Mode and Departure-Time Choice Estimates

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Motivations

What are the determinants of the mode of transportation and departure time chosen by the individuals for their trips?

Example of questions we want to answer:

- What is the minimum incentive amount that I must give you to convince you to switch from car to public transit?
- If road congestion decreases between 7AM and 8AM, will you leave at 07:50 instead of 08:00?
- If a road opening is decreasing your car travel time by 10 minutes, will you switch from public transit to car?

Application: evaluation of transport policies (low-emission zone, Grand Paris Express, public-transit subsidies, etc.)

Desired Arrival Time

- **Desired arrival time (t^*):** time at which the individual would choose to arrive if travel time was null.
- Desired arrival time can be different from *actual arrival time* (trade-off between travel time and schedule delay).
- Desired arrival times are *unknown* and highly *heterogeneous*.

Utility

In the standard **α-β-γ model** (Vickrey, 1969; Arnott, de Palma, Lindsey, 1990s), utility for mode i and departure time t_d is:

$$u(i, t_d) = -\underbrace{c_i}_{\text{Constant}} - \underbrace{\alpha_i \cdot tt_i(t_d)}_{\text{Travel cost}} - \underbrace{\beta \cdot [t^* - t_d - tt_i(t_d)]_+}_{\text{Early penalty}} - \underbrace{\gamma \cdot [t_d + tt_i(t_d) - t^*]_+}_{\text{Late penalty}}$$

- c_i: mode-specific constant cost
- α_i: value of time for mode i
- $tt_i(t_d)$: travel time when leaving at time t_d with mode i
- β: penalty for arriving early
- γ: penalty for arriving late
- t^*: desired arrival time
- $[x]_+ = \max(x, 0)$

Part I: Desired arrival-time distribution

In α-β-γ the model, any individual with a constant travel time will choose to arrive exactly at his / her desired arrival time:

- If my travel time is constant, I choose a departure time such that I arrive at my desired arrival time.
- If my travel time is time-dependent, I might choose to arrive early / late to reduce travel time.

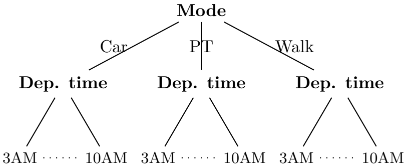
We estimate the distribution of t^* in the population from the distribution of arrival times in the subpopulation of individuals with a constant travel time (all walk trips and car trips without congestion).

Part II: Bayesian estimates

After estimating the distribution of t^*, we are able to estimate the parameters of interest (value of time, early and late penalties, etc.) using **Bayesian estimates** and a **travel survey**.

We estimate a “Mixed discrete-continuous Nested Logit model”:

- Stage 1: mode choice (Multinomial Logit)
- Stage 2: departure-time choice (Continuous Logit)
- Fixed coefficients: mode-specific constants and values of time, early and late penalties
- Random coefficients: desired arrival times (but distribution is known, from Part I)



Literature review

Departure-time choice:

- α-β-γ model using the work start time as desired arrival time (Small, 1982; Thorauge et al., 2021)
- Schedule-delay represented by time-specific constants (Zeid et al., 2006; Popuri et al., 2008; Lemp and Kockelman, 2010; Lemp et al., 2010)
- Kim and Moon, 2022: desired arrival times are estimated using a machine learning method using the arrival times of individuals facing no congestion

Joint mode and departure-time choice:

- Joint discrete-continuous model with time budget constraint (Habib, 2013; Jokubauskaité, 2019)
- Mixed Nested Logit model with stated preferences (Bajwa et al., 2008)

Results

- The desired arrival times t^* can be mostly explained by *profession category* and *workplace area*.
- Value of time is the smallest for public transit and largest for walk.
- Walking is preferred to car and public transit for trips smaller than 1.3 km.
- When there is no congestion, the odd ratio of choosing car over public transit does not depend on trip distance.

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Data

Part I: Desired arrival-time distribution

Part II: Bayesian estimates

Conclusion

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Enquête Globale Transport (EGT)

- 2010 **transport survey** for Île-de-France (Paris' region, with 12 millions inhabitants)
- 14 855 households, 35 175 individuals surveyed
- Observations: households characteristics, individual characteristics, trips of the previous day (including, mode, departure time, purpose)

Details

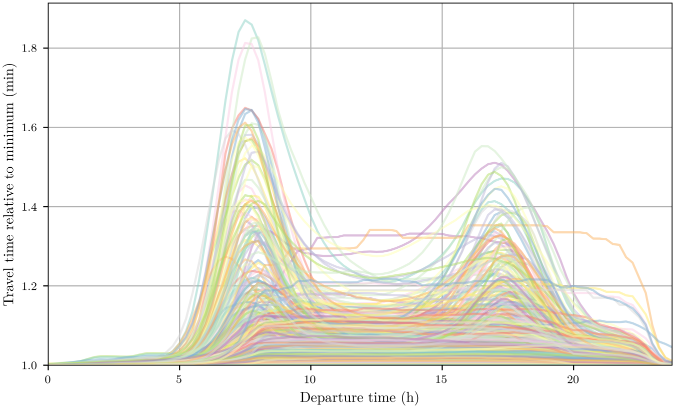
Car Travel-Time

- Source: HERE, Q1 2016
- Historical link-level speed for 15-minute intervals (typical day)
- 977 618 links in the Île-de-France area (18.51 % with a non-constant travel time)
- OD-level travel-time functions computed using a routing algorithm (Time-dependent Contraction Hierarchies)
- Link-level and OD-level travel time functions are piecewise linear functions

▸ OLS regression

Car Travel-Time

Random sample of 500 OD pairs.



Public-Transit / Walk Travel-Time

Public transit:

- Source: OpenStreetMap (walking network) and IDF Mobilités GTFS (timetables)
- Methodology: Least cost path given by OpenTripPlanner (with departure time 2023-06-26 at 8AM)
- 1937 lines, 53 199 stops
- Public-transit travel time is assumed to be constant with departure time (for now)

▸ OLS regression

Walk

- Source: OpenStreetMap
- Methodology: Distance of the shortest path given by a routing algorithm
- Walking travel time is computed assuming a speed of 4.14 km/h (estimated speed based on observed travel times)

▸ OLS regression

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Scope

- Home-to-work trips
- Modes: car (as a driver alone), public transit, walk
- Time window: 3AM – 10AM
- Sample size: 7881 trips

Basic Principle

Claim: When travel-time function is constant, the individual arrives at his / her t^*.

$$u(t_d) = -c - \alpha \cdot tt(t_d) - \beta \cdot [t^* - t_d - tt(t_d)]_+ - \gamma \cdot [t_d + tt(t_d) - t^*]_+$$

$$\text{if } tt(t_d) = \bar{tt} \quad \Rightarrow \quad \arg\max_{t_d} u(t_d) = t^* - \bar{tt}$$

Consequence: For individual facing no congestion, their arrival time reveal their t^* value.

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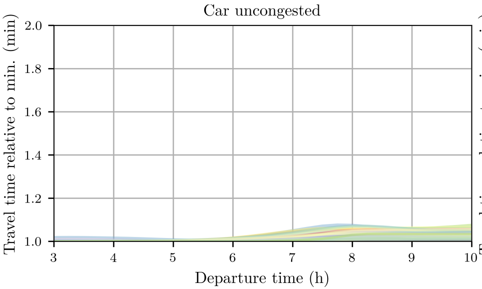
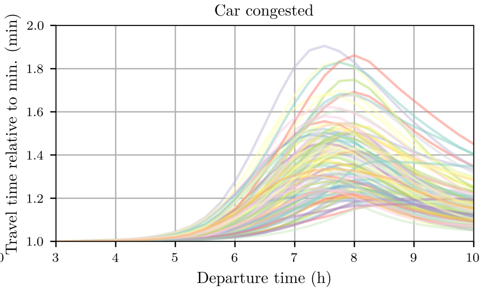
Trip categories

Three trip categories are analyzed:

- **Group A:** Walk (643 trips)
- **Group B:** Car uncongested (1169 trips)
- **Group C:** Car congested (1169 trips)





▸ Congestion

Trip categories

(A: Walk, B: Car uncongested, C: Car congested)

- *Desired arrival time* t^* distribution (unobserved) is F_A, F_B, F_C
- *Arrival time* t_a distribution (observed) is G_A, G_B, G_C

- Goal: estimate F_A, F_B, F_C
- Previous claim: $F_A = G_A$, $F_B = G_B$
- Can we infer F_C from F_A and F_B?

Endogeneity

Variables that could explain t^*:

- Occupation
- Workplace
- Number of children
- Gender
- ...

All these variables also explain mode choice: Desired arrival time distribution is mode-dependent ($F_A \neq F_B$)

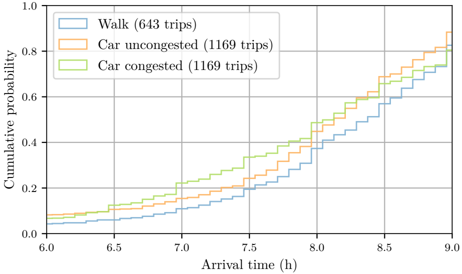
Comparing distribution

- The **two-sample Kolmogorov-Smirnov test** can be used to compare two samples and assert if they come from the same probability distribution.
- Null hypothesis: "The values in the two samples are drawn from the same probability distribution".

All trips, by mode

The null hypothesis is always rejected at the 1 % level (the distributions are different).

	KS statistic	p-value
Walk / Car uncong.	**0.1308**	**0.0000**
Walk / Car cong.	0.1439	0.0000
Car cong. / Car uncong.	0.0915	0.0001

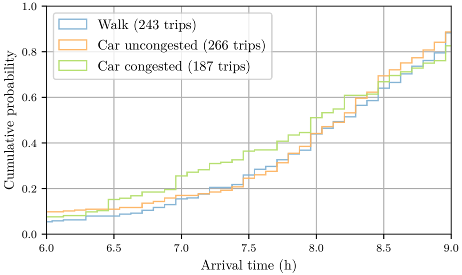


If we split population by profession category (employee, intermediate category, upper category, blue-collar workers), are the arrival-time distributions still explained by mode choice?

Employees

The null hypothesis that *Walk* and *Car uncongested* have the same distribution **cannot** be rejected.

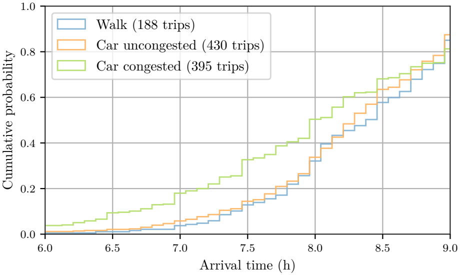
	KS statistic	p-value
Walk / Car uncong.	**0.0678**	**0.5709**
Walk / Car cong.	0.1151	0.1096
Car cong. / Car uncong.	0.1206	0.0738



Intermediate category

The null hypothesis that *Walk* and *Car uncongested* have the same distribution **cannot** be rejected.

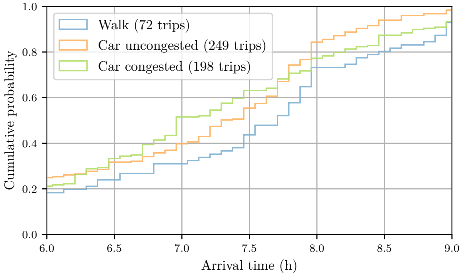
	KS statistic	p-value
Walk / Car uncong.	**0.0711**	**0.4957**
Walk / Car cong.	0.2171	0.0000
Car cong. / Car uncong.	0.1830	0.0000



Blue-Collar Workers

The null hypothesis that *Walk* and *Car uncongested* have the same distribution **cannot** be rejected.

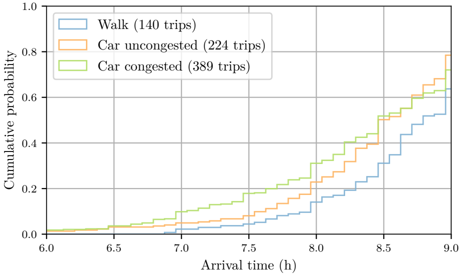
	KS statistic	p-value
Walk / Car uncong.	**0.1735**	**0.0602**
Walk / Car cong.	0.2210	0.0097
Car cong. / Car uncong.	0.1176	0.0856



Upper category

The null hypothesis that *Walk* and *Car uncongested* have the same distribution **can** be rejected.

	KS statistic	p-value
Walk / Car uncong.	**0.2071**	**0.0010**
Walk / Car cong.	0.2213	0.0001
Car cong. / Car uncong.	0.0970	0.1269



Upper category: By workplace area

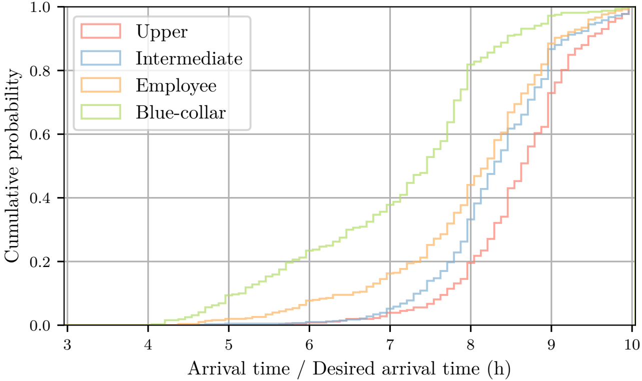
Average arrival time (trip count)

	Paris	Inner suburbs	Outer suburbs
Walk	9:10 (70)	8:50 (51)	8:38 (29)
Car uncongested	9:26 (3)	8:46 (51)	8:34 (185)
Car congested	8:45 (51)	8:32 (222)	8:38 (127)
Average	8:56	8:37	8:34

Conclusion: Ideally, t^* distributions should be split by profession category and workplace area but sample size is too small.

Summary

Conclusion: After controlling by profession category and workplace area, the desired arrival time is no longer explained by mode $\Rightarrow F_A = F_B = F_C$



▸ Robustness Checks

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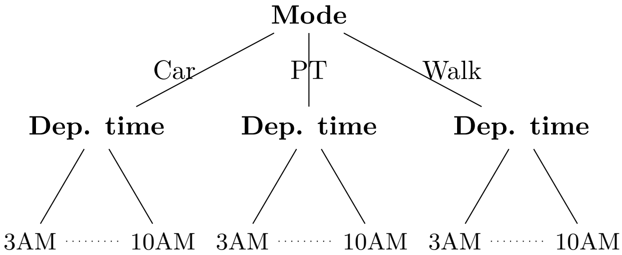
Decision Tree



Likelihood (lower level)

- Observed choice for individual n: $y_n = \{i, [\underline{t}, \bar{t}]\}$, where i is the mode chosen and $[\underline{t}, \bar{t}]$ is the departure-time interval chosen.
- Let $\theta = \{\boldsymbol{c}, \boldsymbol{\alpha}, \beta, \gamma, \boldsymbol{\mu}\}$ be the set of parameters to be estimated.
- The likelihood to observe departure-time interval $[\underline{t}, \bar{t}]$ given that mode i is chosen is (**Continuous Logit** assumption)

$$L_n^{\text{dep}}([\underline{t}, \bar{t}]; i, \theta, t_n^*) = \frac{\int_{\underline{t}}^{\bar{t}} e^{u_n(t; i, \theta, t_n^*)} \, \mathrm{d}\, t}{\int_{t_0}^{t_{M+1}} e^{u_n(t; i, \theta, t_n^*)} \, \mathrm{d}\, t}$$

where

$$u_n(t; i, \theta, t_n^*) = \frac{-c_i - \alpha_i \cdot tt_{n,i}(t) - \beta \cdot [t_n^* - t - tt_{n,i}(t)]_+ - \gamma \cdot [t + tt_{n,i}(t) - t_n^*]_+}{\mu_i}.$$

Likelihood (upper level)

- The log-sum of the departure-time choice for mode i is

$$V_{n,i}(\theta, t_n^*) = \mu_i \ln \int_{t_0}^{t_{M+1}} e^{u_n(t;i,\theta,t_n^*)} \,\mathrm{d}\,t + \mu_i EC$$

  where $EC \approx 0.5772$ is the Euler-Mascheroni constant.

- The likelihood to observe mode i is (**Multinomial Logit** assumption)

$$L_n^{\text{mode}}(i; \theta, t_n^*) = \frac{e^{V_{n,i}(\theta, t_n^*)}}{\sum_j e^{V_{n,j}(\theta, t_n^*)}}.$$

- The likelihood to observe the choice $y_n = \{i, [\underline{t}, \overline{t}]\}$ is

$$L_n(y_n; \theta, t_n^*) = L_n^{\text{mode}}(i; \theta, t_n^*) \cdot L_n^{\text{dep}}([\underline{t}, \overline{t}]; i, \theta, t_n^*).$$

Likelihood

- The previous likelihood is *conditional on* t_n^*.
- The unconditional likelihood is

$$L_n(y_n;\theta) = \int L_n(y_n;\theta,t^*)\,f(t^*)\,\mathrm{d}\,t^*$$

  where f is the probability distribution of t^*.
- Maximum Likelihood is not feasible, instead we can use Maximum Simulated Likelihood or **Bayesian estimates**.

Bayesian estimates

Goal: Find the estimates of $\theta = \{\boldsymbol{c}, \boldsymbol{\alpha}, \beta, \gamma, \boldsymbol{\mu}\}$ and $\boldsymbol{t^*} = \{t^*_n\}_n$ which best "explain" the observed choices $\boldsymbol{y} = \{y_n\}_n$.

- Density of the prior distribution of θ and $\boldsymbol{t^*}$ is $k(\theta, \boldsymbol{t^*})$ (assumed to be diffuse).
- Density of the posterior distribution is

$$K(\theta, \boldsymbol{t^*}; \boldsymbol{y}) \propto \prod_n L_n(y_n; \theta, t^*_n) f(t^*_n) k(\theta, \boldsymbol{t^*}).$$

Values are drawn from the posterior distribution by combining Gibbs sampling and Metropolis-Hastings algorithm.

▸ Details

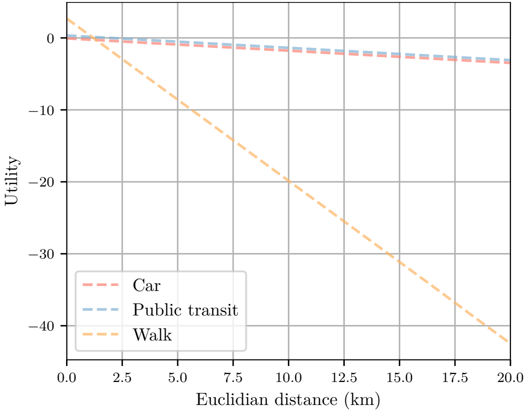
Results: Intermediate category

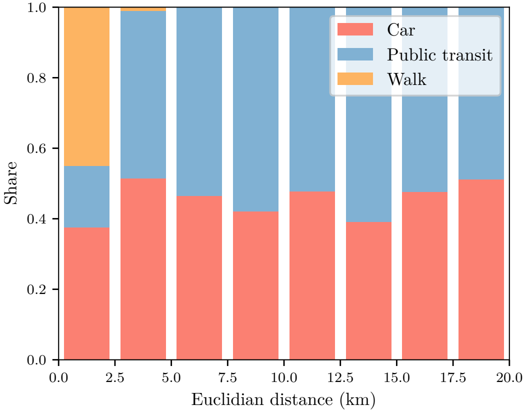
Variable	Estimate	CI [1 %, 99 %]
Const:Public_transit c_{PT}	-0.40	[-0.65, -0.15]
Const:Walk c_{Walk}	-2.76	[-3.38, -2.15]
VOT:Car α_{Car}	3.47	[2.91, 4.03]
VOT:Public_transit α_{PT}	2.18	[1.80, 2.60]
VOT:Walk α_{Walk}	8.02	[6.66, 9.48]
Early penalty β	0.97	[0.82, 1.14]
Late penalty γ	0.82	[0.73, 1.06]
Scale μ	0.16	[0.13, 0.20]

▸ Convergence

Utility as function of distance

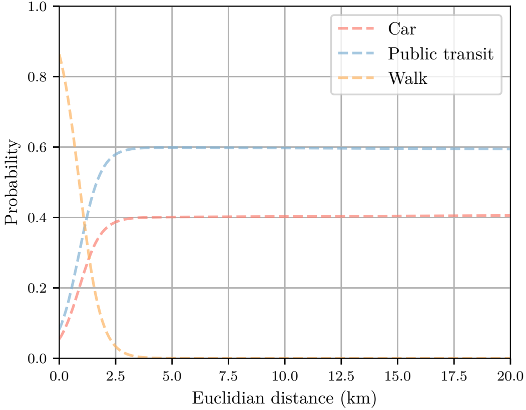
Average observed speeds: Car 20.37 km/h, Public-transit 12.75 km/h, Walking 3.56 km/h

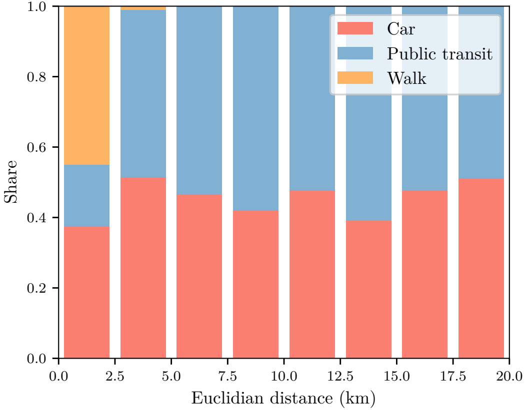




Mode-choice probabilities as function of distance

Average observed speeds: Car 20.37 km/h, Public-transit 12.75 km/h, Walking 3.56 km/h





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Takeaways

We estimate the $\mathbf{t}^*$ **distribution** using *arrival-time* distribution of individuals facing no congestion.

- When controlling by *profession category* and *workplace area*, the desired arrival-time distribution cannot be explained by mode (walk vs uncongested car).

We estimate preference parameters using a **Mixed discrete-continuous Nested Logit model** (for intermediate categories).

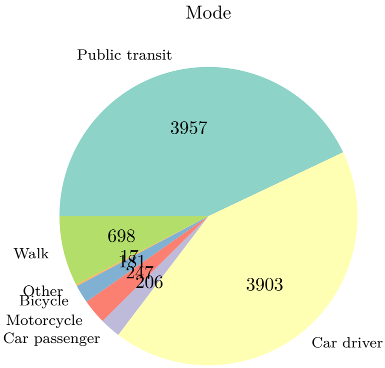
- Value of time is the smallest for public transit and largest for walk.
- Walking is preferred to car and public transit for trips smaller than 1.3 km.
- When there is no congestion, trip distance does not affect the choice between car and public transit.

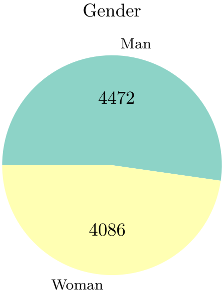
Future works

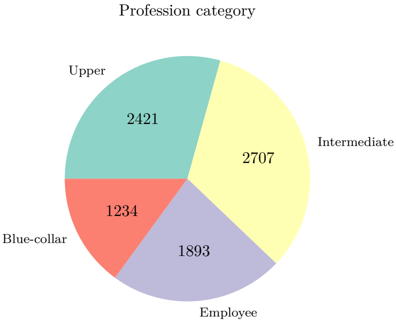
- **Fuel cost** / public-transit fare
- **Evening commute** (desired departure time from origin)
- **Trip chaining** (with t^* at intermediate stop and at destination)
- Car ownership
- Day-to-day travel-time variability

Thank you

Characteristics of home-to-work trips







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Car Travel-Time

Reported travel time for car trips in the travel survey can be well predicted by the computed travel time with HERE data ($R^2 = 66\,\%$).

Dep. Variable:	EGT tt	**R-squared:**	0.664
Model:	OLS	**F-statistic:**	8.274e+04
No. Observations:	41934	**Prob (F-statistic):**	0.00

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
cst	1.5758	0.087	18.061	0.000	1.405	1.747
HERE tt	1.0003	0.003	287.650	0.000	0.993	1.007

Note: Travel-time penalties at intersections are calibrated to reach a slope close to 1.

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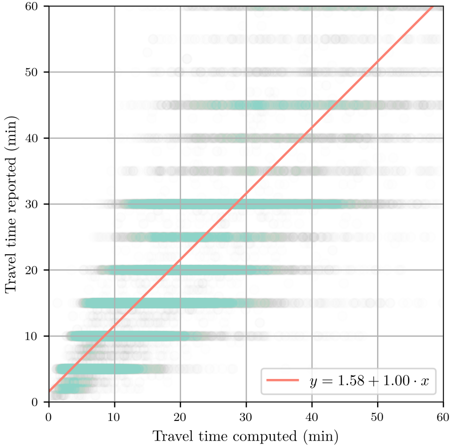
Car Travel-Time



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Public-Transit Travel-Time

Reported travel time for public-transit trips in the travel survey can be well predicted by the computed travel time with OpenTripPlanner ($R^2 = 65\,\%$).

Dep. Variable:	EGT tt	**R-squared:**	0.653
Model:	OLS	**F-statistic:**	3.472e+04
No. Observations:	18453	**Prob (F-statistic):**	0.00

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
cst	6.7029	0.257	26.095	0.000	6.199	7.206
OTP tt	0.9499	0.005	186.330	0.000	0.940	0.960

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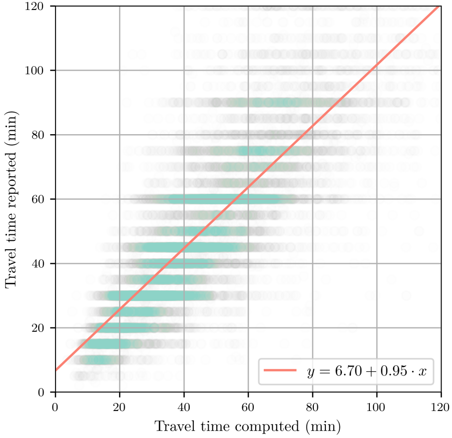
Public-Transit Travel-Time



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Walk Travel-Time

Reported travel time for walking trips in the travel survey can be well predicted by the computed distance with OpenStreetMap.

Dep. Variable:	EGT tt	**F-statistic:**	1.313e+04
Model:	OLS	**Prob (F-statistic):**	0.00
No. Observations:	2141		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
OSM dist	0.0145	0.000	114.571	0.000	0.014	0.015

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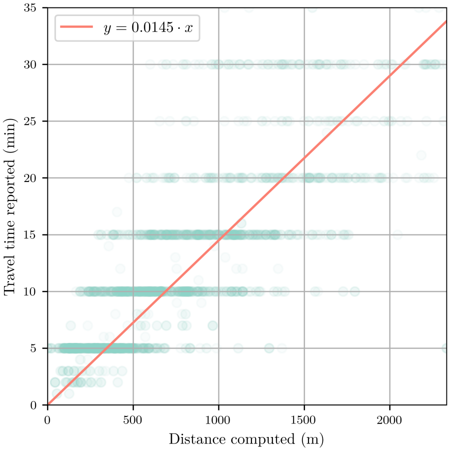
Walk Travel-Time



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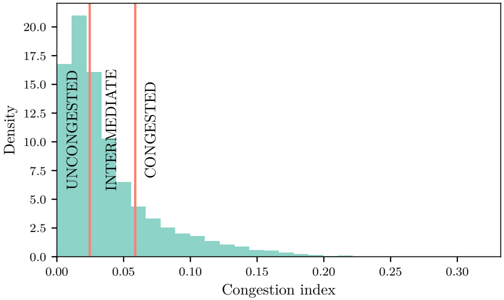
Congestion Index

For each OD pair, we have a travel-time function defined by breakpoints $\{(td_i, tt_i)\}_i$. We compute a congestion index as

$$c = \sigma_{tt}/tt_0,$$

where $\sigma_{tt} = \sqrt{(1/n)\sum_i (tt_i - \bar{tt})^2}$ is the standard-deviation of the travel times and $tt_0 = \min_i tt_i$ is the minimum travel time.



Car trips are split in three categories of equal size based on the congestion index (uncongested, intermediate and congested).

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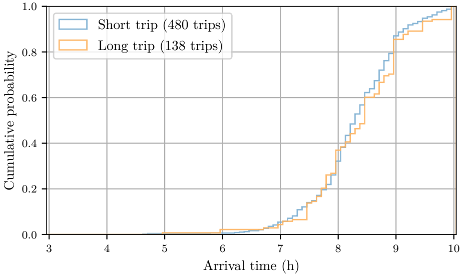
Robustness check: travel time

Comparing long / short trips (intermediate category; walk and car uncongested only).

Long trip: Travel time is longer than 30 minutes.

The null hypothesis that *Short trip* and *Long trip* have the same distribution **cannot** be rejected.

	KS statistic	p-value
Short / Long	0.0923	0.2453



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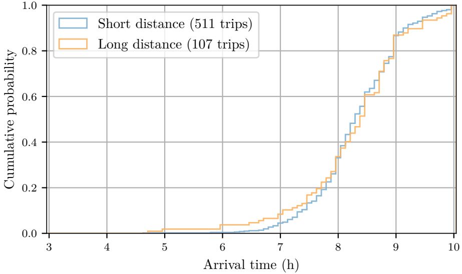
Robustness check: distance

Comparing long / short distance trips (intermediate category; walk and car uncongested only).

Long distance: Euclidian distance between origin and destination is greater than 10 kilometers.

The null hypothesis that *Short distance* and *Long distance* have the same distribution **cannot** be rejected.

	KS statistic	p-value
Short / Long	0.0588	0.8531



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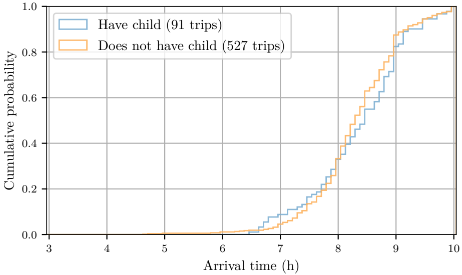
Robustness check: children

Comparing trips of people with / without child (intermediate category; walk and car uncongested only).

The null hypothesis that *Male* and *Female* have the same distribution **cannot** be rejected.

	KS statistic	p-value
Child / No child	0.0914	0.4662



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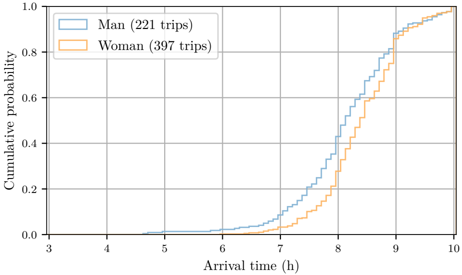
Robustness check: gender

Comparing trips of men / women (intermediate category; walk and car uncongested only).

The null hypothesis that *Man* and *Woman* have the same distribution **can** be rejected.

	KS statistic	p-value
Man / Woman	0.1469	0.0029



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Gibbs Sampling

1. Draw $(t_n^*)^{\tau+1}$, $\forall n$ given θ^τ $\rightarrow$ Metropolis-Hastings

$$K(t_n^*|\theta; y_n) \propto L_n(y_n|\theta; t_n^*) f(t_n^*), \quad \forall n$$

2. Draw $\theta^{\tau+1}$ given $(t_n^*)^{\tau+1}$ $\rightarrow$ Metropolis-Hastings

$$K(\theta|\boldsymbol{t}^*; \boldsymbol{y}) \propto \prod_n L_n(y_n|\theta; t_n^*)$$

Uniform random values are drawn to initialize the first iteration. Each simulation consists in 50 000 iterations of Gibbs sampling.

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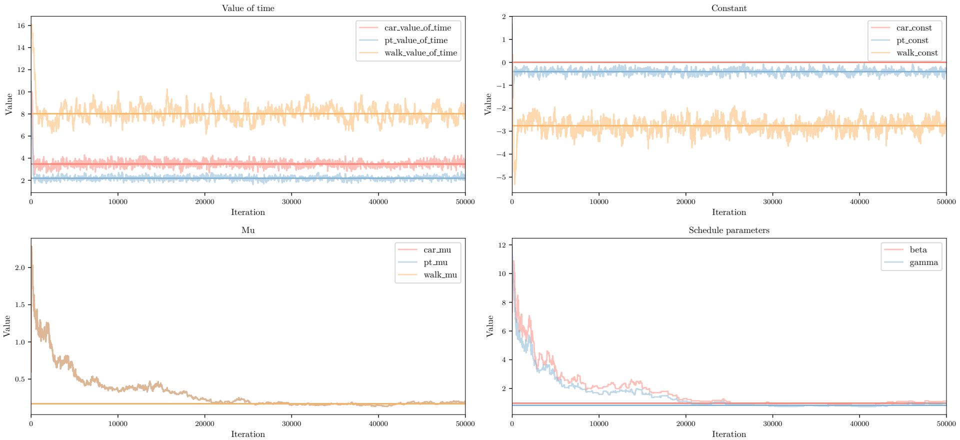
Results: Convergence of simulation



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