PARKING PREFERENCES OF DELIVERY DRIVERS IN THE PARIS GREATER AREA: UNDERSTANDING THE ROLE OF ANTICIPATIONS USING HYBRID CHOICE MODELS

Romain Crastes dit Sourd, Adrien Beziat, Pascal Gastineau, Martin Koning

UNIVERSITY OF LEEDS

Centre for Decision Research
Leeds

Université Gustave Eiffel

LABORATOIRE SPLOTT
SYSTÈMES PRODUCTIFS, LOGISTIQUE, ORGANISATION DES TRANSPORTS ET TRAVAIL

Context

- Interest in the transport literature to understand factors that drive the parking choice of commercial vehicles at delivery stops for:
  - Enhancing logistics
  - Improve the management of freight parking infrastructure
  - Mitigate illegal parking
  - Reduce traffic congestion (Dalla Chiara *et al.*, 2020)

Literature

Large amount of literature on urban freight modelling

Bonnafous *et al*., (2013) discuss how modelling approaches vary in terms of the modelling unit chosen: commodities, handling units, vehicles, trips and routes.

For example, the FRETURB model aims at "*reproducing and simulating urban traffic linked to goods transport with exogeneous variables whose values are generally available in the current statistical databases of urban areas*" with the main statistical unit being the operation observed by the establishment survey.

Let's have a look at an example next slide.

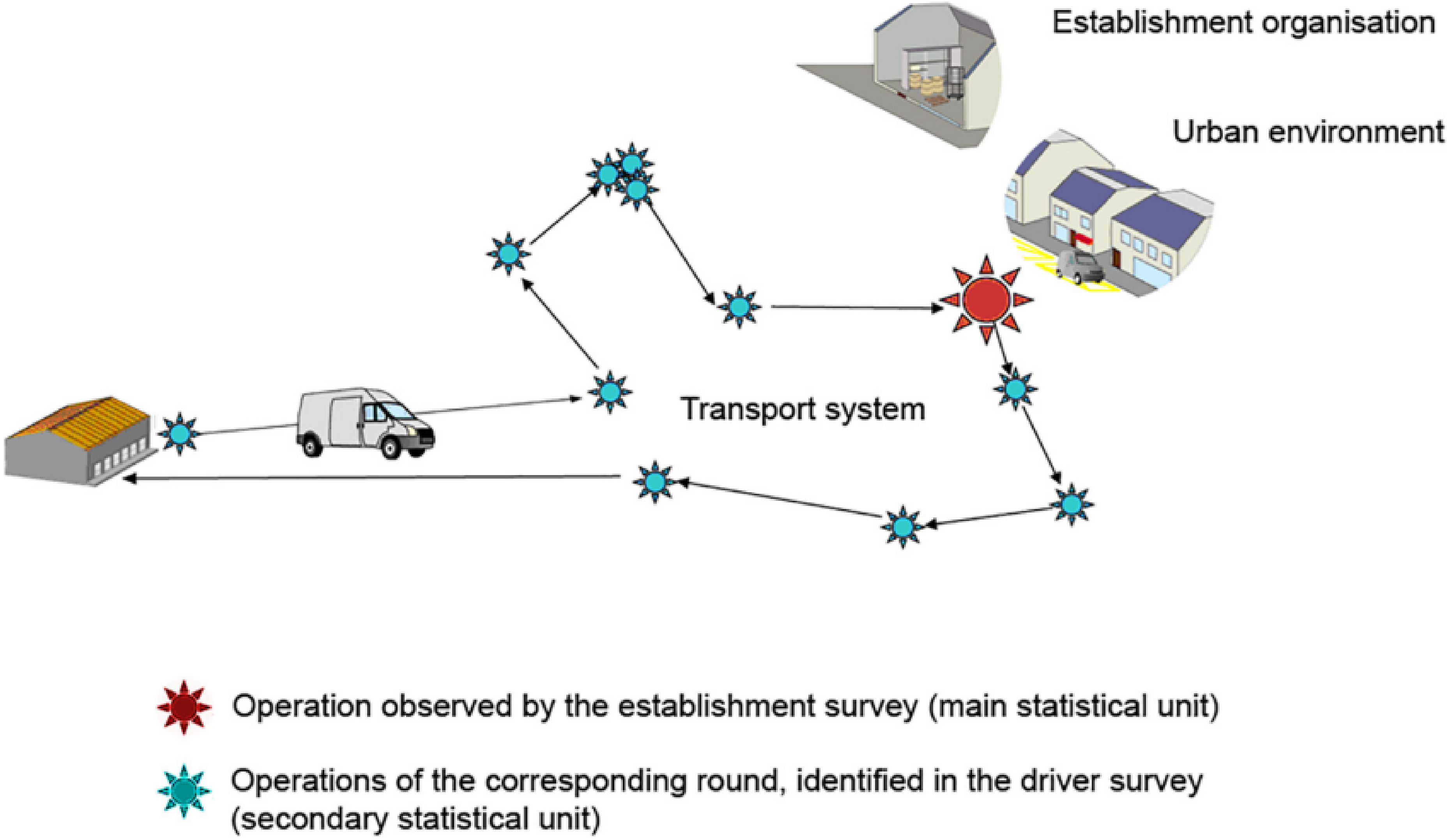


Fig. 2. The operation seen as the main statistical unit. *Source*: LAET by the authors.

(Toilier *et al*., 2018)

Choice modelling literature

A different although somewhat connected literature is interested in understanding behaviour and heterogeneity in preferences of agents in order to inform policy making and improve Agent-Based Models ([Huang *et al.*, 2014]).

Unit = choice level (Stated or Observed/Revealed)

Table 1. Studies on Passenger Vehicles Parking Choice Modeling

Study	Data	Choice	Model	Main covariates: Parking cost	Egress time	Access time	Search time	Parking capacity	Parking duration	Parking fine
Gillen (1978)	RP	Loc	BL	✓	✓					
Van Der Goot (1982)	RP	Loc, Type	MNL	✓	✓				✓	
Axhausen and Polak (1991)	SP	Type	MNL	✓	✓	✓	✓			
Hunt and Teply (1993)	RP	Loc, Type	NL	✓	✓			✓		
Lambe (1996)	RP	Loc	MNP	✓	✓	✓				
Hensher and King (2001)	SP	Loc, Mode	NL	✓	✓				✓	
Golias, Yannis, and Harvatis (2002)	SP	Type	BL	✓	✓		✓		✓	
Hess and Polak (2004)	SP	Type	ML	✓	✓	✓	✓			✓
Anderson, Das, and Tyrrell (2006)	SP	Loc	ML	✓	✓					
Habib, Morency, and Trépanier (2012)	RP	Type, Dur, Dep	DC	✓		✓		✓		
Hilvert, Toledo, and Bekhor (2012)	S&RP	Type	ML	✓	✓	✓	✓		✓	
Kobus et al. (2013)	RP	Type	PL						✓	
Ibeas et al. (2014)	SP	Type	ML	✓	✓		✓			
Chaniotakis and Pel (2015)	SP	Type	ML	✓	✓	✓				
Qin et al. (2017)	SP	Type, Mode	NL	✓		✓				
Soto, Márquez, and Macea (2018)	SP	Type	HDC	✓		✓	✓			

Note. SP, stated preferences; RP, revealed preferences; S&RP, combined stated and revealed preferences; Loc, parking location; Type, parking type (e.g., on-street/off-street/illegal parking types); Mode, travel mode (e.g., private car/public transport); Dur, parking duration; Dep, departure time; BL, binary logit; MNL, multinomial logit; NL, nested logit; PC, probit choice; ML, mixed logit; DC, discrete continuous; HDC, hybrid discrete choice.

(Dalla Chiara *et al.*, 2020)

•

Do you *vs* Would you?

Table 2
Example of a ranking task.

	Policy 1	Policy 2	*Status quo*
Loading/unloading bays (LUB):	1200	800	400
Probability of free l/u bays (PLUBF):	10%	20%	10%
Entrance fee (EF):	1000€	400€	600€
Policy ranking	☐	☐	☐

The planned parking duration is 1 hour. Which alternative will you choose?

	Alternative 1A	Alternative 2	Alternative 3
Parking type	On-street (5 NIS/hr)	Off-street (16 NIS/hr)	Off-street (8 NIS/hr)
Overall parking price (NIS)	5	16	8
On-street parking search time (min.)	10	—	—
Off-street parking entry queue time (min.)	—	0	10
Walking time to destination (min.)	15	0	10

FIGURE 2 Example scenario in stated preference questionnaire (— = not applicable).

Stated Preferences *versus* Revealed Preferences

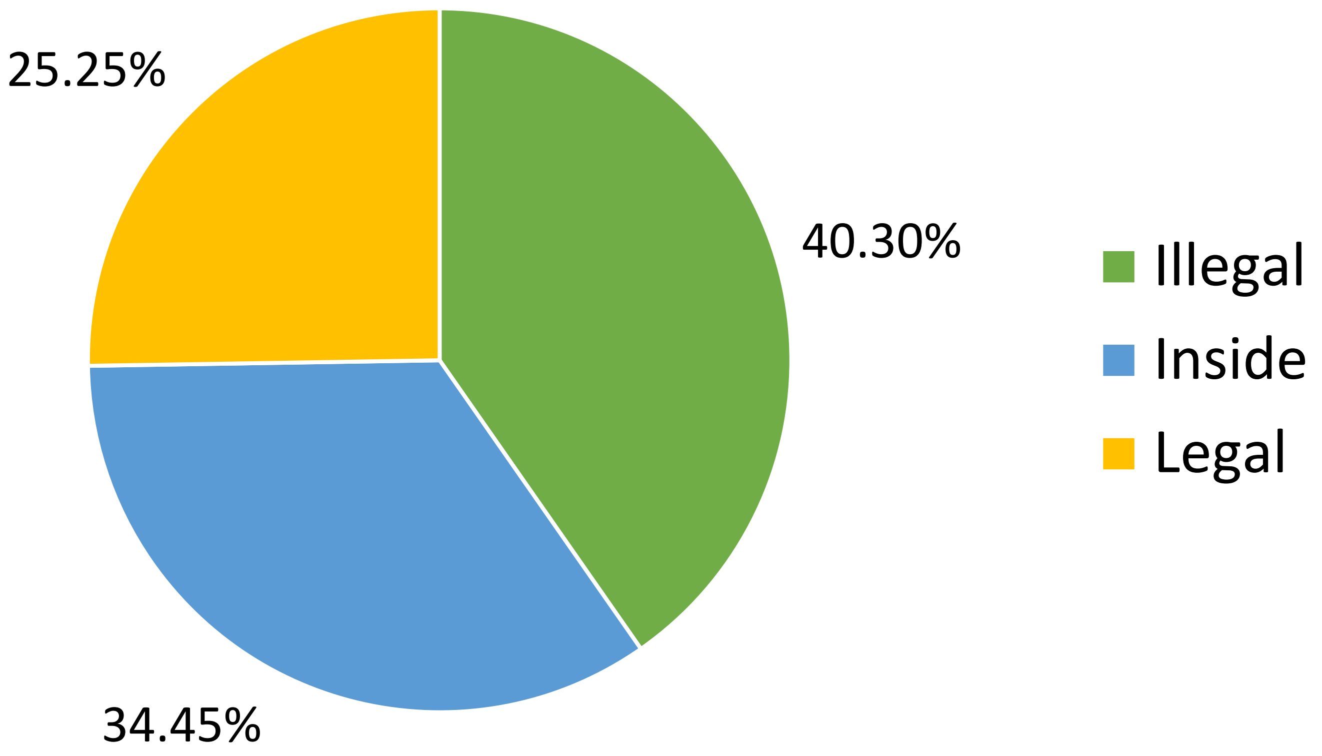
- The external validity of SC surveys can be questionable in some contexts.
- Particularly true when investigating behaviour which are not socially acceptable (*social desirability bias*).
  - An alternative would be to ask delivery drivers to recall their choices over the course of a given day / round of deliveries.
  - This might in turn lead to a *recall bias* which is common in retrospective surveys.
- "*RP data also have problems but at least they are* ***real*** *problems*" (Stephane Hess, at various meetings and conferences)
- **In this paper, we investigate how delivery drivers choose their parking spots using the ETMV-IDF 2011 dataset.**

The TMV-IDF dataset

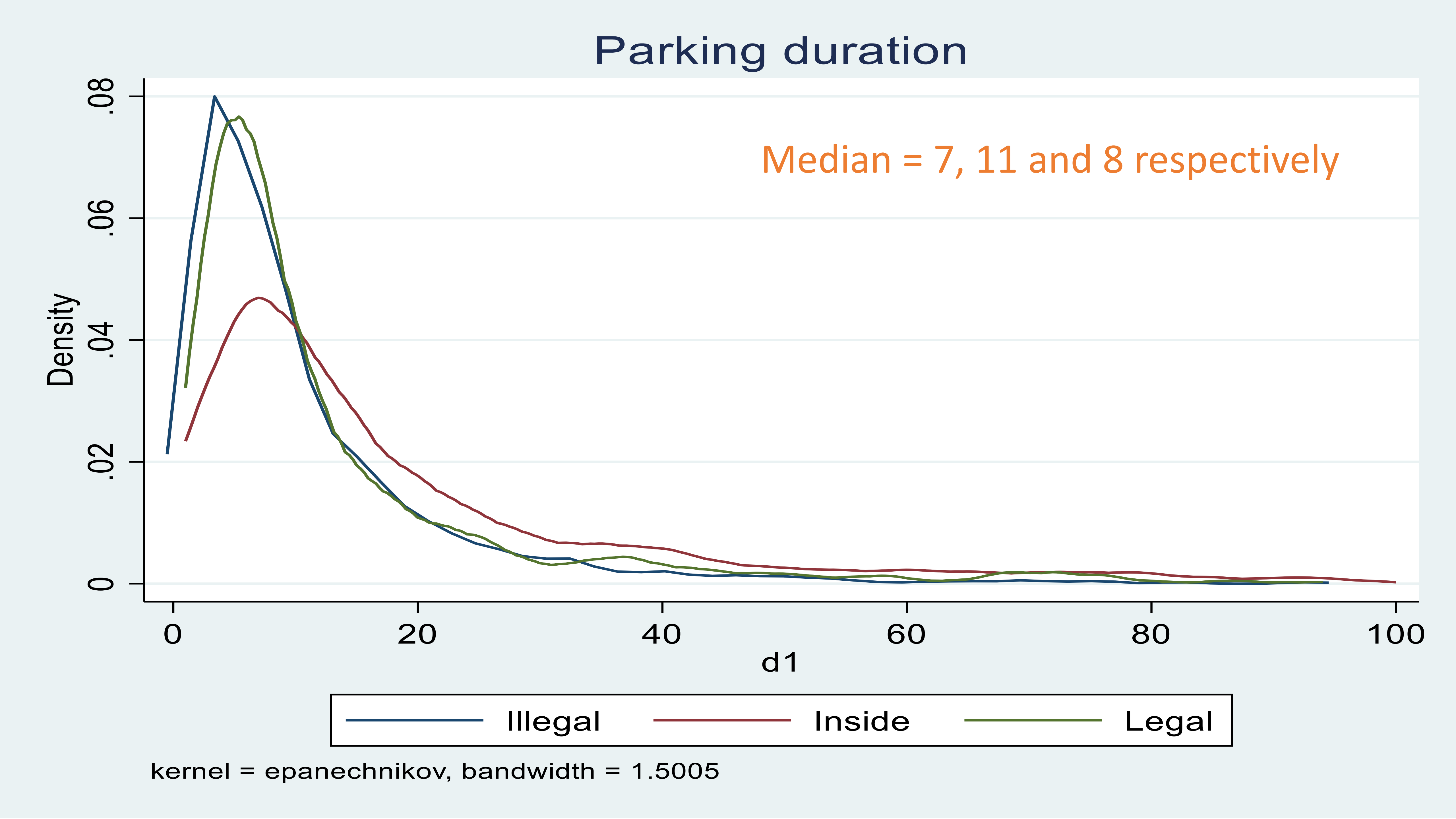
- Large survey effort (2010-2012)
- It’s a LAET project.
- Regroups different databases related to “Companies” (where the deliveries take place) and “Delivery drivers” (who is the delivery and what do they do).
- The delivery drivers survey is composed of many different sub-components. We are interested in the sub-component where the interviewer embarked with the drivers throughout their delivery round.
- 345 tours and 2626 operation recorded for which parking choice is available

Variables

- **Parking choice:** originally 11 alternatives now reduced to 3:



- Aggregating is necessary to avoid proliferation of parameters for alternatives that are almost never chosen.
- Alternatives are mutually exclusives.
- Parking time is only known for the chosen alternative.



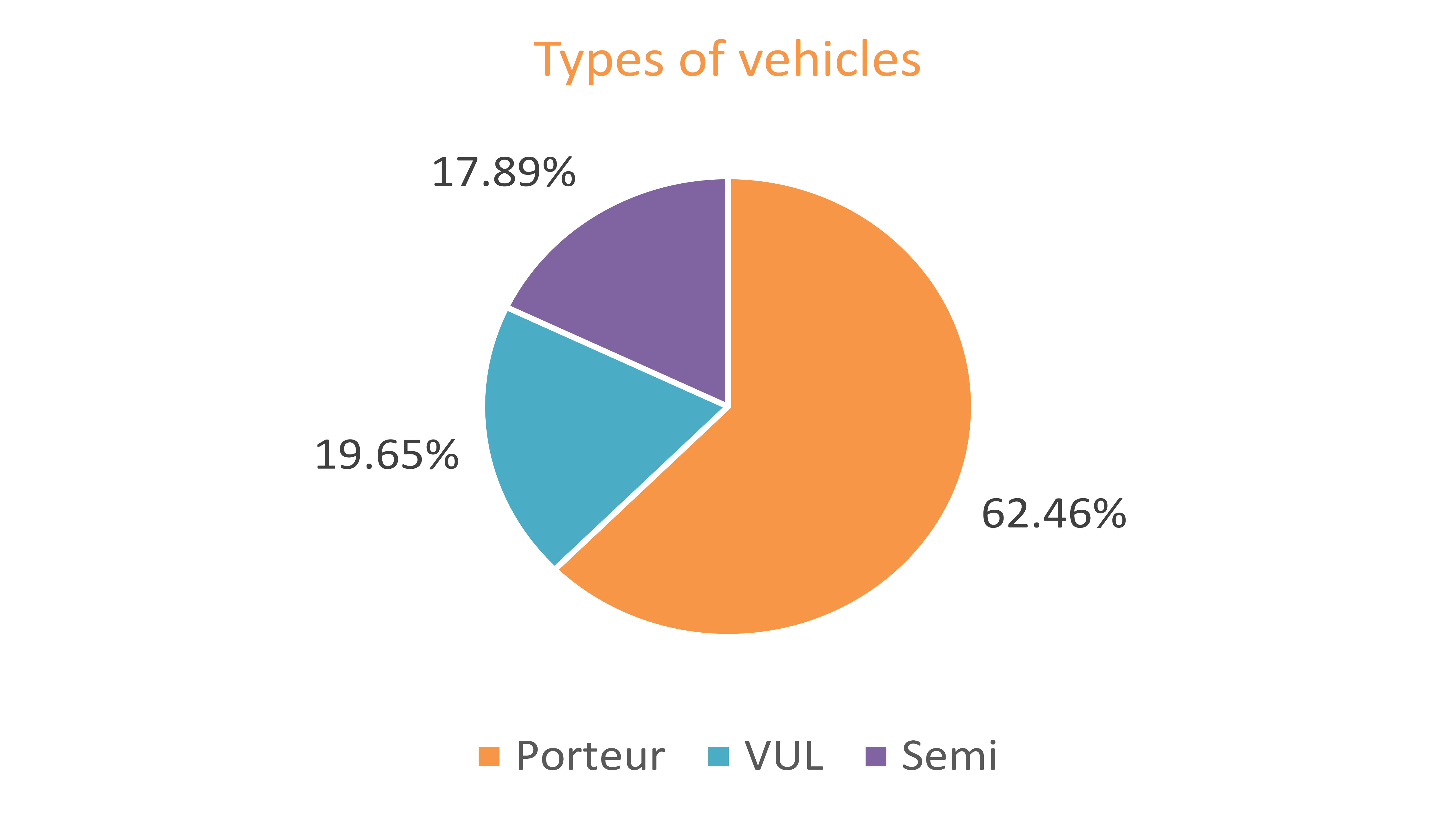
Parking duration
Median = 7, 11 and 8 respectively
Density
0
.02
.04
.06
.08
0
20
40
60
80
100
d1
Illegal
Inside
Legal
kernel = epanechnikov, bandwidth = 1.5005

Lots of heterogeneity in the dataset!

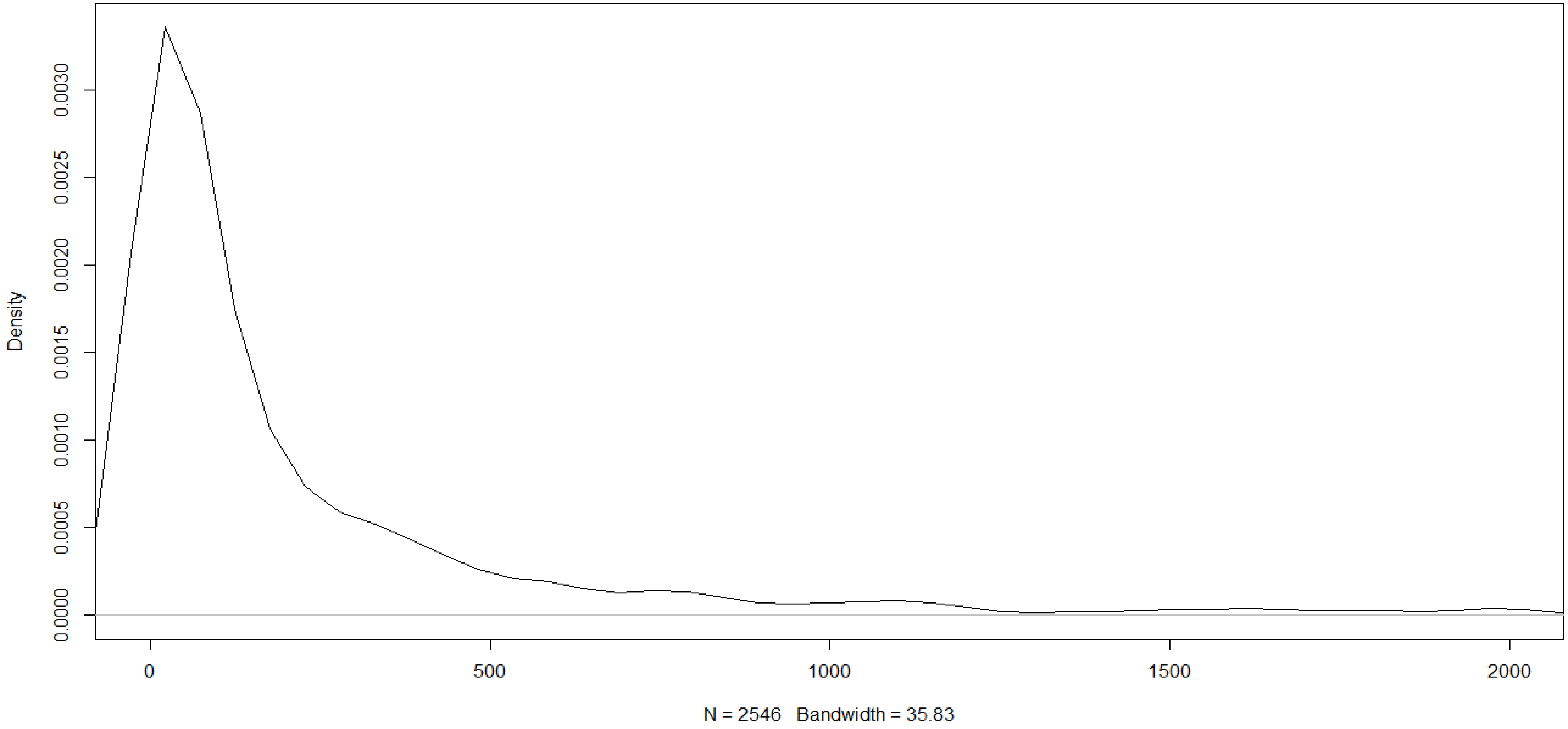
Parking duration (min)			
	Mean	Median	SD
VUL	8.21	5	13.26
Porteur	14.50	9	18.79
Articulé	34.24	22	32.41

	Mean	Median	SD
Indie	14.14	8	20.75
Company	16.45	12	17.38

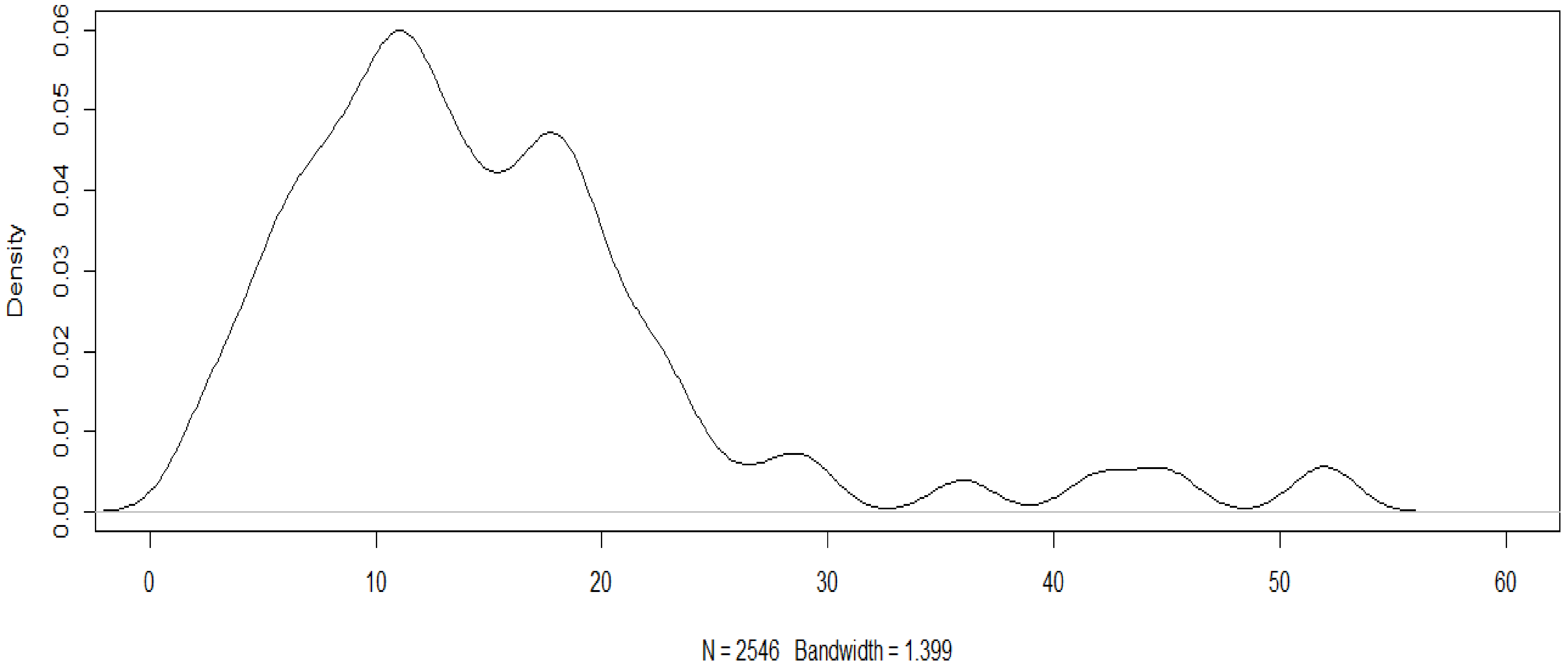
	Mean	Median	SD
Paris IM	18.68	10	26.99
PC	13.15	8	16.08
GC	11.08	8	11.56


Types of vehicles
17.89%
19.65%
62.46%
Porteur
VUL
Semi

Total weight per delivery
(very skewed, goes up to ~ 25 tons)



Number of deliveries (also quite skewed)



Variables (cont.)

- Variables related to:
  - **Drivers' characteristics:** Type of company (independent or not), type of vehicle (<3.5t, semi-trailer, rigid truck).
  - **Time and location:** (proxy for traffic flow and on-street parking usage).
  - **Delivery tasks:** type of operation, weight (to load or unload), nature of the goods, tools required to complete the task, admin required (signature, weighting the load, other kinds of checks).
  - **Schedule:** total number of deliveries, total distance.

NOW LET'S DO SOME CHOICE MODELLING!

Towards a Random Utility Maximisation parking choice model

- Utilities 3 different parking choices: *illegal*, *legal* and *inside*.

$$U_{illegal} = \beta_{illegal} + \beta 1'_{driver} x'_{driver} + \beta 1'_{traffic} x'_{traffic} + \beta 1'_{task} x'_{task} + \epsilon_{illegal}$$

$$U_{inside} = \beta_{inside} + \beta 2'_{driver} x'_{driver} + \beta 2'_{traffic} x'_{traffic} + \beta 2'_{task} x'_{task} + \epsilon_{inside}$$

$$U_{legal} = \beta_{legal} + \beta 3'_{driver} x'_{driver} + \beta 3'_{traffic} x'_{traffic} + \beta 3'_{task} x'_{task} + \epsilon_{legal}$$

$$P_{illegal} = \frac{e^{(V_{illegal})}}{e^{(V_{illegal})} + e^{(V_{inside})} + e^{(V_{legal})}}$$

$$P_{int} = \prod_{t=1}^{T} \frac{e^{V_{int}}}{\sum_{j=1}^{J} e^{V_{jnt}}}$$

Inter-individual heterogeneity

- Not all delivery drivers are the same…
- …but there is only so much an analyst can observe!

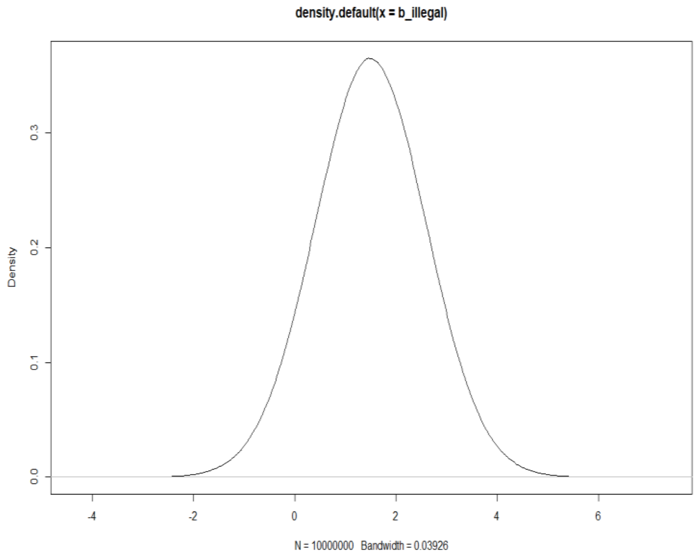
- Type of truck
- Company status
- Traffic conditions
- Parking space availability
- Time pressure
- Attitude towards illegal parking

Random heterogeneity in preferences (inter)

Random inter-individual heterogeneity

- The preference for *illegal parking* can be specified as randomly distributed across the population of drivers.

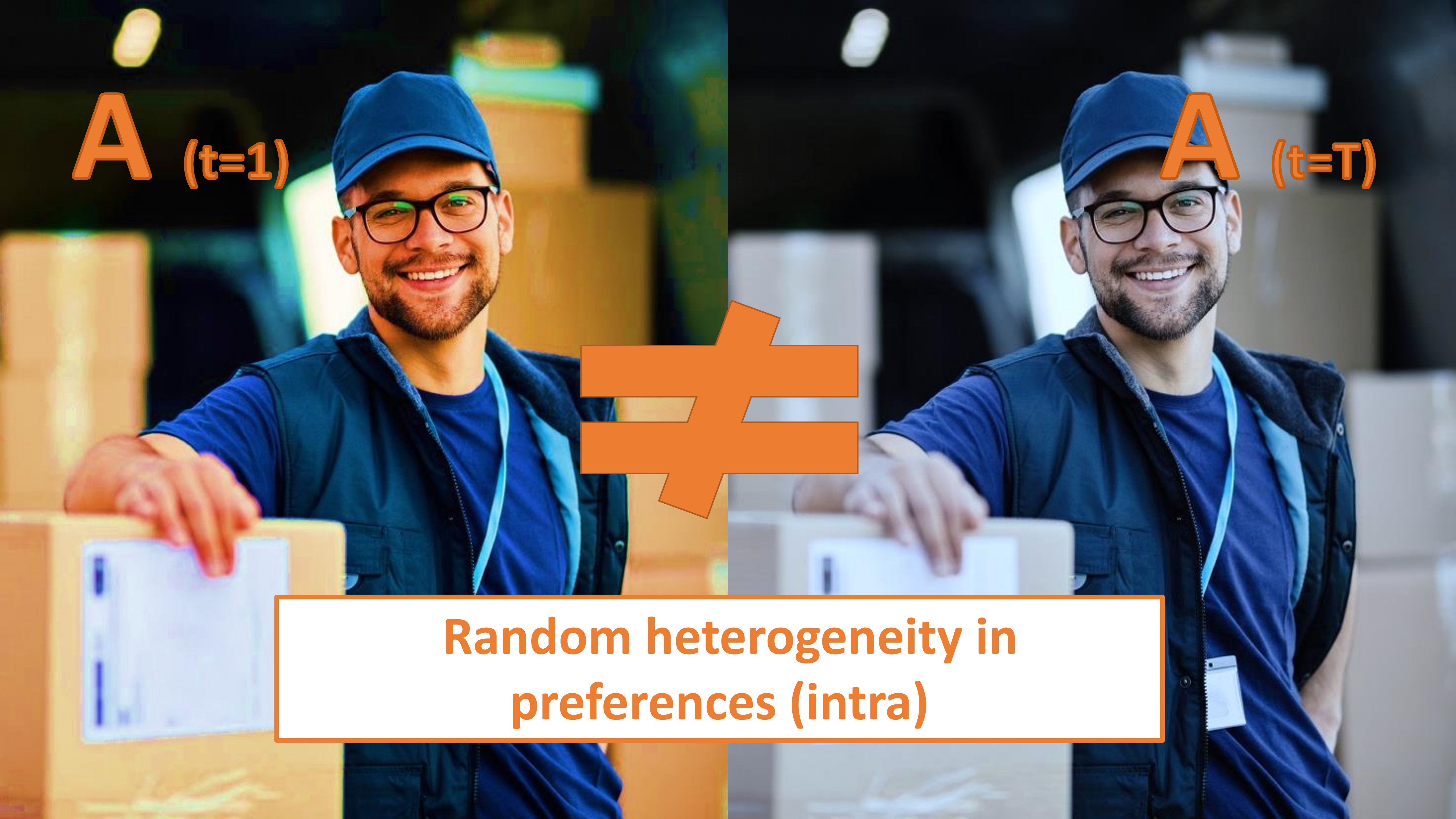
- $\beta_{illegal} = \mu_{illegal} + \sigma_{illegal}\eta_{illegal}$ with $\eta_{illegal} \sim N(0,1)$



- The model becomes a **mixed** multinomial logit model:

$$L_{nt} = \int_{\eta} \prod_{t=1}^{T} P_{nt}(\beta_n) f(\beta_n|\Omega)\delta\eta$$

- The integral is approximated via simulation techniques (maximum simulated likelihood).


A (t=1)
A (t=T)
Random heterogeneity in preferences (intra)

Random intra-individual heterogeneity

- A driven at time t=1 is not the same at t=T (fatigue, different reaction to environment etc).

- We can include *lead* variables related to the remaining number of stops

- And use intra-respondent heterogeneity to capture the rest (random heterogeneity within random heterogeneity)

$\beta_{illegal} = \mu_{illegal} + \sigma_{illegal}\eta_{illegal} + \sigma2_{illegal}\alpha_{illegal}$ with $\alpha_{illegal} \sim N(0,1)$

$$L_{nt} = \int_{\eta} \left(\prod_{t=1}^{T} \left(\int_{\alpha} P_{n,t}(\beta_n | \eta, \alpha) h(\alpha) d(\alpha) \right) \right) f(\eta) d\eta$$

Our model so far

But what about parking time?

Parking choice – where AND how long?

- A joint-choice or an action in anticipation? The time to perform the operation is actually not known by the driver until the operation is completed.

- Modelling parking choice from the drivers' perspective requires to model the **anticipated parking time for the chosen alternative** which is unknown.

- Different approaches:

  - Simply consider that how long a driver parks is simply a function of where they decide to park

  - Heckman discrete-continuous model

  - Hybrid choice model

Hybrid choice models

- One of the big flavors of the decade in the choice modelling literature.
- Mainly used to account for attitudinal data in discrete choice models.
- Assumes that attitudes (and anticipations!) are not observed but latent, and indicators should not be treated as explanatory variables, but as dependent variables.
- Propose a structure that jointly models the response to choice model component and the response to attitudinal questions (usually)
- The different model components are linked by one or several latent variables

Hybrid choice models for modelling anticipations

- First suggested by Choudhury *et al*. (work in progress)

- Used to model whether car purchase at time *t* is linked to birth of a child at time t+1.

- Different models are linked together by a LV related to *anticipations*.

- Meaning of LV derived from the different model components it is interacted with.

- LV can be just a random disturbance or informed by other exogenous variables.

Please indicate in the calendar about important household issues/events –

	1990	1991	1992		2008	2009	2010
Household status							
5. Mention number of person in household at 1990 and only when it is different from earlier.							
6. Please indicate in the calendar by "X" or "√" when you had experienced one or more of the following events.							
(1) You left parent home							
(2) Marriage/Cohabitation							
(3) Birth of children							
(4) Child's home leaving							
(7) Divorce/Separation							
(6) Death of household member (please mention the relationship with the person died)							

Please indicate appropriate response for you in the calendar depicting last few years of your life and also mention the initial status at 1990 for each question –

	1990	1991	1992		2008	2009	2010
Travel and transport							
25. Please mention the number of cars available in your Household							

Modelling anticipations – task level

- Drivers know about the characteristics of the delivery (weight, number of boxes, procedure, etc).

- This can be used to **evaluate the efforts** required for the delivery task

- We introduce task level effort as a latent variable which jointly inform where drivers park and how long it takes to perform the task

- Preferences for illegal parking dynamically change with the context of the delivery and the expected parking time

The latent variable

$$\alpha_n = \alpha_{weight}x_{weight} + \alpha_{weight_{NA}}x_{weight_{NA}} + \alpha_{fragile}x_{fragile} + \alpha_{food}x_{food} + \alpha_{living}x_{living} + \alpha_{chemicals}x_{chemicals} + \alpha_{hazardous}x_{hazardous} + \alpha_{other\ special}x_{other\ special} + \alpha_{package\ NA}x_{pakage\ NA} + \alpha_{Carton\ boxes}x_{Carton\ boxes} + \alpha_{large\ boxes}x_{large\ boxes} + \alpha_{No\ package}x_{No\ package} + \alpha_{Other\ packages}x_{Other\ packages} + \alpha_{pallet\ truck}x_{pallet\ truck} + \alpha_{hand\ trolley}x_{hand\ trolley} + \alpha_{dolly}x_{dolly} + \alpha_{roll}x_{roll} + \alpha_{Crane}x_{Crane} + \alpha_{Additional\ checks}x_{Additional\ checks} + \alpha_{Checks\_NA}x_{Checks\_NA} + \alpha_{Remaining\ stops}x_{Remaining\ stops} + \alpha_{Remaining\ distance}x_{Remaining\ distance} + \sigma\varphi_n + \tau_n$$

$\sigma\varphi_n$ with $\varphi \sim N(0,1)$

τ_n with $\tau \sim N(0,1)$ (intra)

Utilities

$$V_{Illegal} = \beta_{illegal} + \beta_{morning}x_{morning} + \beta_{afternoon}x_{afternoon} + \beta_{afternoon\_peak}x_{afternoon\_peak} + \beta_{independent}x_{independent} + \beta_{medium\_truck}x_{medium\_truck} + \beta_{large\_truck}x_{large\_truck} + \beta_{"Petite\_Couronne"}x_{"Petite\_Couronne"} + \beta_{"Grande\_Couronne"}x_{"Grande\_Couronne"} + \theta_{Task}\alpha$$

- Same structure but different parameters for *Inside*.
- Constants are randomly distributed across drivers.
- *Legal* is the base alternative.
- The latent variable affects choice probabilities

Modelling parking time

- Continuous variable

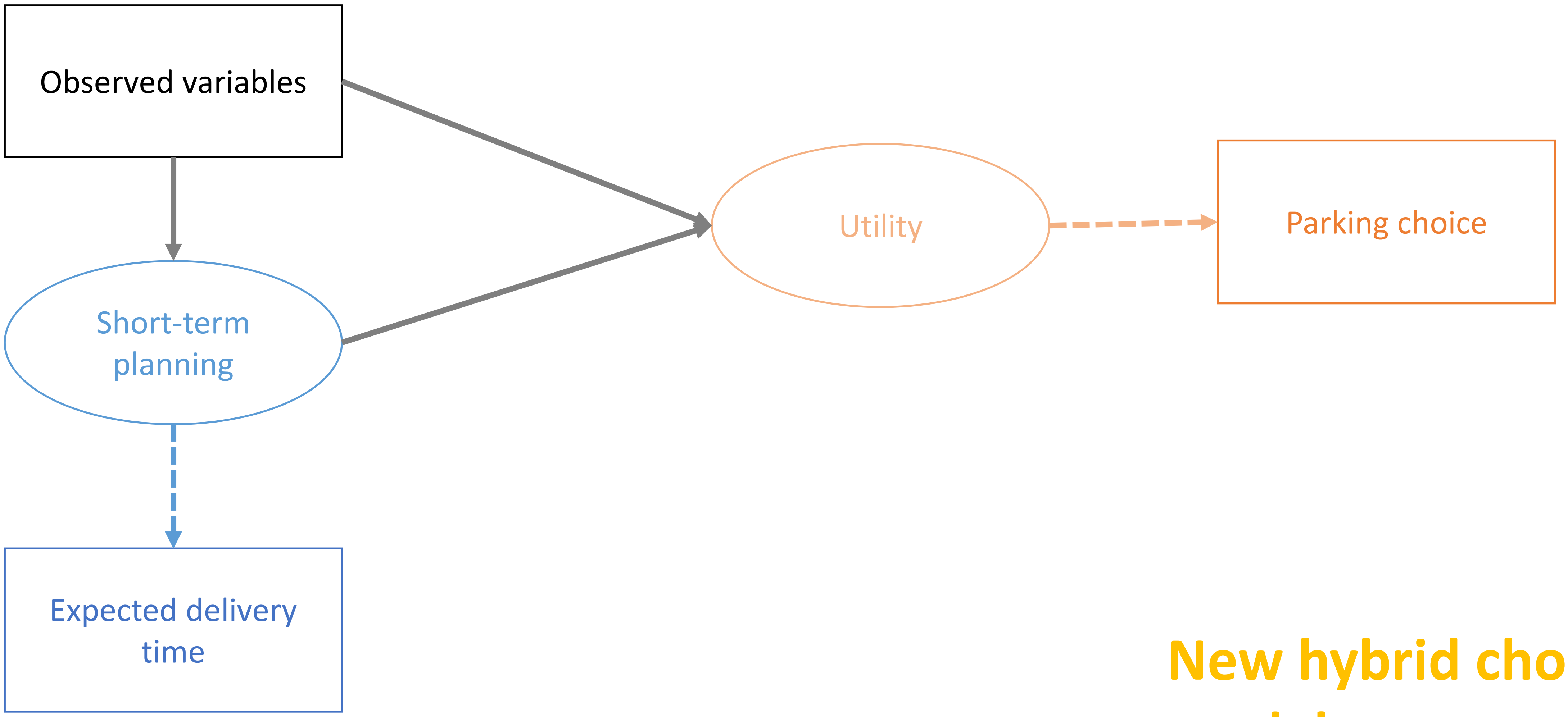
- A simple log-linear regression is adequate

$$P\left(Y = ln\left(y_{n,t}\right) \middle| \mu_{const}, \alpha_{n,t}, \sigma_{time}\right) = \frac{\phi\left(\frac{ln\left(y_{n,t}\right) - \mu_{const} - \zeta_{time}\alpha_{n,t}}{\sigma_{time}}\right)}{\sigma_{time}}$$

- Here yn,t is the observed parking time for each operation

- σ is the estimated standard deviation of the normal distribution

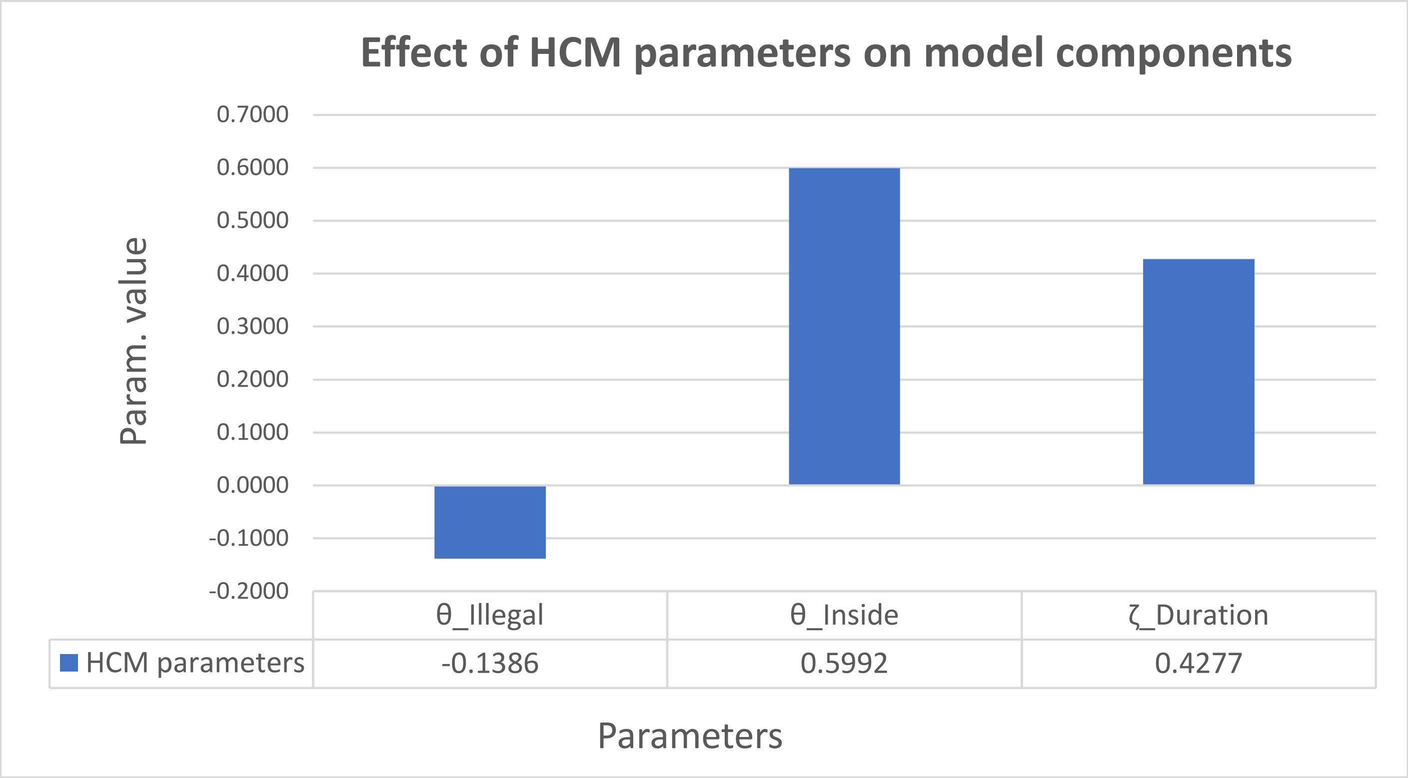
- The latent variable also affects parking time



New hybrid choice model structure (joint maximisation)

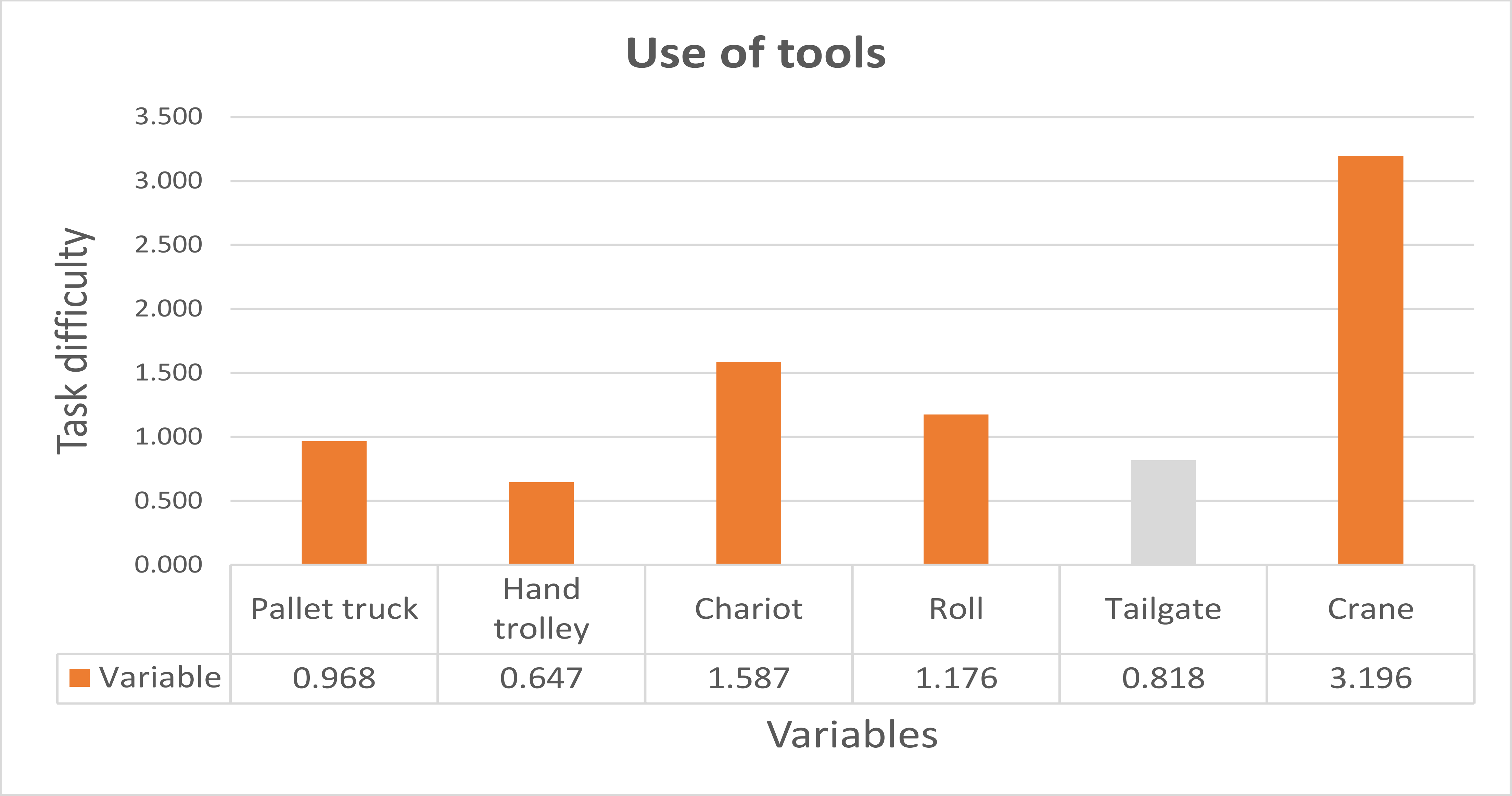
Results

- We start by looking at the parameters linking the different model components together

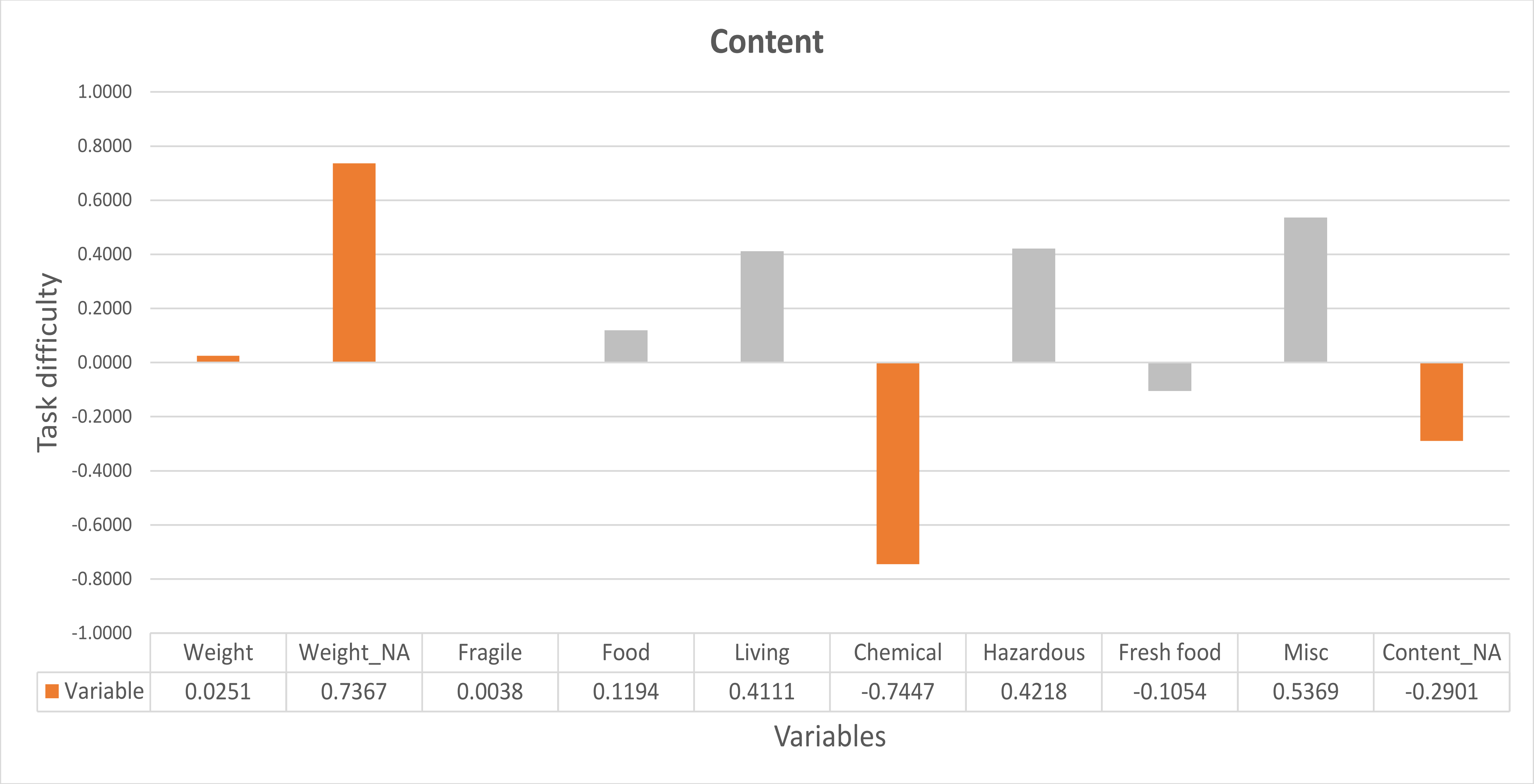


- When task difficulty increases, the probability that a driver parks illegally decreases and the probability of observing a higher parking time increases

Drivers of task difficulty



Drivers of task difficulty



	Weight	Weight_NA	Fragile	Food	Living	Chemical	Hazardous	Fresh food	Misc	Content_NA
Variable	0.0251	0.7367	0.0038	0.1194	0.4111	-0.7447	0.4218	-0.1054	0.5369	-0.2901

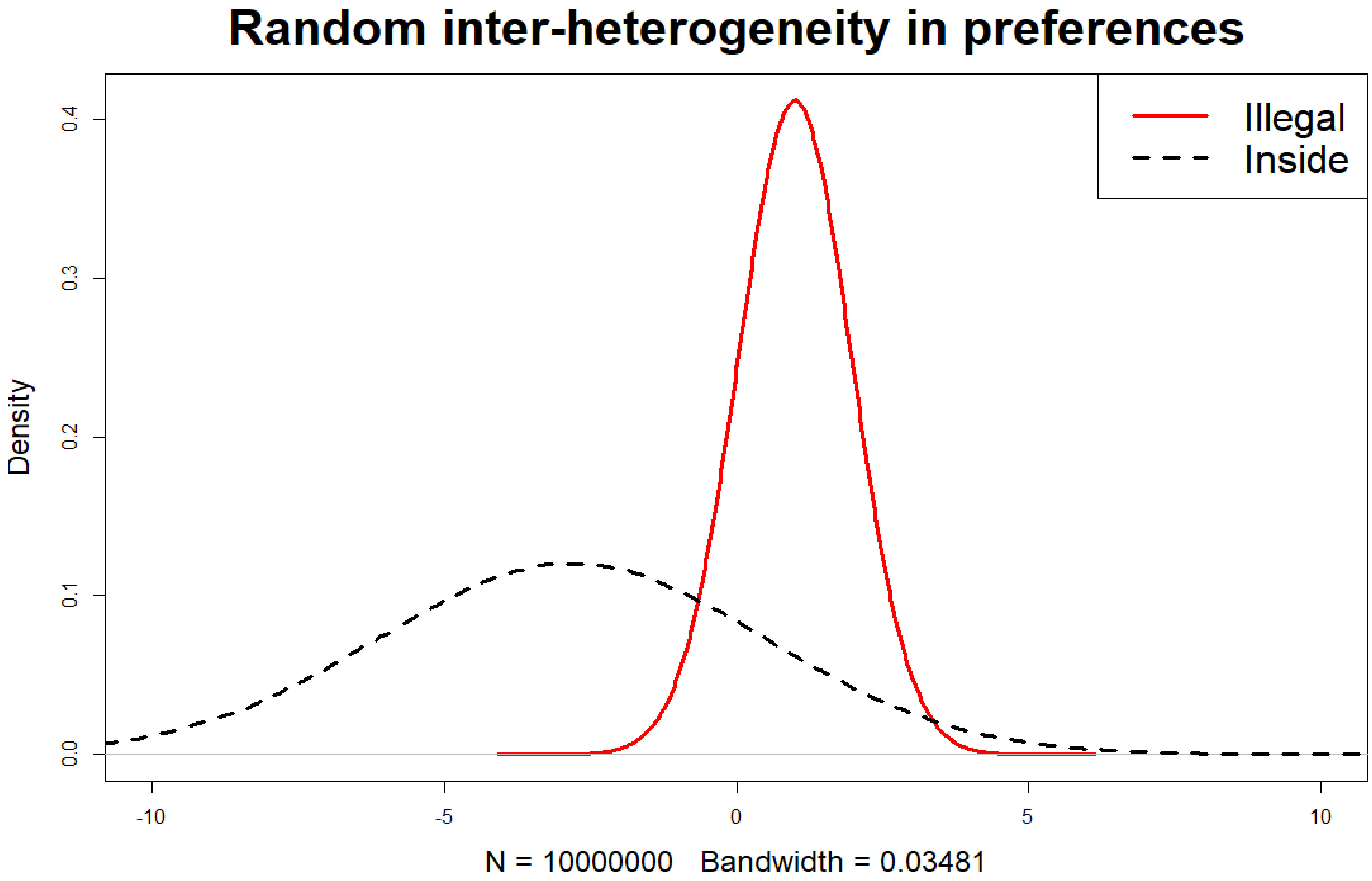
Drivers of task difficulty

Drivers of task difficulty

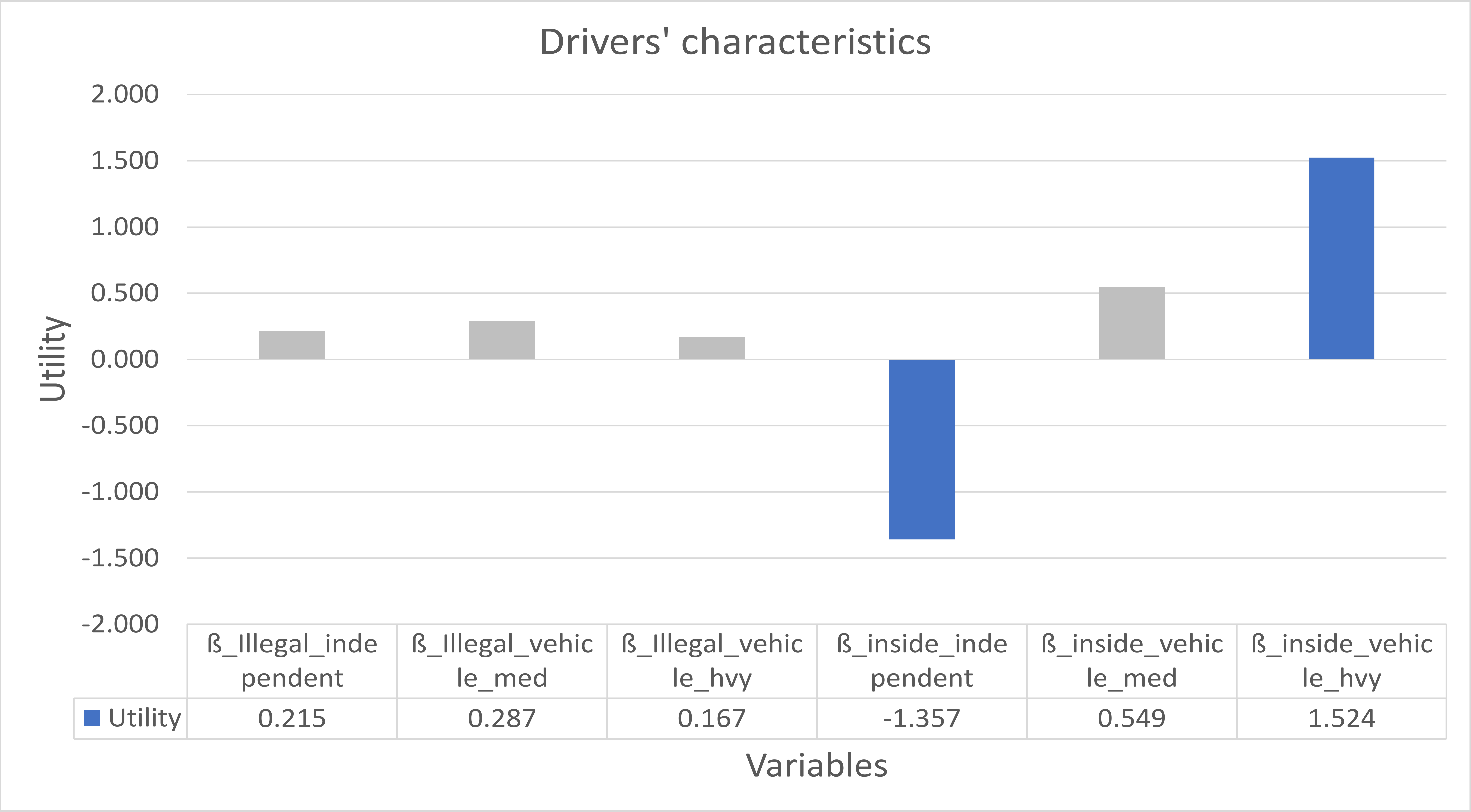
$$\alpha_{Remaining\ stops} = -0.03138$$

- The probability of illegal parking increases and the duration of parking decreases when the number of stops remaining is high.
- Drivers anticipate that some future stops can go wrong and so try to make more efforts at the start rather than the end.
- It is a clear *lead* effect.
- Highly significant ($p < 0.01$).

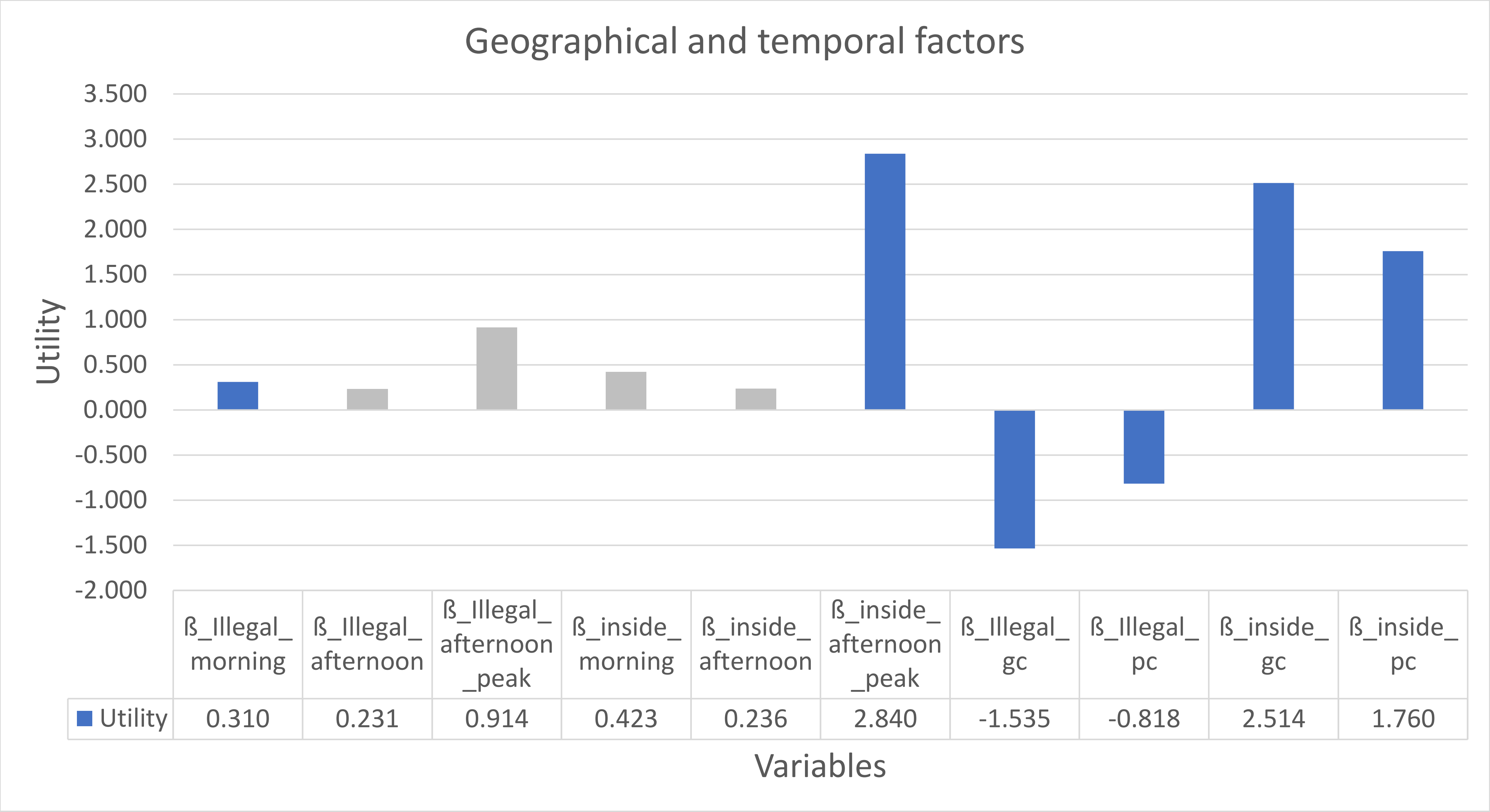
Utility


Random inter-heterogeneity in preferences
Illegal
Inside
Density
0.0
0.1
0.2
0.3
0.4
-10
-5
0
5
10
N = 10000000 Bandwidth = 0.03481

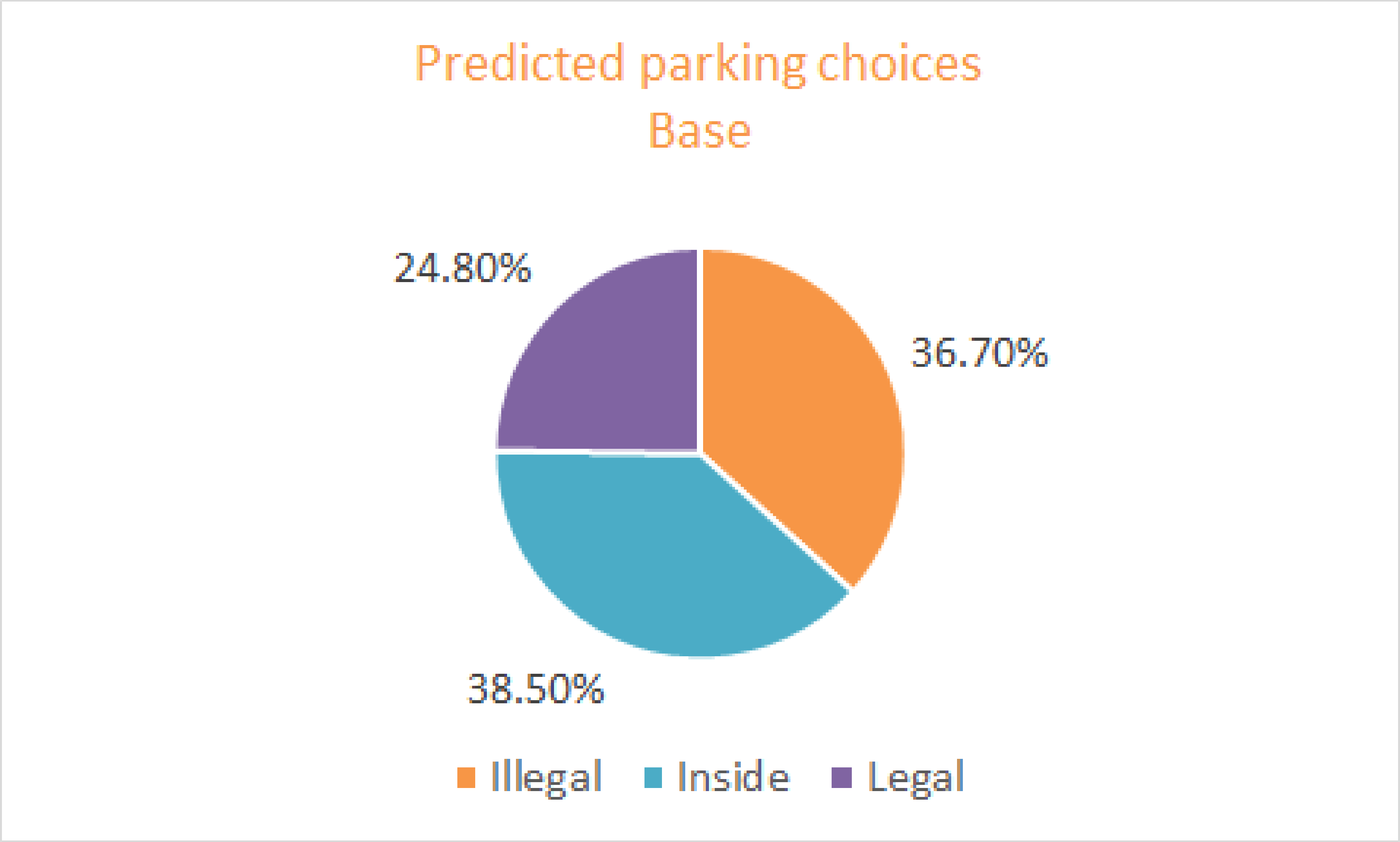
Utility


Drivers' characteristics
2.000
1.500
1.000
0.500
0.000
-0.500
-1.000
-1.500
-2.000
Utility
ß_Illegal_independent
ß_Illegal_vehicle_med
ß_Illegal_vehicle_hvy
ß_inside_independent
ß_inside_vehicle_med
ß_inside_vehicle_hvy
Utility
0.215
0.287
0.167
-1.357
0.549
1.524
Variables

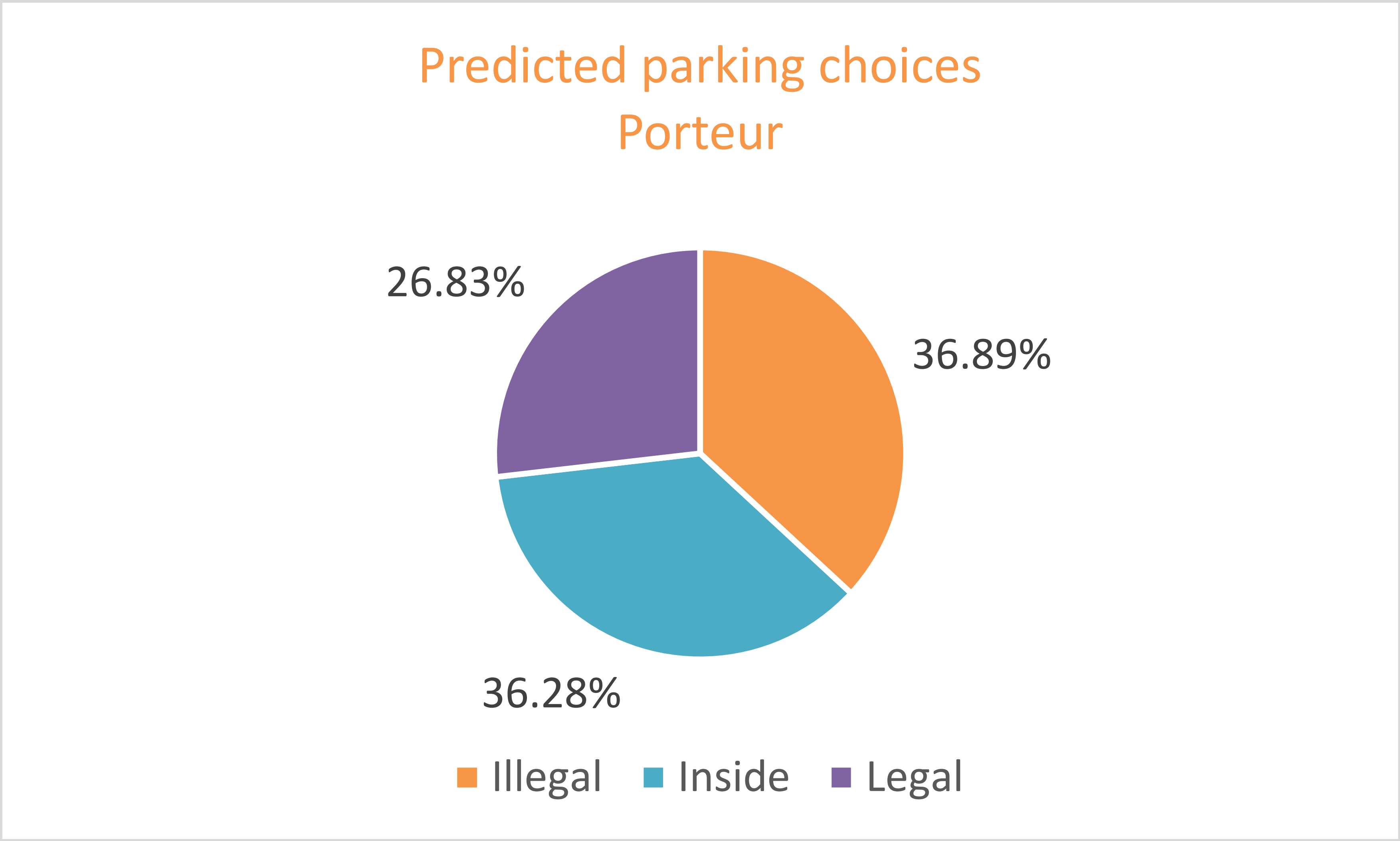
Utility


Geographical and temporal factors
Utility
3.500
3.000
2.500
2.000
1.500
1.000
0.500
0.000
-0.500
-1.000
-1.500
-2.000
ß_Illegal_morning
ß_Illegal_afternoon
ß_Illegal_afternoon_peak
ß_inside_morning
ß_inside_afternoon
ß_inside_afternoon_peak
ß_Illegal_gc
ß_Illegal_pc
ß_inside_gc
ß_inside_pc
Utility
0.310
0.231
0.914
0.423
0.236
2.840
-1.535
-0.818
2.514
1.760
Variables

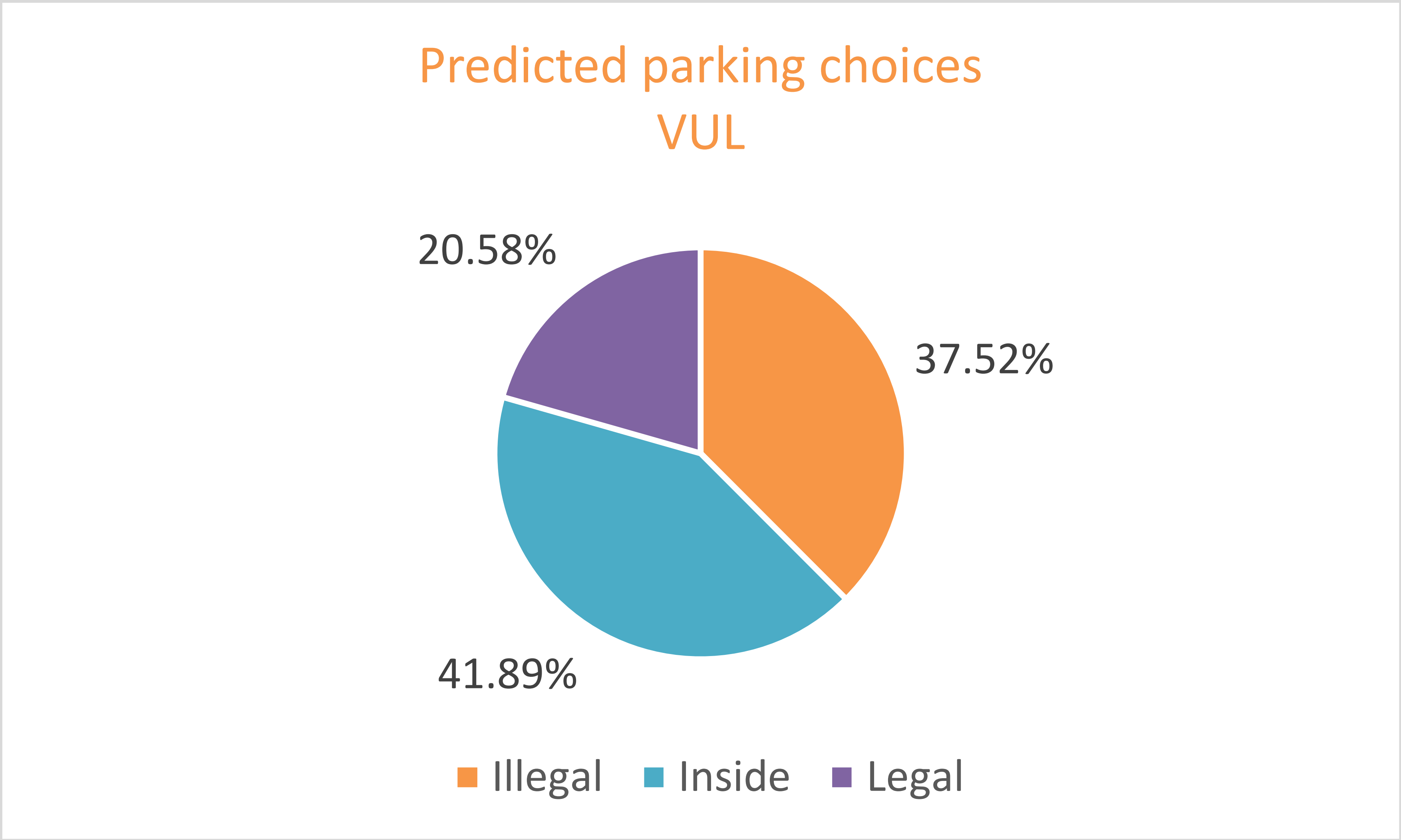
Base predictions



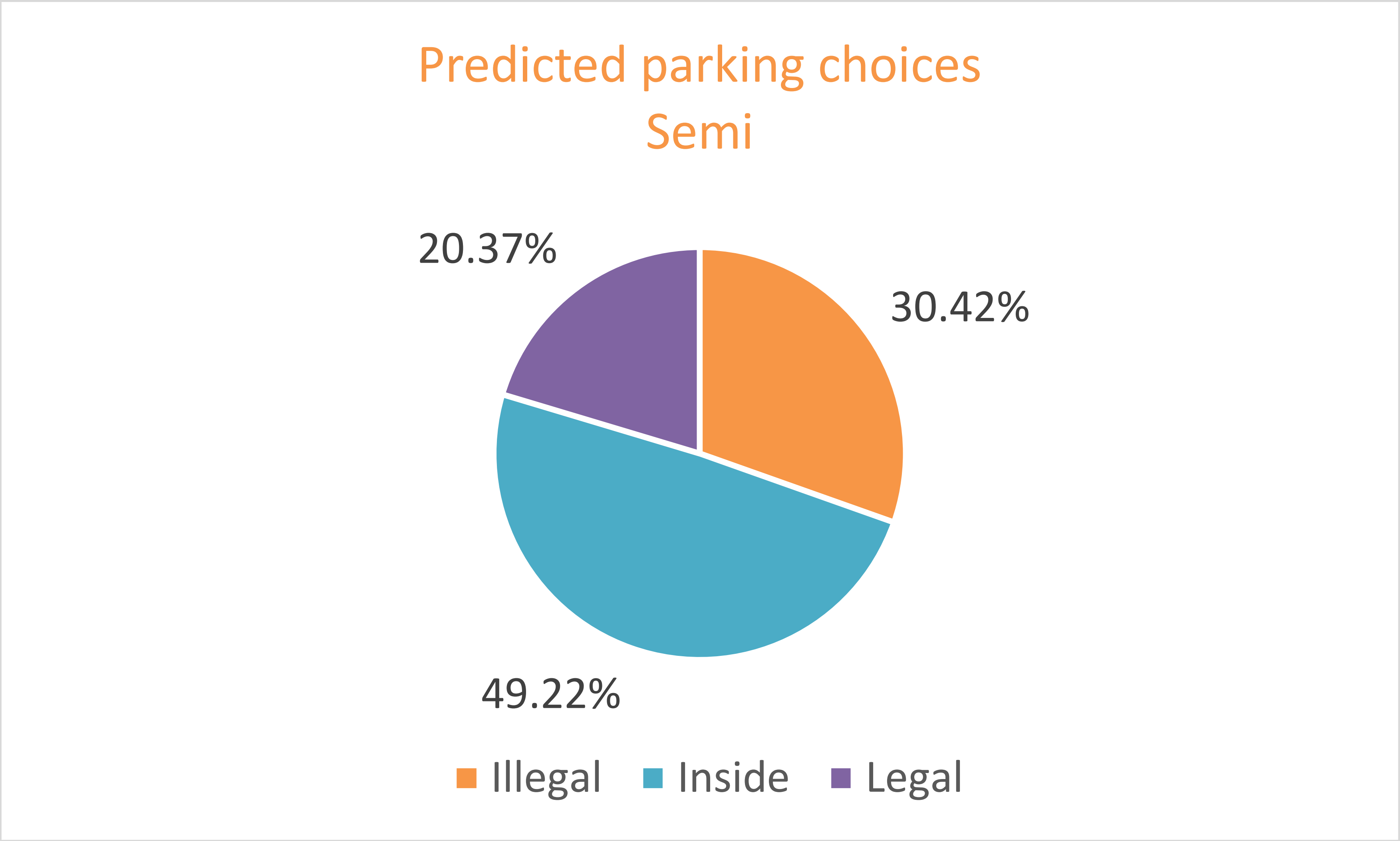
Choice probabilities (mfx)



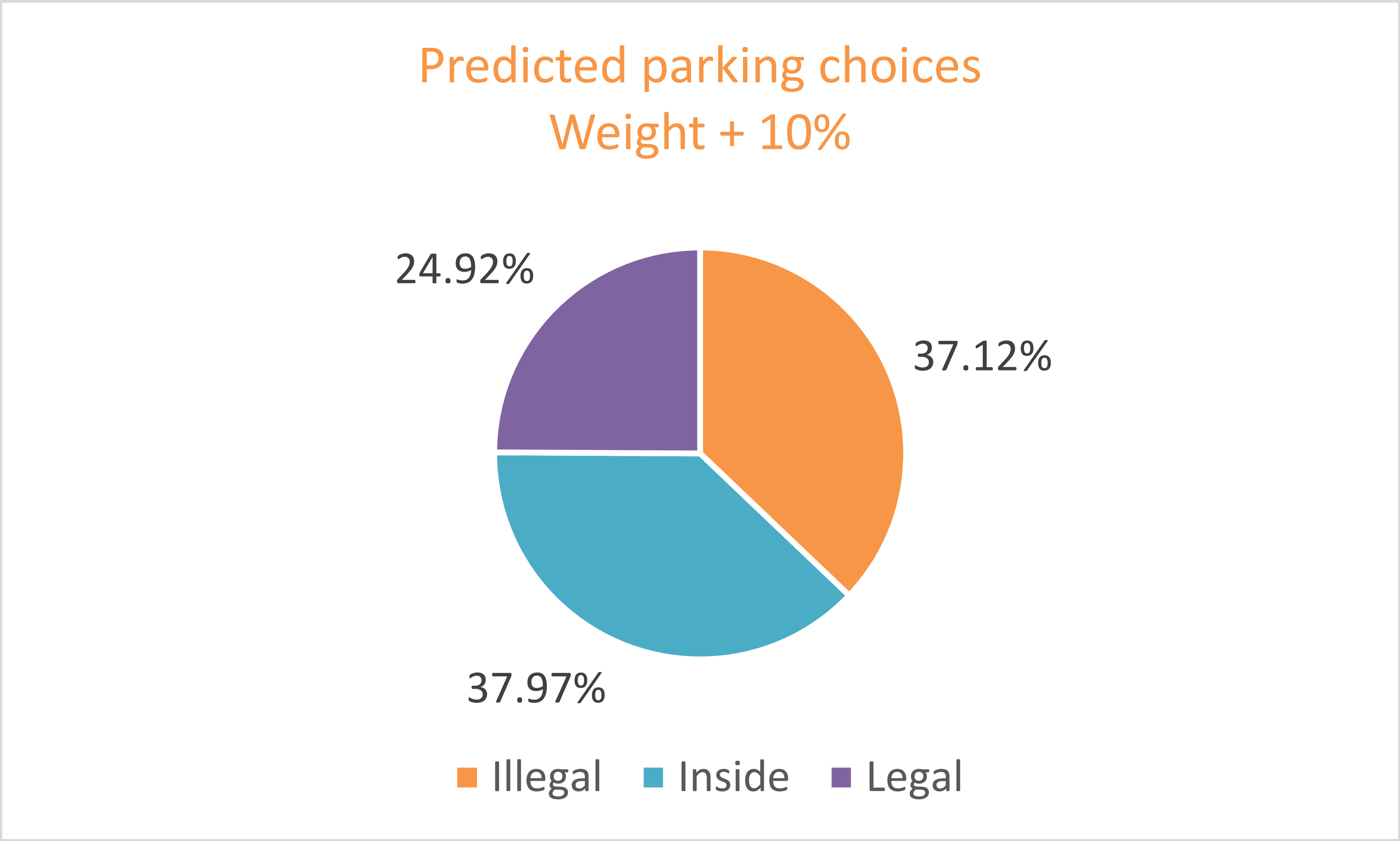
Choice probabilities (mfx)



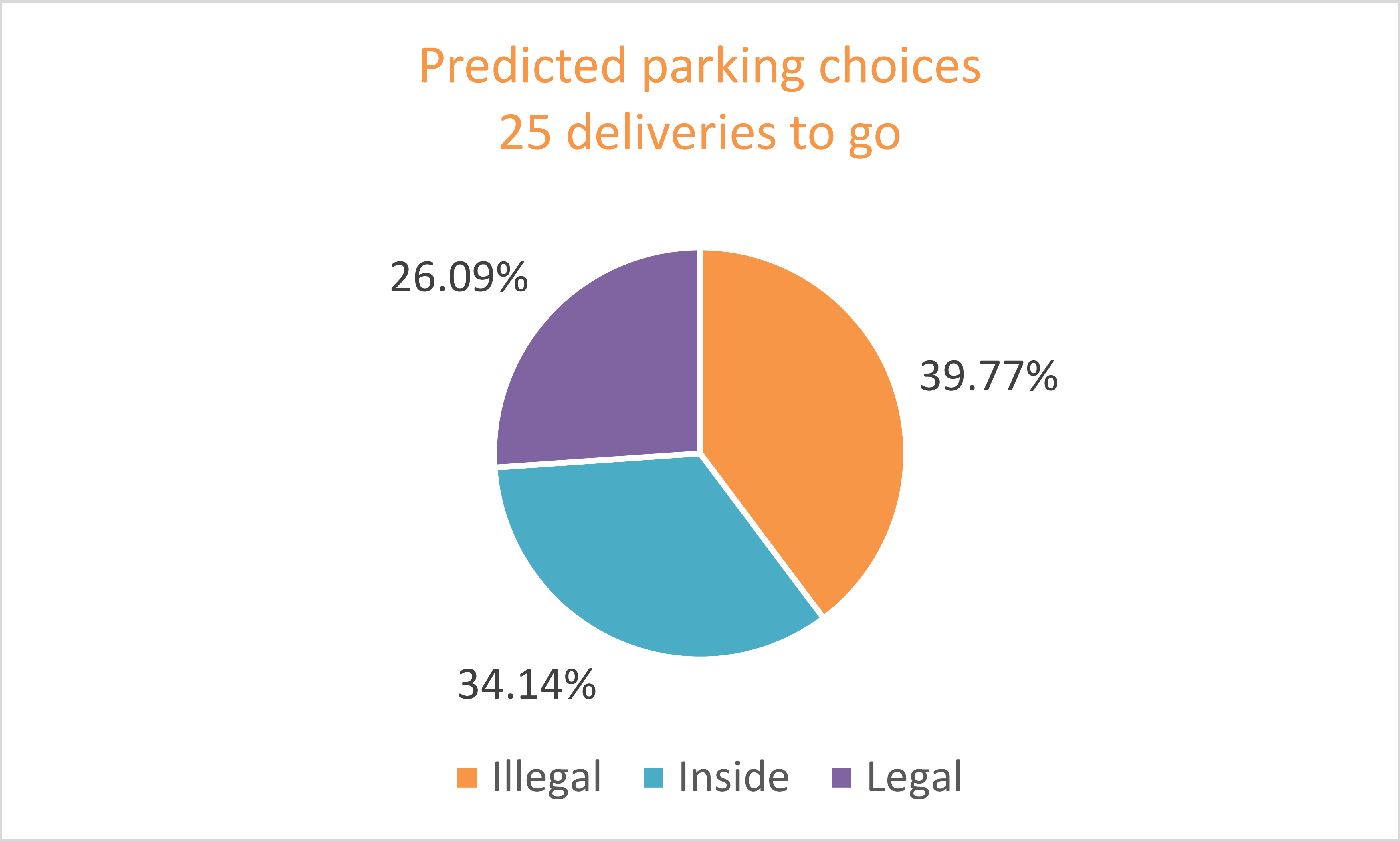
Choice probabilities (mfx)



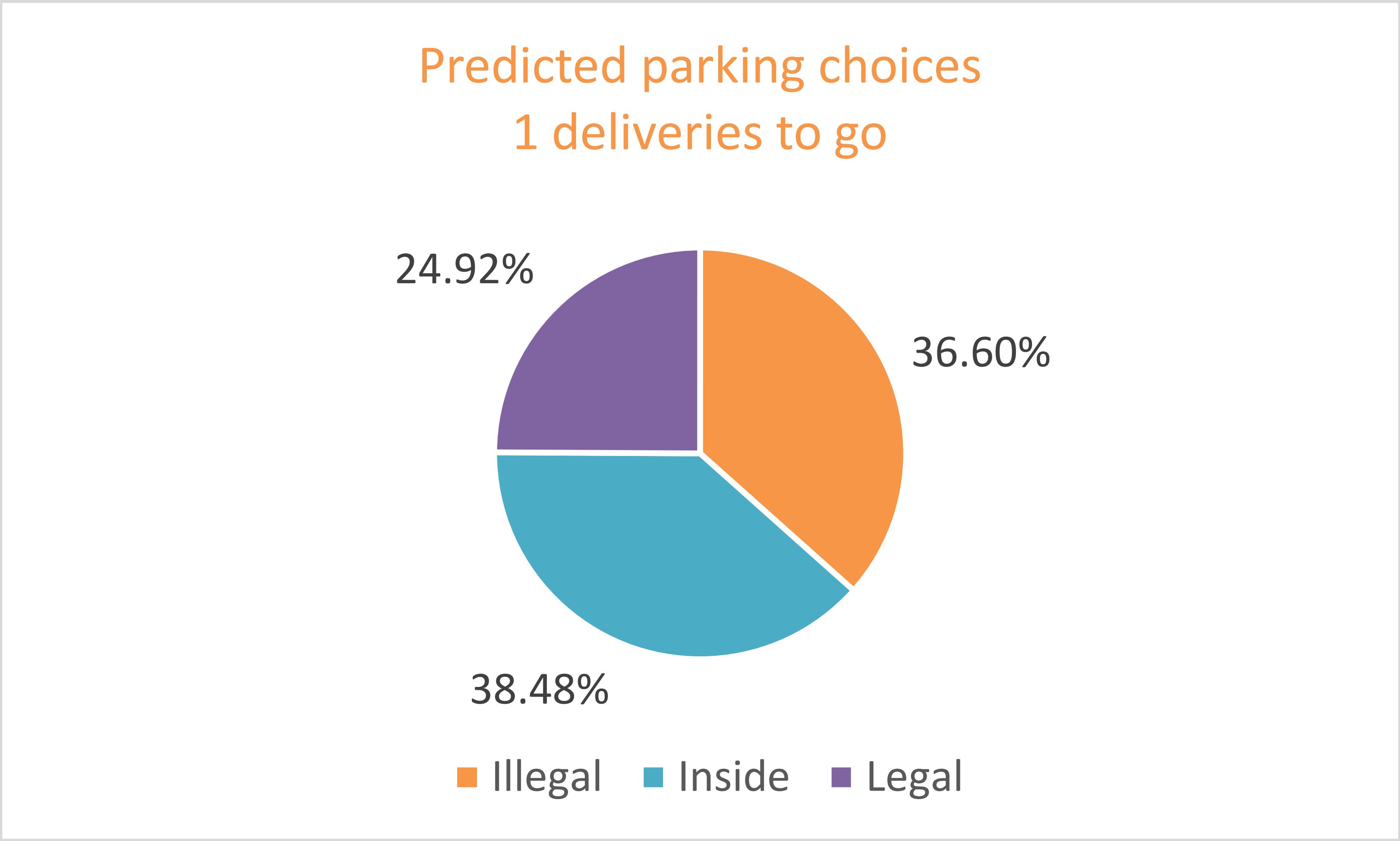
Choice probabilities (mfx)

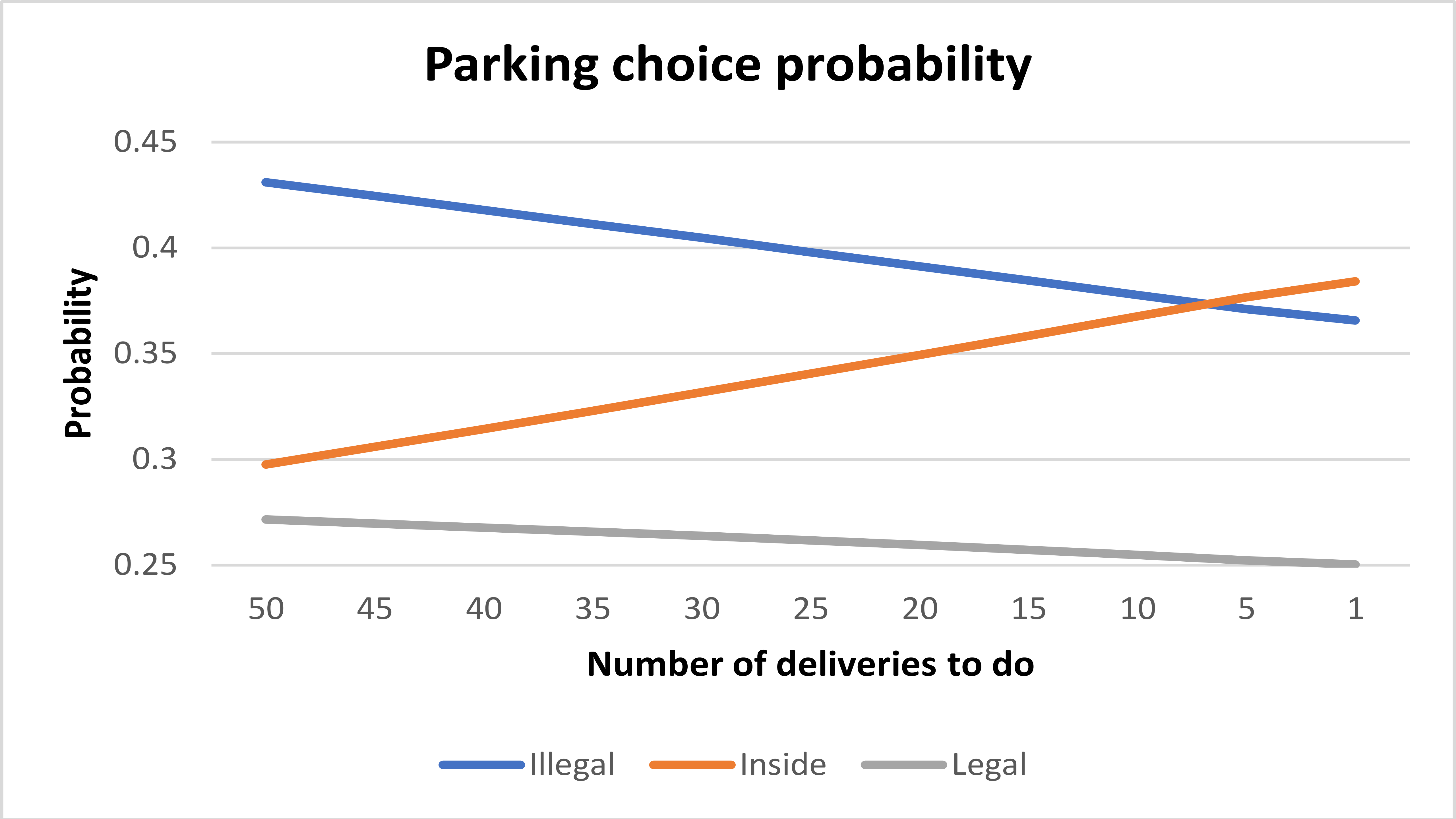


Choice probabilities (mfx)



Choice probabilities (mfx)




Parking choice probability
0.45
0.4
0.35
0.3
0.25
Probability
50
45
40
35
30
25
20
15
10
5
1
Number of deliveries to do
Illegal
Inside
Legal

Conclusion & future work

- Results are found to be behaviourally sound
- Significant anticipation effects found
- Choice models found to be a suitable complement to further understand the choices made by delivery drivers
- More models to come!
- Simplified models can be used to directly inform agent-based models. That’s our next objective!