The Welfare Consequences of Urban Traffic Regulations

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Motivation

Rise in regulations to reduce road traffic externalities:

- Traffic congestion
- Pollution (CO_2, PM, NO_X)

Challenge to analyze policy effects: road traffic is an equilibrium outcome

This paper

- We build and estimate a structural model to represent individual transportation decisions and traffic conditions inside a city
  - Application: Paris metropolitan area ("Île-de-France")
- Quantify the surplus changes and environmental benefits of hypothetical urban traffic policies
- Analyze and compare simple regulations:
  - Driving restrictions
  - Fixed and per-km tolls
- Confront the performance of simple instruments to a first-best benchmark
  - Welfare-maximizing personalized tolls

Model overview

The model has two components:

- Choice of a transportation **mode** and departure **period**
  - Trips' origins, destinations and itineraries are fixed
- Congestion technologies for road traffic
  - Represent how speeds change with road traffic levels
  - Heterogeneous across different areas of the city

Equilibrium outcomes of the model: car speeds and number of drivers in each area of the city, in each period

Overview of the results

- Policies decrease the aggregate consumer surplus:
  - Substitution to other modes/periods decrease individuals' utility
  - Gains from speed improvements only partly mitigate the surplus losses
- When we consider welfare (CS + tax revenue + emissions saved), moderate tolls are welfare-improving
- Variable tolls are better than uniform tolls because they target long-distance commuters, but they imply winners and losers
- The variable toll generates 61% of the welfare gains from first-best personalized tolls

(selected) Related literature

Structural models of transportation decisions:

- Discrete choice models: McFadden (1974), etc...
- Jia Barwick et. al (2022, WP): Housing location and commute decisions
- Almagro et al. (2023, WP): Optimal congestion charge and public transport service

Reduced-form models of congestion:

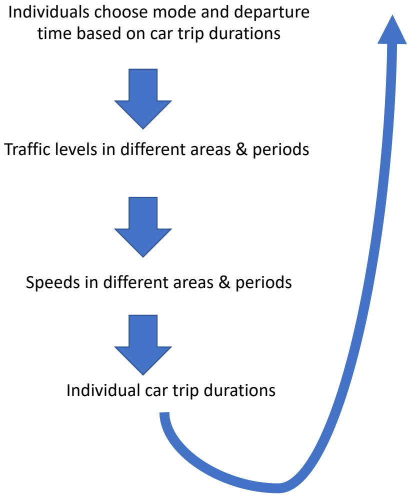
- Couture et al. (2018, ReStat): Determinants of speed
- Yang et al. (2020, AEJ), Anderson (2014, AER): Exogenous shocks to identify congestion technology

Structural "bottleneck" models of congestion:

- Arnott et al. (1990 JUE, 1993 AER): Theory
- Hall (2019, JEEA): Distributional effects of road pricing
- Kreindler (2022, Eca): Welfare effects of congestion charges using experimental data
- De Palma et al.: METROPOLIS traffic model

Outline

Illustration



Outline

Model in equations

Discrete choice nested logit model:

1. Transportation mode $\in$ {car, public transport, walk, bicycle, motorbike}
2. Departure period: peak or off-peak hours

Utility function for individual n, mode j, period t:

$$u_{njt} = \underbrace{\beta_n \log(d_{njt})}_{\text{duration}} + \underbrace{\alpha p_{nj}}_{\text{cost}} + \underbrace{\rho_n (t - t_n^*)}_{\text{schedule constraints}} + \underbrace{X_{njt}\delta}_{\text{mode charac.}} + \underbrace{\zeta_{nj} + \sigma\tilde{\epsilon}_{njt}}_{\text{pref. shocks}}$$

Assumptions:

- t_n^*: preferred hour of departure, t_n^* = peak hour $\forall n$
- β_n, ρ_n are functions of demographic characteristics
- X_{njt}: mode $\times$ period dummies, pub. transit characteristics
- $\zeta_{nj} + \sigma\tilde{\epsilon}_{njt}$: iid shocks, independent across modes correlated between periods, assumed to be extreme value
- σ: degree of independence between peak & off-peak hour shocks

Estimation of the preference parameters by maximum likelihood

Data

- Survey data from 2010-2011: "Enquête Globale Transport"
- Restrict to study and work-related trips (non-avoidable trips), first trip of the day, trips $\geq$ 700 meters
- $\Rightarrow$ 12,975 choices, representing $\sim$ 4 million individuals ($\sim$ 1/3 population)
- Demographics: age, socio-professional activity, household composition, and wealth proxy from housing surface area and neighborhood
- Trip cost: information on the type of public transport ticket, some car and motorbike characteristics ▸ estimates
- Emissions per km, based on car characteristics
  - CO_2, NO_X, PM, HC, with social values from OECD 2014

Data

- The departure period modifies:
  - Trip duration for car
  - Overcrowding level in the public transport
  - Nothing for walking, motorcycle, bicycle

- Public transport overcrowding for metro line l, at period t:

$$\text{overcrowding}_{l,t} = \frac{\#\text{ passengers per hr}_{l,t}}{\text{metro capacity}_{l} \times \#\text{ metros per hr}_{l,t}}$$

- Expected car and public transport durations from TomTom, Google Maps APIs ▸ more

Descriptive statistics

- Average trip distance = 12.9 km
- Average trip duration = 31.3 minutes
- 82% of individuals hold a car, 35.2% choose to drive
- Peak hours chosen by: 65% of drivers, 67.6% of pub. transit users
- Driving at peak hours is on average 30% slower
- Public transit overcrowding:

Line	**Off-peak**	**Peak**
1	0.43	0.72
3B	0.18	0.36
4	0.6	1.11
13	1.62	1.93
A	2.35	4.37
⋮	⋮	⋮
Average	0.89	1.43

- Average cost = €0.92, average driving cost = €1.17, average pub. transit cost = €1.25

Estimation results: Summary

- Preferences are such that:
  - Average WTP to drive at peak hours instead of off-peak hours = €2.6
  - Average Δ% duration accepted to drive at peak hours: +73%
  - Average WTP to decrease overcrowding by 10% = 3.1 cents
- Value of travel time (€/hr):

Min	Q1%	Mean	Median	Q99%	Max
0.44	1.34	15.9	10.3	81.1	389

Note: weighted by the survey weights.

Full estimates

Outline

Congestion technology

$$v_t^a = f^a(\tau_t^a) + \eta_t^a$$

- v_t^a: speed at period t in area a (in km/hr)
- τ_t^a represents traffic conditions (occupancy rate)
- f^a: technology in area a, to be estimated
- η_t^a: speed shock, assumed to be independent of τ_t^a

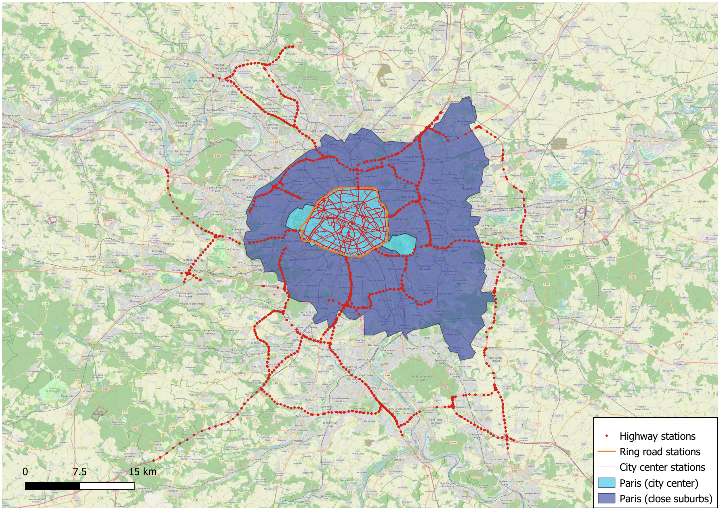
We approximate f^a by polynomials of degree L:

$$f^a(\tau) = \sum_{l=0}^{L} B^l(\tau)\theta_l^a$$

B^l: basis Bernstein polynomials
$\boldsymbol{\theta}^a = (\theta_0^a, ..., \theta_L^a)$: parameters to be estimated

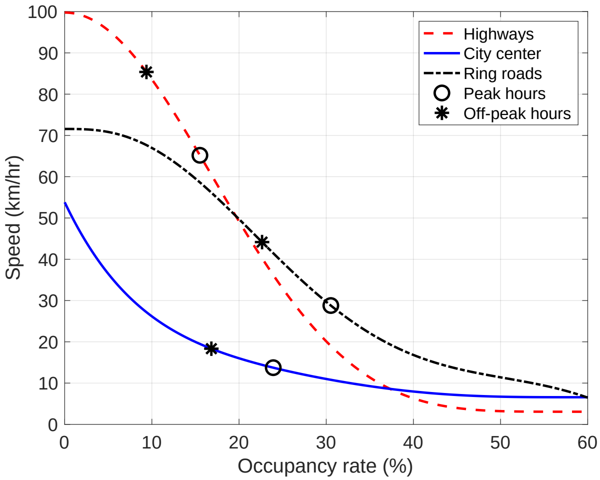
We estimate $\boldsymbol{\theta}$ by constrained least squares using hourly traffic data from 1,371 road sensors over 2016-2017

Definition of the areas



Sources: DRIF (highways) and “Mairie de Paris” (city center and ring roads)

Estimated congestion technologies



Note: Initial traffic conditions = average speeds from TomTom predicted durations.

▸ Robustness analysis

Closing the model

- From individual decisions to traffic conditions:
  - Mapping between the occupancy rate (τ_t^a) and number of kilometers driven by area (K_t^a):

$$\tau_t^a = \phi^a \times K_t^a + \gamma^a$$

  - with $K_t^a = \sum_{n=1}^{N} \underbrace{\omega_n}_{\text{indiv. weight}} \times \underbrace{s_{nt}}_{\text{proba. driving period } t} \times \underbrace{k_n^a}_{\text{distance in area } a}$
  - ϕ^a: scale parameter, γ^a: irreducible traffic (trucks, delivery cars, buses...)
- From speeds to individual trip durations:

$$\text{duration}_n^t = \left(\sum_a \frac{\text{distance}_n^a}{\text{speed}_a^t} \right) \times \varepsilon_n^t$$

  - ε_n^t: multiplicative speed shocks that shift individuals' trip durations

Fit of the model

Equilibrium uniqueness

Multiple areas: no general result about uniqueness

- We provide a method to check uniqueness
- Propose an algorithm to compute speeds that depends on a parameter κ

$$(v_t^a)^{m+1} = g(\mathbf{v}^m) = (1-\kappa) \times (v_t^a)^m + \kappa \times f^a\left(\phi^a \times K_t^a(\mathbf{v}^m) + \gamma^a\right)$$

- Algorithm is a contraction for $\kappa \in]0,1]$ if the Lipschitz coefficient of $g(.)$ is strictly lower than 1

Outline

Policy instruments

Compare the effects of three simple policies:

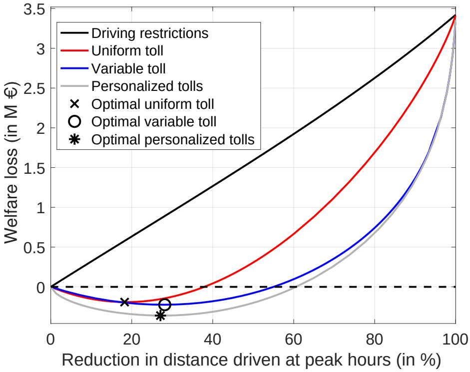
- Driving restrictions
- Uniform tolls
- Variable tolls

We compare these simple instruments with a first-best benchmark:

- Personalized tolls
- Set to maximize welfare, for a given traffic reduction objective
- Tolls must be $\in [0, €50]$

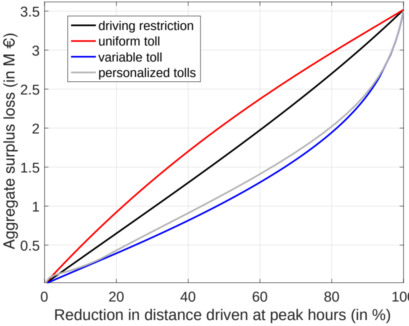
Comparison between policies: welfare

ΔWelfare = Δ CS + Tax revenue - ΔEmissions

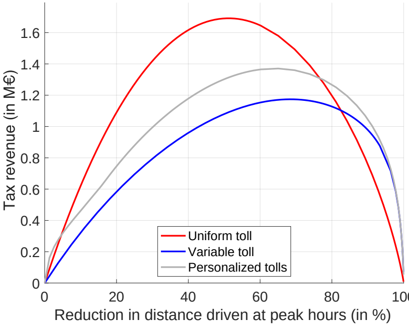


Optimal uniform toll: €1.4, traffic reduction = 18.2%
Optimal variable toll: 8 cents/km, traffic reduction = 28.2%
Optimal personalized tolls: traffic reduction = 27%

Comparison between policies: surplus and tax revenue



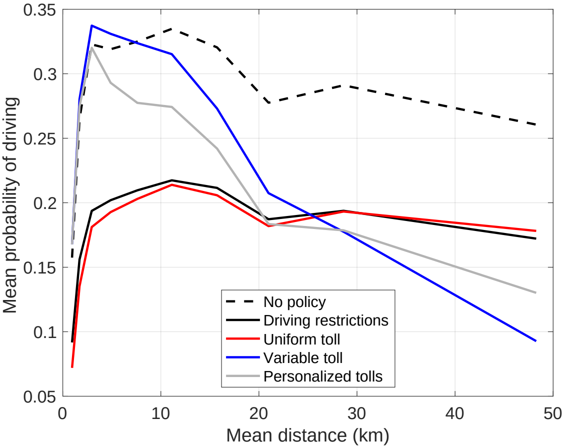
(a) Consumer surplus losses.



(b) Tax revenues.

Targeting of the policy instruments

Policy stringency at a benchmark level: traffic reduction = 34%



Summary: performance of the simple tolls

Policy stringency at a benchmark level: traffic reduction = 34%

	ΔWelfare (in million €)	%ΔW w.r.t personalized tolls
Personalized	0.347	100%
Fixed and variable	0.24	69.3%
Variable	0.212	61.2%
Area-specific	0.127	36.7%
Uniform	0.064	18.3%

Note: ΔWelfare for one trip. For annual figures, multiply by $\sim$ 500.

Conclusion

- We develop a new structural model for individual transportation decisions with endogenous car trip durations
- We measure the welfare changes from driving restrictions and road tolls
- Moderate tolls can be welfare improving under redistribution of the tax revenue
- The variable toll generates 61% of the potential welfare gains
- Model is general, fairly simple and estimated from publicly available data

Appendix: queries

Car trip durations (TomTom):

- Queries done in July 2021
- Predictions for Thursday September 16th, 2021
- Peak hours: departure time = 8.30 a.m
- Off-peak hours: departure time = 6.30 a.m

Public transport duration and itinerary (Google Maps):

- Queries done on June 2nd, 2019
- Queries for Tuesday June 4th, 2019
- Departure time = 9.30 a.m

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Appendix: cost estimation

Table: **Summary statistics: Cost estimates**

Variable	Mean	Median	Std. dev.	Min	Max
Bike	0.64	0	0.82	0	1.7
Public transport	1.25	1.24	1.27	0	10.55
Motorbike	1.21	0.72	1.39	0	13.72
Car	1.17	0.76	1.25	0	14.24

Note: Cost is expressed in euros.

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Estimation results: mean coefficients

Variable	Est.	Std. err.
Log(duration)	-1.92**	0.065
Cost	-0.407**	0.019
Bicycle	-3.48**	0.082
Public transport, peak	-4.88**	0.2
Public transport, off-peak	-5.51**	0.403
Motorcycle	-7.35**	0.226
Car, peak	-6.22**	0.211
Car, non peak	-7.27**	0.214
No. layovers in public transport	-0.346**	0.036
Railway only	0.052	0.057
Public transport overcrowding	-0.064**	0.024
σ	0.788**	0.063

*Significance level: **1%. Duration in minutes, cost in €. Standard errors computed using the delta-method.*

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Estimation results: heterogeneity of preferences

Variable	Est.	Std. err.
Log(duration) $\times$ wealth $\in$ q2	-0.05	0.08
Log(duration) $\times$ wealth $\in$ q3	-0.01	0.08
Log(duration) $\times$ wealth $\in$ q4	-0.11	0.08
Log(duration) $\times$ wealth $\in$ q5	$0.15^{\dagger}$	0.09
Log(duration) $\times$ Age $\in$]18-25]	-0.4^{**}	0.1
Log(duration) $\times$ Age $\in$]25-35]	-1.59^{**}	0.09
Log(duration) $\times$ Age $\in$]35-45]	-1.7^{**}	0.08
Log(duration) $\times$ Age $\in$]45-60]	-1.45^{**}	0.08
Log(duration) $\times$ Age > 60	-2.03^{**}	0.2
Log(duration) $\times$ Effort	-1.66^{**}	0.06
Off-peak hours $\times$ white collar	-0.57^{**}	0.09
Off-peak hours $\times$ blue collar	$0.16^{\dagger}$	0.08
Off-peak hours $\times$ below high school	-0.98^{**}	0.12
Off-peak hours $\times$ higher education	0.01	0.1
Off-peak hours $\times$ family	$-0.08^{\dagger}$	0.04

Significance level: **1%, *5%, †10%. Reference category is Age < 18, wealth $\in$ q1, independent worker, single.

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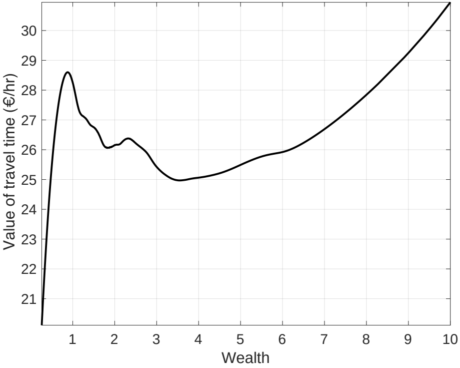
Estimation results: Value of travel time

- $\text{VOT}_{njt} = \frac{\partial U_{njt}}{\partial \text{duration}_{njt}} \Big/ \frac{\partial U_{njt}}{\partial \text{cost}_{njt}} = \frac{\beta_n^{\text{duration}}}{\beta^{\text{cost}}} \times \frac{1}{\text{duration}_{njt}}$



Note: Wealth in €100,000 per consumption unit.

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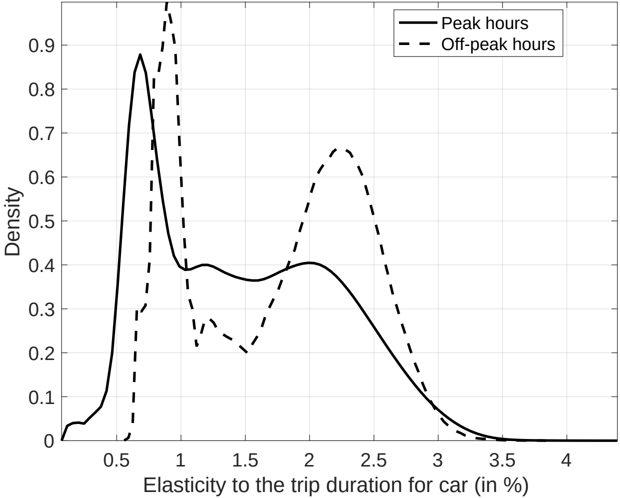
Elasticities to trip duration



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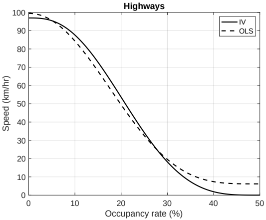
Robustness analysis of congestion technologies

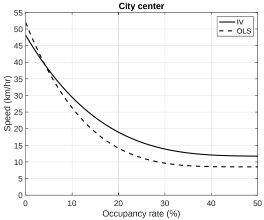
Exclude observations with extreme weather (low/high temperature, snow, rain, wind)

GMM estimation with instrumental variables:

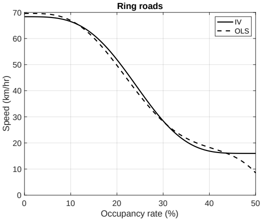
- Hour, day-of-the-week dummies
- Low public transport traffic dummy (strikes)
- Dummy for an accident in a donut of 5 km, distance to the accident
- Dummy for an accident the previous hour in a radius of 5 km, distance to the accident
- Dummies if hourly temperature $\in$ (4-9) or (19-25)°C,
- Dummies for school holidays, banks holidays, driving restrictions



(a) Highways.



(b) City center.



(c) Ring roads.

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Fit of the model

Shares of transportation modes (in %):

	Observed	Predicted shares
Bicycle	2.1	2.09
Public transport	30.32	30.28
Motorbike	2.08	2.08
Walking	15.8	15.8
Car, peak	22.88	22.92
Car, off-peak	12.3	12.27
PT, off-peak	14.52	14.57

Speeds (in km/hr):

	Peak hour		Off-peak hour	
Area	Traffic	TomTom	Traffic	TomTom
Highway	44.9	65.2	67	85.4
City center	22.4	13.7	31.7	18.3
Ring roads	30.4	28.8	57.9	44.2
Close suburb		15.8		20.2
Far suburb		25.5		29.2

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