/merchant-year - and we discuss local vs. aggregate impact of the infrastructure

Plan Vélo (PV) - Paris 2015 to 2020

- Initial project: 80km of new bike lanes (€150 million);
- as of November 2019, 57km were developed (71%).

▸ Volume of bike trips over time



Notes: hover with the cursor to play the animated GIF.

Bike lane development:

- Daily updates of the network from July 2017 - Nov 2019 (*Observatoire Plan Vélo*)

Economic activity:

- Quarterly value and volume of card transactions at merchant level (*Groupement de cartes bancaires*)
  Time series of total value | Representativeness of CB | Stat Desc
  - keep merchants in **retail, restaurants, accommodation, personal services, sports and entertainment**

Neighborhood characteristics:

- Population, young population, foreigners, unemployment, house prices

Mobility:

- Car traffic, public transport usage, other bike infrastructure

Conceptual framework

Consumers living in neighborhood j consume housing, a tradable and a non-tradable good sold in location i (Gorback, 2020):

$$U_j = \left(\frac{h_j}{\alpha}\right)^{\alpha} \left(\frac{c_j}{\beta}\right)^{\beta} \left(\frac{n_j}{1-\alpha-\beta}\right)^{1-\alpha-\beta} z_{ij} \exp(-\tau d_{ij})$$

- z_{ij} is a Frechet distributed preference shock $F(z_{ij}) = e^{-E_i z_{ij}^{-\varepsilon}}$, where the higher is E_i, the more consumers like shopping in location i ($E_i \simeq$ location FE)
- d_{ij} is the commuting cost to go shopping from neighborhood j to location i by bike

The share of consumers living in j deciding to go shopping in i:

$$\text{share}_{ij} = \frac{E_i \exp(-\tau\varepsilon d_{ij})}{\sum_s E_s \exp(-\tau\varepsilon d_{sj})}$$

$\Rightarrow$ consumers trade-off locations with better amenities (E_i) for locations that are closer (d_{ij}).

Defining bike market access

Define bike market access, BMA_{it}, for business location i:

$\rightarrow$ the demand that can reach location i by bike "sufficiently easily"

The more difficult it is to reach by bike location i from neighborhood j, the lower the weight given to demand coming from neighborhood j:

$$\text{BMA}_{it} = \underbrace{\sum_j}_{\text{sum across } j} \underbrace{\frac{\exp(-\tau\varepsilon d_{ij,t})}{\sum_s \exp(-\tau\varepsilon d_{sj,t})}}_{\text{share consumers } j \to i} \underbrace{\text{Median income}_j \times \text{Population}_j}_{\text{total income in } j}$$

where $\tau\varepsilon = 0.05$ (calibrated ▸ Go and same as Ahlfeldt et al. (2015); Gorback (2020)) and $d_{ij,t}$ are **bilateral commuting costs by bike**.

We do not include the amenity parameter because we include location fixed effects

Measuring bilateral commuting costs by bike ($d_{ij,t}$)

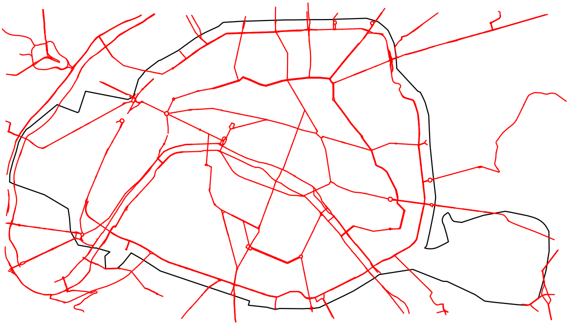
Create **equally-sized locations** spanning the municipality of Paris:

- 1,418 grid cells of 180×180 meters

For each quarter during 2015-2019 calculate **bilateral commuting costs *by bike*** using the **Fast-Marching Method algorithm** (Allen and Arkolakis, 2014):

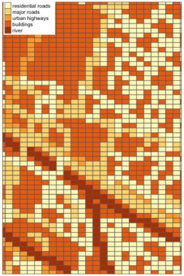
1. Get different types of road infrastructure from **Open Street Map**
2. Build 500-by-600 pixels of 20-by-20 meters
3. Define the **cost raster** Go → cost of crossing a *pixel* depends on the type of road infrastructure it features: **highest for urban highways, lowest for Plan Vélo**
4. Run the FMM algorithm → finds the **optimal path between any two centroids of the main grid given the cost raster**

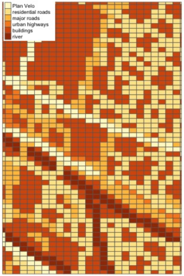
Get road infrastructure from Open Street Map



Notes: Layers are added in increasing order of *bike-friendliness*.

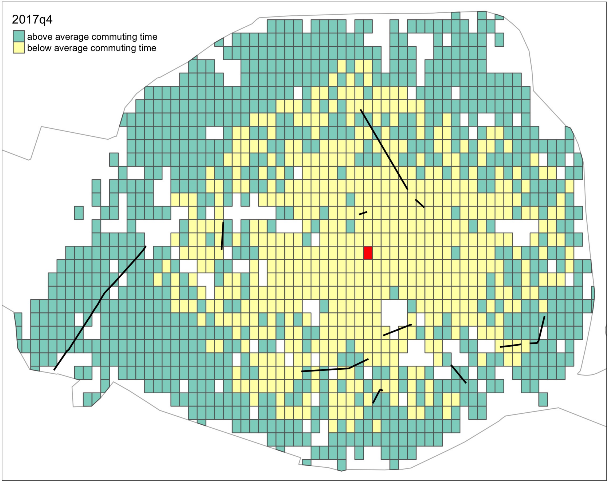
Cost raster: an illustration





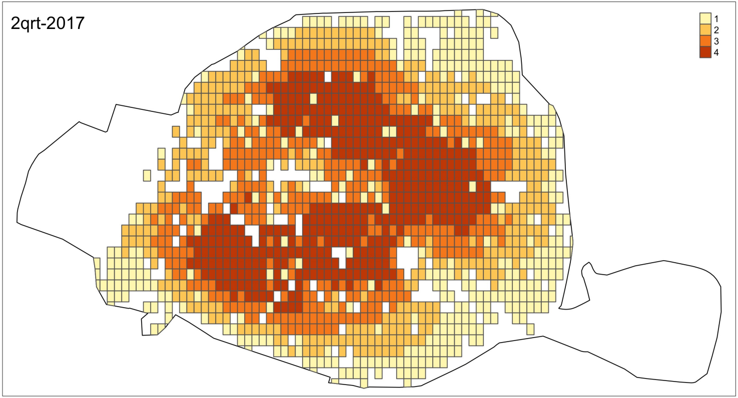
Notes: street network in the surroundings of the Hôtel de Ville (left), cost raster in 2015q1 (middle), cost raster in 2019q4 (right).

LCP calculation: an illustration



Notes: bilateral cost from the Hôtel de Ville to other destinations. Black lines corresponding to the Plan Vélo developed up to that stage overlaid. Hover with the cursor on the picture to play the animated GIF.

Evolution of bike market access



Notes: overlaid black lines capture the extent of Plan Vélo developed as of that moment.

BMA 2015

Empirical strategy 1: TWFE estimation with local bike lane density control

$$\ln Y_{it} = \alpha_i + \alpha_{dt} + \beta \ln BMA_{it} + \delta LBLD_{it} + \gamma X_{it} + e_{it}$$

- Y_{it} is either:
  1. the total value of card transactions taking place in a given quarter across merchants located in a given location,
  2. or the total number (volume) of card transactions,
  3. or the average value of individual card transactions
- α_i are location FE and α_{dt} are district $\times$ quarter FE
- X_{it} includes (log) population, (log) 25-39 yrs old population, unemployment rate and share of foreigners
- control by endogenous development of total length of bike lanes built "nearby" (local bike lane density or **LBLD**) (Hornbeck and Rotemberg, 2021):
  $\Rightarrow$ **identification comes from more-distant developments in the network**

Empirical strategy 1: measures of local bike lane density (LBLD)

Endogenous development of total length of bike lanes built "nearby" (local bike lane density or **LBLD**).

- Measure at the **project** level: all units crossed by the same bike lane (ex: a given street, boulevard). $LBLD_{it}$ = total length of the bike lane of project p
- **Neighbor** grids: equal to the total length of bike lane in a given grid plus the length of bike lanes of all closest neighboring grids.
- **Project** + **Local**: both $LBLD_{it}$ at the project level as in the first measure and the total bike lane length of each individual grid

LBLD also accounts for the "amenity effect" of bike lane development

Empirical strategy 2: 2SLS estimation, IV strategy

First Stage:

$$ln(\text{BMA}_{it}) = \alpha_i + \alpha_{dt} + \beta ln(\text{BMA}_{it}^{1Km}) + \gamma X_{it} + e_{it}$$

where BMA_{it}^{1Km} relies on bilateral commuting costs with locations that are at least 1km away

Advantage

- We don't control for (potentially endogenous) local bike market access
- Again: identification comes from more-distant developments in the network

Results

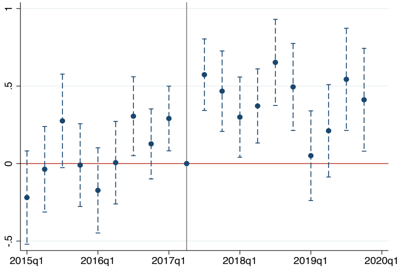
Panel A:	Log total revenues				
	(1)	(2)	(3)	(4)	(5)
Log BMA	0.334*	0.449**	0.359	0.356*	0.395**
	(0.180)	(0.207)	(0.225)	(0.209)	(0.18)
Panel B:	Log transactions' volume				
Log BMA	0.534**	0.497**	0.502**	0.393*	0.534***
	(0.208)	(0.222)	(0.241)	(0.224)	(0.21)
Panel C:	Log average revenues p/transaction				
Log BMA	-0.190	-0.038	-0.132	-0.026	-0.131
	(0.130)	(0.141)	(0.147)	(0.136)	(0.13)
N	27,617	27,617	28,297	27,617	27,617
Controls	X	X	X	X	X
Unit FE	X	X	X	X	X
District$\times$Time FE	X	X	X	X	X
LBLD	None	Same project	Neighbors	Same project/ same unit	None
FS F-stat					1938.94
Estimation	OLS				2SLS

Notes: standard errors are clustered at the location level. Magnitude interpretation: average $\Delta BMA = 7\%$, hence, average Δ Total revenues is 3pp ($0.449\times$ 7) p/merchant-year.

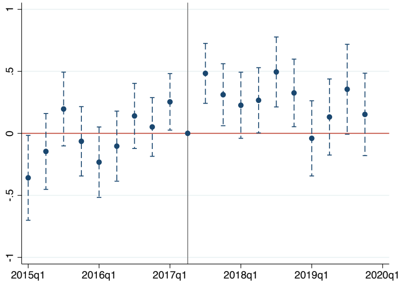
Pre-trends analysis

$$ln(Y_{it}) = \alpha_i + \alpha_{dt} + \sum_t \beta^t \Delta ln(BMA_{i,15-19}) \times \tau_t + \gamma X_{it} + \delta LBLD_{it} + e_{it}$$

- Areas with a larger increase in BMA did not feature a statistically significantly different evolution of the outcome before development.



Log total revenues



Log transactions' volume

Robustness checks

1. Centrality bias (Borusyak and Hull, 2020)
   - Exclude central and connected districts Go
2. Exploiting the unfinished Plan Vélo
   - Restrict sample to cells on original Plan Velo Go
3. Alternative transportation modes Go
4. Alternative cost raster calibrations Go
5. Card vs cash test Go
6. Other potentially confounding factors Go

Accounting for centrality bias/other changes in infrastructure

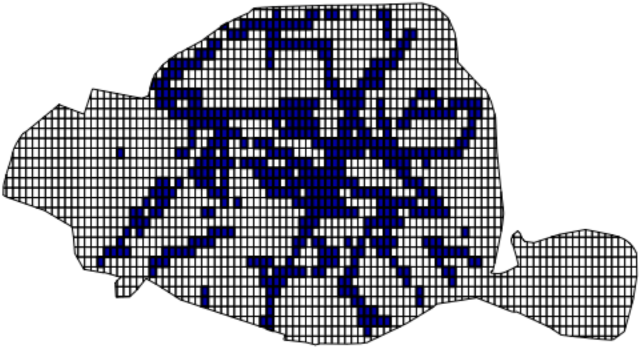
Panel A:		Log total revenues	
	(1)	(2)	(3)
Log BMA	0.449**	0.454**	0.423*
	(0.207)	(0.222)	(0.224)
Panel B:		Log transactions' volume	
Log BMA	0.497**	0.517**	0.450*
	(0.222)	(0.238)	(0.241)
N	27,617	25,697	23,237
Test	Baseline	Remove central districts	Remove connected areas

Notes: central districts are district 1-4; grid cells are considered as influential if they are located within 500 meters of metro/train stations featuring at least three connections; grid cells are considered as affected by T3b extension if located within 500 meters from it. Source: *Île-de-France Mobilités*.

Back to robustness checks list

Unfinished Plan Vélo: only locations with planned development

- Use a **more homogeneous** sample of **locations where there was some planned development**
- Exploit the variation introduced by the fact that of these locations were developed, while some others were not



Results using only locations with planned development

	Log total revenues	Log transactions' volume
Log BMA	0.677**	0.974***
	(0.264)	(0.295)
N	9,480	9,480

▸ Balancing Test ▸ Timing of treatment test ▸ Back to robustness checks list

Accounting for substitution with other transport modes

Panel A:		Log value	
	(1)	(2)	(3)
	0.449**	0.429**	0.528***
	(0.207)	(0.208)	(0.194)
Panel B:		Log volume	
Log BMA	0.497**	0.477**	0.503**
	(0.222)	(0.223)	(0.214)
N	27,617	27,467	25,887
Controls	X	X	X
Unit FE	X	X	X
District $\times$ Time FE	X	X	X
Test	Baseline	Augmented with # cars	Augmented with # metro trips

Notes: the number of cars transiting in a given area is calculated as the weighted mean of the number of cars recorded by monitoring stations located within 500 meters (weight $\approx$ distance); the number of metro trips in a given area is calculated as the average number of metro trips recorded in metro/train stations located within 500-meter distance. Source: *Comptage routier, Île-de-France Mobilités*.

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Alternative cost raster calibration

Route discrepancy minimisation procedure between our LCP routes and Google Maps routes

- Optimal GoogleMap API route for 30 itineraries, by bike
- We allow for 2 types of ways: roads (with cost c_r) and streets (with cost c_s)
- We choose 49 combination of numbers for parameters c_r and c_s
  - each parameter can range between 1 and 5 and we do not impose $c_r > c_s$
- We obtain optimal LCP routes for each combination
- We select the combination (c_r, c_s) that results in a route that is the most similar to the GoogleMap route. This is $(2, 3.5)$.

Alternative cost raster calibrations

Run main estimation with new BMA measure (using calibrated cost raster parameters)

	Log total revenues	Log transactions' volume
Log BMA	0.488**	0.399*
	(0.211)	(0.234)
N	27,617	27,617

Back to robustness checks list

Other robustness checks - miscellanea

Panel A:	Log total revenues				
	(1)	(2)	(3)	(4)	(5)
Log BMA	0.449**	0.348*	0.535**	0.518**	0.443**
	(0.207)	(0.203)	(0.236)	(0.227)	(0.208)
Panel B:	Log transactions' volume				
Log BMA	0.497**	0.453*	0.447*	0.527**	0.490**
	(0.222)	(0.238)	(0.233)	(0.237)	(0.222)
N	27,617	26,238	27,617	26,437	27,617
Test	Baseline	Sectoral shares	Including non-PV bike lanes	Remove closeby by new tram	Sunday Law trend

Notes: included lagged sectoral shares refer to 5-digit industries within retail/restaurant sectors; pre-existing bike lanes exclude bike lanes for which we could not determine with certainty the date of construction. Source: Opendata.Paris.fr

▸ Pre-existing bike lanes ▸ Map of areas affected by "Loi Dimanche" ▸ Back to robustness checks list

Card vs Cash Test

Is the effect driven by and increase in credit card usage?

- Card usage intensity index (share of CB merchants over total SIRENE establishments)
- Run main estimation on card usage intensity

	(1)	(2)	(3)	(4)
Log BMA	0.031			
	(0.056)			
First lag log BMA		0.029		
		(0.076)		
Second lag log BMA			0.031	
			(0.086)	
Third lag log BMA				0.030
				(0.090)
N	23,341	23,341	23,341	23,341

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Heterogeneity

Clustering Algorithm on

- Narrow industries (bars, fast food restaurants, non-fast food restaurants, food retail stores, nonspecialized retail stores, specialized retail stores), Size and Age → 5 clusters

	Log total revenues	Log transactions' volume
Log BMA×Small and new businesses	0.672**	0.500
	(0.305)	(0.305)
Log BMA×Spec. food stores/fast food/bars	0.637*	0.641
	(0.343)	(0.403)
Log BMA×Spec. retail + old businesses	-0.201	-0.218
	(0.492)	(0.453)
Log BMA×Retail + old businesses	0.709	0.445
	(0.450)	(0.381)
Log BMA×Spec. retail/restaurants	0.425	1.310*
+ new businesses	(0.452)	(0.696)
N	27,617	27,617

Greater effect for smaller/younger merchants + young oriented (bars, fast food)

Results on other outcomes

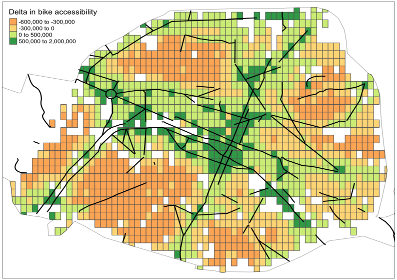
- Administrative data on individual businesses entry → **business entry** ▸ Not significant
- Data on the number of cars transiting through a given location (*Comptage routier*) → **car traffic** ▸ Negative
- House price index from an hedonic regression → **House prices** ▸ Lagged but positive

Focus on restaurants:

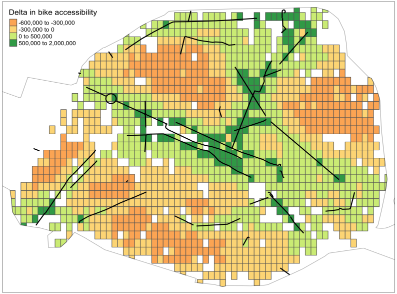
- Regress the number of reviews on Trip Advisor while controlling for time spent on the website → **Trip Advisor Reviews** ▸ Positive

Geographic heterogeneity of the impact of Plan Vélo

- The market access measure depends on *relative commuting costs*
- There are winners and losers
- Drawback: we are silent about any general equilibrium effect



Planned



Realized (as of November 2019)

Conclusion

- The elasticity of non-tradables revenues to investments in cycling infrastructure is positive and economically significant
- Results are robust after accounting for alternative travel modes and centrality bias (among other tests)
- Young and small establishments seem to benefit the most
- The impact of Plan Vélo has not been homogeneous across the city: central locations have gained at the expenses of more peripheral and densely populated ones $\Rightarrow$ potential room for improvement during the next round of Plan Vélo

Thanks

Thank you for your attention!

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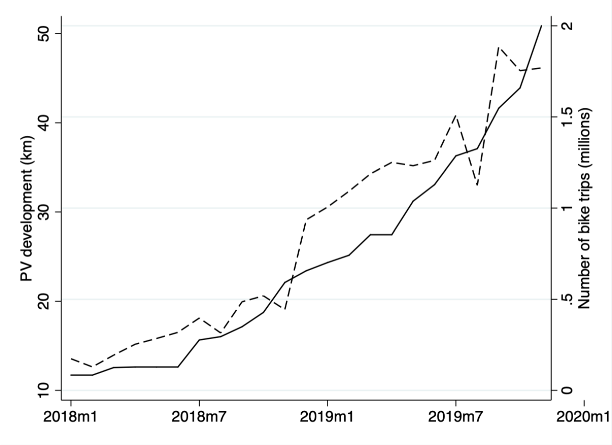
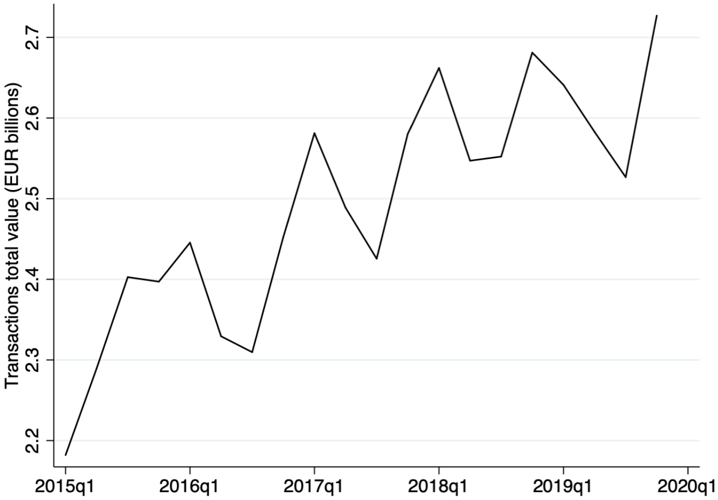
Total number of bike trips recorded in Paris by year/month



Source: *Comptage vélo - Données compteurs* (https://opendata.paris.fr/). Back

Card transaction data: time series



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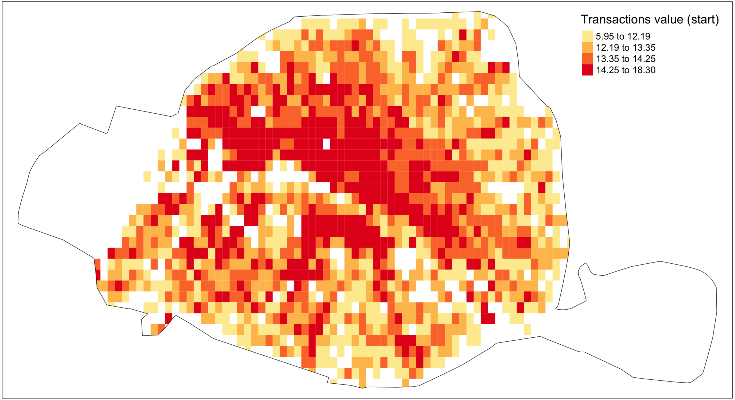
Card transaction data: spatial distribution (2015)



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Representativeness of card transaction data

NAF Code	Name of industry	Value (CB)	Value (INSEE)	VAT (%)	Value + VAT (INSEE)	Ratio
47	Retail	276,301	472,733	10%	520,006	53.1%
56	Restaurants	44,633	75,636	10%	83,199	53.6%
79	Travel agencies	9,067	12,682	10%	13,950	65.0%
55	Accommodation	15,355	29,223	10%	32,146	47.8%
96	Personal services	6,835	15,726	10%	17,298	39.5%
1071+4724Z	Bakeries and pastry shops	4,384	24,489	10%	26,938	16.3%
1071A	Bread makers	40	11,509	10%	12,660	0.3%
1071B	Bread bakers	199	692	10%	761	26.1%
1071C	Bakery and pastry shop	2,904	10,679	10%	11,746	24.7%
1071D	Pastry shop	493	1,038	10%	1,141	43.2%
4724Z	Bread retail	677	572	10%	629	107.7%
9312Z	Sports clubs	428	2,651	20%	3,181	13.5%
5914Z	Cinemas	748	2,146	5.5%	2,264	33.0%
9001Z+9004Z	Theatre and shows	545	3,548	3.8%	3,683	14.8%

Note: total expenditure in *Cartes Bancaires* data and revenues in INSEE data in selected non-tradable industries. Back

Calibrating commuting elasticity τ

Using cardholder level data for 2019:

1. Estimate most likely residence location (bakeries on weekends or after 6pm)
2. Calculate bilateral consumption flows
3. Estimate
$$\ln x_{ij} = \alpha_i + \alpha_j + \beta d_{ij} + e_{ij} \tag{1}$$
4. $\tau\varepsilon = -\widehat{\beta}$
5. We run (1) for each quarter of 2019 and obtain $\widehat{\beta} \in (-0.06, -0.04)$
6. Equivalent to $\varepsilon = 5$ and $\tau = 0.01$

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Defining the cost raster for LCP calculations

Cost of crossing a pixel (using Open Street Map) capturing both time and inconvenience/comfort

Baseline calibration:

- Buildings, Waterways = 200
- Urban Highways = 6
- Secondary Road = 4
- Residential Street = 2
- (Old Bike lane = 2)
- Bike lane in Plan Vélo = 1

We assume symmetric bilateral commuting costs $d_{ij} = d_{ji}$

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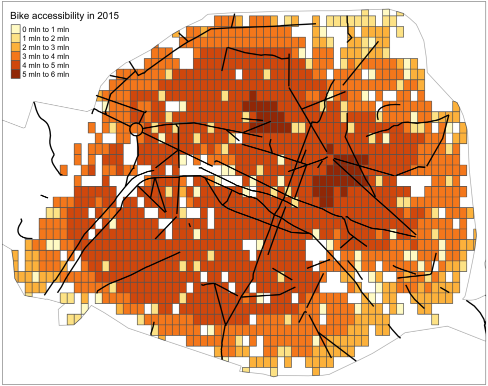
Starting of the sample bike market access



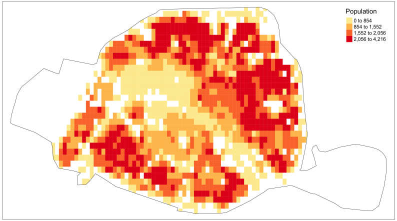
Notes: the data refer to 2015q1. The overlaid lines correspond to "planned" PV. The measurement unit of bike market access is €. Back

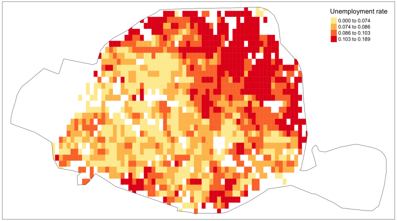
Summary statistics

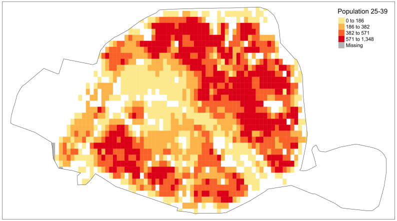
	Mean	Std. Dev.	Min	Max
Volume	27,492	42,041	5	453,622
Value (in000s €)	1,652	4,857	0	95,003
Avg. value p/transaction (€)	68	126	8	2,693
Avg. value p/merchant (€)	61,716	190,524	388	4,302,915
Merchants (#)	28	27	1	232
Population	1,478	773	0	4,216
Population 25-39	395	248	0	1,348
Jobseekers (%)	9	2	0	19
Foreigners (%)	15	6	0	81
Cars (#)	20,782	22,714	29	166,834
House price (€p/m2)	8,543	1,441	6,118	12,733
N	1,418			

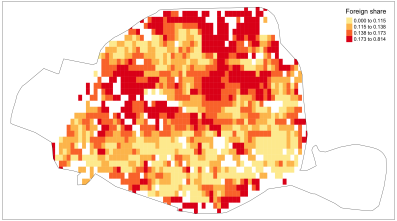
Note: the data refer to 2015. Back Maps of socioeconomic variables

Socioeconomic variables









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Balancing test - planned vs. all

	Planned		Not planned				
	Mean	Std Dev	Mean	Std Dev	Diff	t-value	p-value
BMA (in000s)	3882	1075	3778	1084	-104	2.72	0.01
BMA Planned (in000s)	4183	1155	3778	1119	-405	10.58	0.00
Roads (m)	1139	331	1070	348	-70	5.69	0.00
Planned bike lanes (m)	189	107	68	111	-121	53.43	0.00
Population	1365	811	1478	773	113	-4.13	0.00
Foreigners (%)	15	4	15	6	-0	2.33	0.02
Jobseekers (%)	9	2	9	2	0	-0.78	0.44
Population 25-39	375	257	395	248	20	-2.31	0.02
Entrant firms (#)	0	0	0	0	-0	4.84	0.00
Car flow (#)	23365	22677	20782	22714	-2583	3.21	0.00
House price (p/m2)	8925	1587	8543	1441	-383	7.63	0.00
Value (in000s)	2156	6128	1652	4857	-504	2.93	0.00
Volume	34781	49974	27492	42041	-7290	4.92	0.00
Avg. value p/transaction	70	101	68	126	-2	0.53	0.60
Avg. value p/merchant	59795	108177	61716	190524	1921	-0.28	0.78
Merchants (#)	33	29	28	27	-5	5.44	0.00
N	508	.	1417	.	.	.	.

Notes: the data refer to 2015. Back

Balancing Test: only locations with planned development

	Developed		Not developed				
	Mean	Std Dev	Mean	Std Dev	Difference	t-stat	p-value
BMA (in000s)	3874	1075	3892	1078	19	-0.20	0.84
BMA Planned (in000s)	4235	1166	4125	1142	-110	1.07	0.29
Roads (m)	1153	346	1123	312	-30	1.01	0.31
Planned bike lanes (m)	205	117	170	90	-35	3.71	0.00
Population	1357	858	1375	755	17	-0.24	0.81
Foreigners (%)	16	5	15	4	-1	1.46	0.14
Jobseekers (%)	9	2	9	2	-0	0.91	0.36
Population 25-39	380	277	369	232	-11	0.48	0.63
Entrant firms (#)	0	0	0	1	0	-0.01	0.99
Car flow (#)	25747	23754	20641	21100	-5105	2.55	0.01
House price (p/m2)	8867	1568	8992	1610	124	-0.88	0.38
Value (in000s)	1713	3238	2663	8258	949	-1.75	0.08
Volume	32112	46523	37834	53585	5722	-1.29	0.20
Avg. value p/transaction	70	122	70	71	0	-0.01	0.99
Avg. value p/merchant	54912	79646	65378	133507	10465	-1.09	0.28
Merchants (#)	30	30	35	28	5	-1.94	0.05
N	271	.	237	.	.	.	.

Notes: the data refer to 2015. Back

Timing of treatment test

Test whether lagged covariates consistently predict timing of treatment for locations not yet treated at a given date (Deshpande and Li, 2019):

$$\text{Treatment date}_i | (D_i^{t_0} = 0) = \alpha + \beta X_i^{t_0 - 1} + e_i$$

	t_0 =2017q2	t_0 =2018q1	t_0 =2018q4
Log population	-1.548**	-0.748*	-0.314
	(0.717)	(0.415)	(0.266)
% foreigners	15.477***	-1.998	-1.873
	(4.774)	(2.875)	(1.929)
% unemployed	-20.125**	-14.376**	-0.801
	(9.121)	(5.670)	(3.903)
Log population 25-39 yrs old	0.972	0.501	0.189
	(0.610)	(0.351)	(0.222)
N	271	201	146

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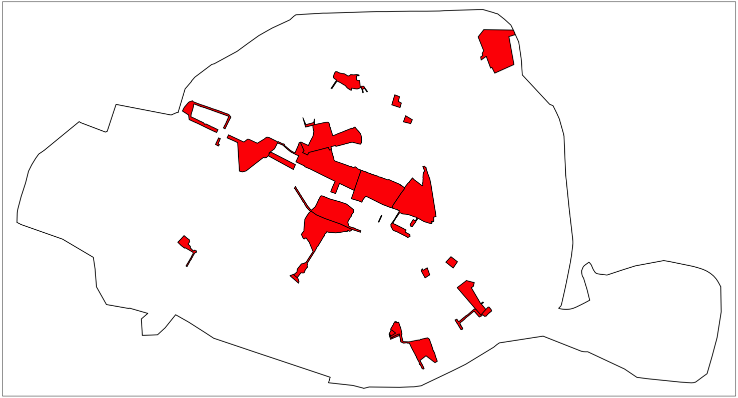
Map of areas affected by "Loi Dimanche"



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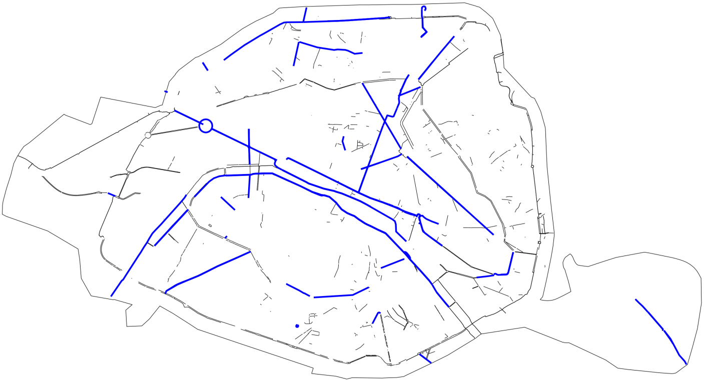
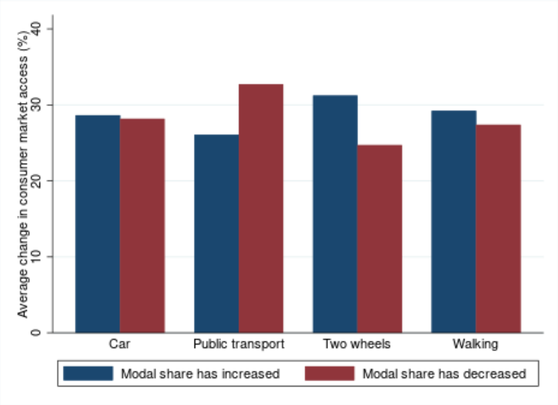
Pre-existing bike lanes



Note: the blue lines identify the PV bike lanes developed by the end of our sample; the black lines the pre-existing bike lanes. Back

Evolution of modal shares and consumer market access

Districts where consumer market access increased the most
$\Rightarrow$ active mobility transport modes also increased their modal share.



Source: INSEE (2017) and Enquête Globale de Transport (2020). ▸ Back

Other outcomes: merchant entry

Panel A:	Entry			
	(1)	(2)	(3)	(4)
Log BMA	0.042			
	(0.082)			
First lag log BMA		0.049		
		(0.096)		
Second lag log BMA			0.067	
			(0.100)	
Third lag log BMA				-0.055
				(0.107)
N	23,480	23,480	23,480	23,480

Notes: the dependent variable is a dummy taking value 1 if at least a new business opened in a given location and quarter, and 0 otherwise. Source: business registry (SIRENE). Back

Other outcomes: car traffic

Panel B:	Log traffic			
Log BMA	-0.457**			
	(0.221)			
First lag log BMA		-0.623**		
		(0.269)		
Second lag log BMA			-0.790**	
			(0.326)	
Third lag log BMA				-0.775**
				(0.351)
N	23,350	23,350	23,350	23,350

Notes: the dependent variable is the log of car traffic in a given location and quarter, measured as the weighted mean of the number of cars recorded by monitoring stations located within 500 meters (weight $\approx$ distance).

Source: *Comptage routier*. Back

Other outcomes: house prices

Panel C:	Log house prices			
Log BMA	-0.004			
	(0.011)			
First lag log BMA		-0.021		
		(0.015)		
Second lag log BMA			0.028*	
			(0.017)	
Third lag log BMA				0.063***
				(0.020)
N	23,382	23,382	23,382	23,382

Notes: property prices are regressed (in logs) on a number of property characteristics; the house price index in a given location and quarter is obtained as the average of residuals corresponding to properties located either within the location or its neighbors. Source: *Demandes de valeurs foncières*. Back

Other outcomes: TripAdvisor reviews

Panel A:	Number of reviews			
	(1)	(2)	(3)	(4)
Log BMA	1.147*			
	(0.622)			
First lag log BMA		1.996***		
		(0.762)		
Second lag log BMA			1.943**	
			(0.846)	
Third lag log BMA				1.848**
				(0.915)
N	134,273	134,273	134,273	134,273
Panel B:	Average review grade			
Log BMA	-0.029			
	(0.124)			
First lag log BMA		-0.139		
		(0.153)		
Second lag log BMA			-0.188	
			(0.169)	
Third lag log BMA				-0.011
				(0.184)
N	104,753	104,753	104,753	104,753

Source: *TripAdvisor*. Back