Transportation Research Part E 204 (2025) 104420

Contents lists available at ScienceDirect

Transportation Research Part E

journal homepage: www.elsevier.com/locate/tre

Parking preferences of delivery drivers in the Paris Region: Understanding the role of anticipation using hybrid choice models

Romain Crastes dit Sourd [a,b,*], Pascal Gastineau [c], Adrien Beziat [b], Martin Koning [d]

[a] Centre for Decision Research, Analytics, Technology and Operations Department, Leeds University Business School, Leeds, LS2 9JT, United Kingdom
[b] Univ Gustave Eiffel, AME-SPLOTT, F-77454, Champs sur Marne, France
[c] Univ Gustave Eiffel, AME-SPLOTT, F-44344, Bouguenais, France
[d] Univ Gustave Eiffel, AME-SPLOTT, F-69500, Bron, France

ARTICLE INFO

Keywords:
Parking choice
Urban freight
Revealed preferences
Obstructive parking

ABSTRACT

This study explores the determinants of parking choices for commercial vehicles in the Paris Region (France). The analysis is based on data from the 2010 Paris Region Urban Goods Movement Survey (UGMS), which offers insights into the parking preferences of delivery drivers. By examining real-world decision-making, the dataset allows us to consider spatial and temporal characteristics as well as the role of parking decision within the delivery process. An integrated choice and latent variable model is employed, whereby drivers select parking locations based on urban environmental attributes, service type, and a latent variable reflecting anticipated delivery difficulty. This difficulty is inferred from observed delivery times and service characteristics; furthermore, temporal variations are incorporated to assess driver behavior, including fluctuations in parking preferences throughout the day. The model also accounts for parking space availability by the means of latent classes. Our findings contribute to a nuanced understanding of delivery drivers' behavior, providing valuable insights for policy-making and operational strategies. These results, as well as our modeling approach, can also be incorporated into broader frameworks such as agent-based models.

1. Introduction

Urban delivery operations have become an essential element of daily life in cities, meeting the growing demand for goods from households and businesses. In densely populated metropolitan areas, light-duty vans and trucks already account for 5 to 10 % of total traffic (Kauf, 2016; Coulombel et al., 2018). These vehicle flows can impose substantial external costs, including congestion, safety issues, pollutant emissions, and encroachment on public space (Lopez et al., 2019; Nourinejad et al., 2014; Yang et al., 2020). In circumstances where dedicated loading zones are in short supply or difficult to locate, delivery drivers frequently engage in behaviors such as double-parking, obstructing bus stops, and occupying sidewalks, thereby exacerbating these impacts (Morillo and Campos, 2014; Ramirez-Rios et al., 2023). Understanding the factors that influence commercial vehicle drivers' parking decisions at delivery stops is therefore critical given the significant impacts of trucks and light-duty vehicles on urban transport networks.

Despite the implementation of urban logistics policies by many municipalities, including new loading bays and dynamic curb pricing, the factors that influence delivery drivers' parking choices remain underexplored. While understanding the decision-making

* Corresponding author.
E-mail addresses: r.crastesditsourd@leeds.ac.uk (R. Crastes dit Sourd), pascal.gastineau@univ-eiffel.fr (P. Gastineau), adrien.beziat@univ-eiffel.fr (A. Beziat), martin.koning@univ-eiffel.fr (M. Koning).

https://doi.org/10.1016/j.tre.2025.104420
Received 15 May 2024; Received in revised form 8 September 2025; Accepted 8 September 2025
Available online 3 October 2025
1366-5545/

processes involved in commercial vehicles parking is of significant concern, Ghizzawi et al. (2024) did note that the corresponding literature is limited to 34 relevant studies. This relative lack of research on delivery driver behaviors is believed to have originated from two main and interrelated factors. Firstly, the decision-making process is characterized by inherent complexity, which is influenced by factors such as heterogeneity between drivers, parking space availability, and freight attributes. Secondly, the scarcity of high-quality revealed-preference data is a significant contributing factor (Holguín-Veras and Sánchez-Díaz, 2016). Private actors are often unwilling to share operational information, which in turn hinders the collection of detailed and context-specific data.

The present study relies on the Paris Region Urban Goods Movement Survey (UGMS) dataset, which offers valuable information not available in the existing literature on commercial vehicle parking choices. Unlike conventional studies, which often rely on fixed observation points and reported or declared data, this dataset provides quantitative insights into the entire journey of delivery drivers, where delivery time, parking choice and shipment weight (among other variables) are recorded by an on-board investigator for each stop. Such data helps us better understand the drivers of parking duration and parking choice. Our dataset features detailed information about 2546 stops performed as part of 335 delivery rounds. This sample is large enough to allow for the use of discrete choice model techniques, whereas previous studies based on observations have used qualitative methods. For example, Dalla Chiara et al. (2021) investigated driver behavior based on observations of six ride-alongs in Seattle (USA).

Our contribution to the transport research literature, specifically in the context of commercial vehicle parking decisions, is twofold. First, we employ an econometric approach linking parking location ("where to park") and parking duration ("for how long") by introducing a latent variable measuring anticipated difficulty from the perspective of the driver. This approach is inspired by the work of Choudhury et al. (2017) and proposes to use a hybrid choice framework to jointly model parking choice (obstructive, non-obstructive or on a private spot) and parking duration, which represents a departure from the recent literature on this topic (Kalahasthi et al., 2022; Ramirez-Rios et al., 2023; Castrellon et al., 2023; Schmid et al., 2018). In addition, our research sheds light on the characteristics influencing parking location and parking duration, including shipment weight, packaging, handling tools, type of truck and transport company structure, among other variables. This underscores the relevance of collecting revealed preference data in order to further understand the main factors affecting commercial parking preference.

The remainder of this article is structured as follows. Section 2 surveys the literature on commercial-vehicle parking. Section 3 presents the data and the case study. Section 4 details the econometric framework. Section 5 provide the main results, and Section 6 discusses these results along with the limitations of our methodology and then offers a conclusion.

2. Literature review

Delivery vehicles contribute significantly to the level of parking demand, due to their multi-stop delivery rounds, which can strain available parking resources. They are larger than passenger cars and therefore occupy a significant amount of road space, which in turn can negatively impact traffic flow and capacity (Lopez et al., 2016, 2019; Nourinejad et al., 2014). In addition, commercial vehicles are more prone to illegal on-road parking, thus leading to significant congestion issues (Morillo and Campos, 2014; Kim and Wang, 2022; Ramirez-Rios et al., 2023). According to Béziat (2017), this vehicle category tends to stop for longer periods than passenger cars when double-parked. In correlating pollutant emissions with urban traffic speeds (Coulombel et al., 2018; Yang et al., 2020; Savadogo and Beziat, 2021), it becomes clear why the direct and indirect contributions of freight vehicles to air pollution is a growing concern. Policymakers must balance the needs of freight operators with those of local residents and businesses, while also considering the inherent impacts on traffic flow, safety and the environment (Jaller et al., 2013; Marcucci et al., 2015).

Modeling parking behavior choices, such as obstructive or illegal parking, are inherently complex due to their heterogeneous nature. Typically, researchers employ multinomial or mixed logit models originating from the field of passenger-car parking (Hess and Polak, 2004). Such frameworks consider random variations in driver preferences for parking-related attributes, e.g. exit time, parking duration, parking costs and fines. It is important to note that commercial vehicle parking differs significantly from passenger vehicle parking due to the underlying incentives to minimize driving time in order to meet delivery schedules, as noted by Kim and Wang (2022). Additionally, freight-related parking preferences are influenced by various factors, such as the level of complexity of the task being performed, which depends on the type and weight of goods, urban environment, and handling tools required. As a result, commercial drivers may park illegally or obstruct traffic to reach their destination more quickly, thereby making their job less complex and time-consuming. According to a study conducted by Nourinejad et al. (2014), delivery drivers prefer parking in loading bays rather than on-street parking spots, with all other factors being equal. Also, the proximity of a parking space to the delivery location affects its usage, as drivers are less likely to occupy spaces located further away from their destination. According to Dalla Chiara et al. (2020), parking decisions are affected by parking fees, anticipated penalties, and traffic congestion. Research has also found that the choice of parking location for commercial vehicles is influenced by vehicle type, ownership status, volume of goods being delivered, and the presence of a second driver in the vehicle.

Parking-behavior research has extensively focused on the dichotomy between stated and revealed preferences. Stated preferences are typically collected through surveys, which require individuals to express their preferences or intentions (Amaya et al., 2023). However, the external validity of such surveys can be questionable, particularly in contexts where certain behaviors are not socially acceptable, such as illegal parking, thus leading to social desirability bias (Norwood and Lusk, 2011). To address this challenge, an alternative approach consists of asking delivery drivers to recall their parking decisions during a given day or round of deliveries. However, this method may be subject to recall bias, which is common in retrospective surveys, and might not mitigate the social desirability bias previously discussed. Another solution calls for observing actual parking behavior, yet such observations are often limited to a specific area and only a single delivery over the entire route (Dalla Chiara et al., 2020). Finally, the data collected on driver and delivery characteristics are often poor or missing.

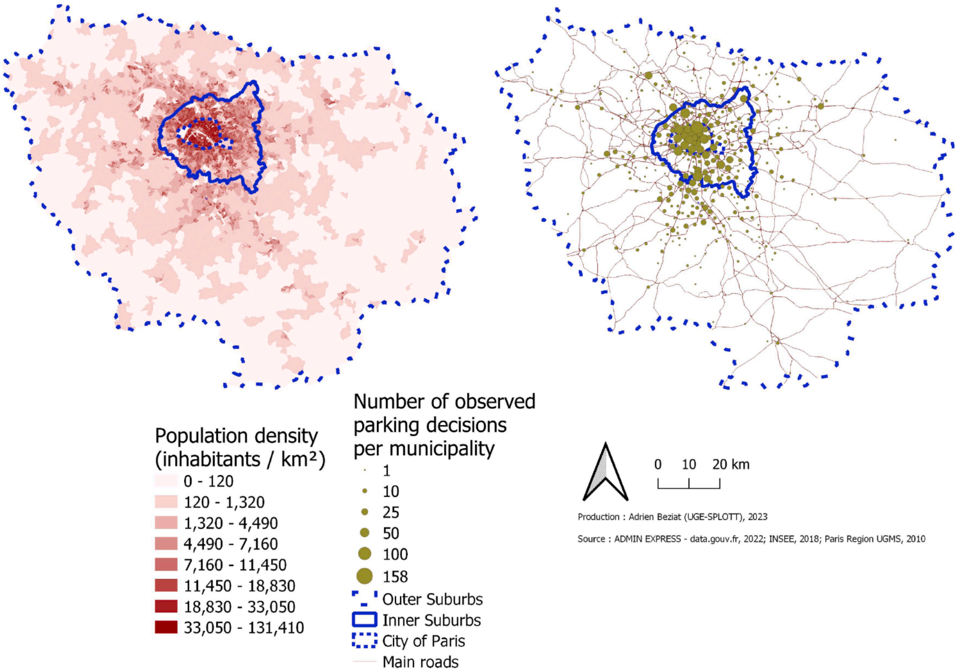

Fig. 1. Map of the Île de France (IDF) Region.

Taken together, these empirical limitations underline the need for modeling approaches that can capture unobservable factors. Even when models capture heterogeneity in parking behavior by using detailed data on tasks and environments, they still fail to explain every dimension of the choice process. To provide a more comprehensive approach that takes into account unobservable explanatory factors, particularly attitudinal variables, hybrid choice models have emerged over the last decade as one of the most appropriate solutions in the choice modeling literature (Abou-Zeid and Ben-Akiva, 2014). Despite their potential, few hybrid models have been applied to the study of parking preferences. To the best of our knowledge, only two studies have used this type of modeling, based on stated preference data. In focusing on passenger transport, Soto et al. (2018) showed that the parking choice process depends not only on observable factors, but also on individual-specific latent attributes, such as risk-averse attitudes and positive car care attitudes. Amaya et al. (2023) reported that last-mile delivery drivers are less likely to choose illegal parking due to a latent variable influenced by factors like the type of truck, driver's age and experience, and the entity responsible for paying parking fines.

Overall, knowledge gaps in commercial vehicle parking stem from limited data and theoretical frameworks that fail to account for the role of anticipation in delivery drivers'tt parking choices. The UGMS dataset and the proposed modeling approach aim to address these issues.

3. Case study and data collection

3.1. The Paris Region urban goods movement survey (UGMS)

The French Urban Goods Movements Surveys (UGMS) and its application to the Freturb software have been widely documented in the past (Ambrosini et al., 2010; Routhier and Toilier, 2007). In 2010, a UGMS was performed in the Paris Region (Île de France). The French UGMS consist of two questionnaires: one for firms (shippers and recipients of goods), the other for delivery drivers. The latter represents a valuable and underutilized data source for understanding real-world freight vehicle parking and the structure of delivery rounds within our case study (Fig. 1).

In the case of the 2010 Paris Region UGMS, the driver surveys included ride-along surveys of various logistics carriers. Observers accompanied drivers on rounds that began and ended at the carrier's depot. While onboard, the observers were able to record the various characteristics of each stop. Through this data collection approach, comprehensive insights into the practical aspects of freight vehicle parking and all stop-related tasks could be obtained, offering a rich and detailed dataset for research purposes. Fig. 1 illustrates the spatial population density of the Paris Region (on the left), juxtaposed with the location of observed parking choices (on the right). It shows that while a majority of observations (i. e. observed delivery stops) are, understandably, located in the dense city center, a substantial portion were observed in other areas, which highlights the fact that our data covers various spatial contexts. During the ride-along, observers collected data on several aspects of the delivery driver activities, namely:

- **Parking choice data**: The UGMS distinguish between 11 parking categories.[1] These 11 categories have been aggregated as follows :
  - 'obstructive parking': *On the sidewalk*, *in an area marked as prohibited for parking*, *in a bus or bicycle lane*, *double-parked on the road*, or *other types of unauthorized on-road parking*;
  - 'private parking': *On the establishment's premises* or *in its courtyard*;
  - 'non-obstructive parking': *Free public parking*, *paid public parking*, or *delivery areas*;
- **Carriers' and vehicles' characteristics**: type of carrier (third-party transport service provider or own-account supplier), type of vehicle (three categories based on Gross Vehicle Weight Rating (GVWR), i.e. total vehicle operating weight : light commercial vehicle (LCV) ($\leq$ 3.5 t), truck (3.5–26 t), articulated truck ($\geq$ 26 t));
- **Time**: We distinguish between four time periods, namely AM off-peak (until 10:00 AM), AM peak (10:00 AM to 12:00 PM), PM off-peak (12:00 PM to 4:00 PM), and PM peak (after 4:00 PM).
- **Location**: We divide the study area between three different zones, Paris, the inner suburbs and the outer suburbs. The different zones are characterized by different levels of urban density, traffic flow and on-street parking usage, among other factors. The type of shipper or recipient of the shipment is also recorded;
- **Task-related data**: main purpose of the stop (we distinguish between deliveries, pick-ups, delivery and pickup at the same stop, and collection of end-to-end shipments, in this context shipments that are collected and delivered within the same round), handling tools required, and additional tasks performed by the driver (order processing, load securement checks, etc.);
- **Shipment characteristics**: total weight of shipment, nature of the goods, type of packaging;
- **Delivery round scheduling**: total number of stops, total distance, time / location of the itinerary origin and destination, duration of each stop.

3.2. Data description

The dataset includes 335 rounds and 2546 stops involving a parking choice.

3.2.1. Delivery data

Table 1 provides descriptive statistics for 2546 delivery stops. The first column lists the variables describing all stop-related characteristics. Each subsequent column contains specific indicators for these variables: the number of observations, their percentage in the dataset, the average number of remaining stops (i.e. the average number of stops remaining after a particular stop is completed), the average duration of stops (in minutes) and the average shipment weight (in kilograms).

This presentation highlights important features of our parking analysis. To account for the spatial heterogeneity of parking practices, while keeping the analysis simple, we decided to represent the Paris Region (Île de France) as three concentric zones (see Fig. 1). The three zones are Paris, the inner suburbs ("Petite Couronne") and the outer suburbs ("Grande Couronne"). This is a common approach in the literature, see for example Gouriéroux and Laferrère (2009), Gavaud and Douet (2012), Nguyen and Kim (2024) and Yin et al. (2018). It is hence important to note that the scope of our analysis goes beyond Paris and covers in fact a whole region of France. At the center is the City of Paris, which is characterized by a very dense historical urban center, where parking infrastructure is scarce, and where most businesses are tertiary activities (retail and service outlets, business offices, etc.). This urban center is surrounded by a relatively less densely populated urban ring corresponding to the "Petite Couronne" area introduced above. Finally, the outer suburbs, or "Grande Couronne", are characterized by suburban and rural zones. These peripheral zones are characterized by their lower density as well as a greater share of industrial and logistics activities. This spatial heterogeneity is highlighted in the data, which show on average lighter shipments and quicker stops in the city of Paris, as part of freight rounds composed of more stops than in the suburbs.

Table 1 also illustrates the operational characteristics of freight rounds and how these characteristics can impact deliveries. Larger vehicles usually mean heavier shipments and longer stoppage times, as well as fewer stops per round on average. Interestingly, own-account suppliers deliver lighter shipments than third-party carriers, yet on average these stops are longer.

Obviously, shipment characteristics will also influence parking decisions. Chemicals and specialized goods typically mean heavier and longer deliveries. Pallets and bulk goods also imply heavier shipments and longer stops compared to parcels. Less sophisticated handling tools (handcart, roll) or the absence of handling tools translates into shorter stops and lighter shipments compared to the use of heavier tools (forklift, whether manual or motorized).

The data also allows to investigate whether the main purpose of the stop, be it a delivery, a pick-up, a combination of the two or a collection (i.e. picking up goods and delivering them elsewhere during the same tour) affect parking choice and duration. It is worth noting that we have removed the stops for which the delivery was canceled due to closure or for another reason from the estimation sample (3 observations in total).

Lastly, drivers performing additional tasks, such as control procedures (e.g. checking goods with the shipper or recipient) will require longer stoppage time compared to those who must only obtain a signature or a receipt. Other tasks such as browsing through the content of the vehicle to select the shipment for the next stop take more time than all the other categories.

[1] French traffic laws distinguish between parking ("*stationnement*") and stopping ("*arrêt*"). For the sake of consistency with the established literature, we will refer to "parking" in the remainder of this paper, although some deliveries are indeed performed while the vehicle has "stopped". It is important to note that obstructive parking can be tolerated depending on the context (for example when traffic is low), meaning that framing it as "illegal" would not adequately describe the actual choice situations experienced by drivers.

Table 1
Descriptive statistics.

Variables	Categories	Number of Observations	Percent of Observations	Remaining stops	Duration (mn)	Weight (kg)
Zone	*Paris*	751	29.50	7.96	11.08	187.01
	Inner Suburbs	850	33.39	6.70	13.15	486.13
	Outer Suburbs	945	37.12	5.33	18.68	771.15
Period	*AM off-peak*	830	32.60	6.44	12.54	398.50
	AM peak	1072	42.11	8.78	16.13	609.92
	PM off-peak	585	22.98	3.19	14.09	463.32
	PM peak	59	2.32	1.39	20.39	698.13
Carrier	*Third-party*	2051	80.56	6.80	14.14	520.86
	Own-account	495	19.44	5.58	16.45	445.16
Vehicle Type	*LCV (< =3.5t)*	595	23.37	10.45	8.21	50.26
	Truck (3.5-26T)	1750	68.74	5.71	14.50	457.16
	Art. Truck (> =26t)	201	7.89	2.49	34.24	2,530.52
Type of shipper or receiver	*Individual*	90	3.53	9.01	9.25	82.86
	Small establishment	1135	44.58	6.89	11.36	247.93
	Large establishment	1321	51.89	6.10	17.72	767.34
Type of goods	*Fragile*	87	3.42	5.44	14.45	353.95
	Food	742	29.14	6.78	16.57	513.13
	↪ (if) *Fresh*	326	12.80	5.18	18.87	598.96
	Alive	3	0.12	10.00	6.00	117.00
	Chemicals	94	3.69	7.17	13.95	1,516.80
	↪ (if) *Hazardous*	22	0.86	2.91	24.05	4,846.24
	Specialized	84	3.30	3.61	25.65	2,374.20
	Manufactured	1266	49.72	6.88	13.18	381.92
	NA	270	10.60	5.47	12.63	224.77
Packaging of goods	*Envelopes*	91	3.57	7.77	6.95	22.24
	Parcels	954	37.47	7.91	8.68	85.11
	Pallets	1215	47.72	5.01	18.55	773.34
	Bulk	195	7.66	10.13	18.45	1,044.28
	Other	23	0.90	2.09	36.26	1,996.95
	NA	68	2.67	4.94	18.69	369.10
Handling tools	*None*	730	28.67	9.27	8.90	237.10
	Manual forklift	1067	41.91	5.21	16.97	693.98
	Handcart	369	14.49	7.42	11.82	140.42
	Motorized forklift	167	6.56	3.54	25.05	1,376.94
	Roll	65	2.55	7.29	21.72	213.14
	Tailgate	33	1.30	3.61	17.94	454.84
	Crane	2	0.08	0.50	86.50	9,000.00
	NA	113	4.44	4.01	16.07	453.24
Main purpose	*Delivery*	2106	82.72	7.31	12.81	396.11
	Pick-up	296	11.62	2.40	21.07	927.60
	Delivery and pick-up	81	3.18	4.00	27.05	1180.43
	Collection	60	2.36	4.53	28.11	1974.72
	Canceled due to closure	2	0.08	3.50	24.50	.
	Canceled for another reason	1	0.04	5.00	6.00	.
Additional tasks	*Signature*	594	23.33	5.51	16.43	696.82
	Control	1027	40.34	8.32	12.68	312.43
	Other	108	4.24	4.36	21.15	691.16
	NA	817	32.09	5.40	14.78	631.17
Total		2546	100.00	6.56	14.59	346.53

Note: NA stands for Not Available.

Figs. 2 and 3 show the distribution of the number of stops and the total weight of shipments for all the routes in the database, yielding fat-tailed distributions. Our sample consists mainly of shipments weighing less than 300 kg.

3.2.2. *Parking data*

The three parking alternatives (obstructive, non-obstructive, private) are mutually exclusive, i.e. choosing one precludes either of the other two. Fig. 4 illustrates the number of observations in the UGMS dataset for each of these parking alternatives. We see that obstructive parking is the most important category (40.37 % of the stops), followed by private (36.29 %) and non-obstructive (23.34 %).

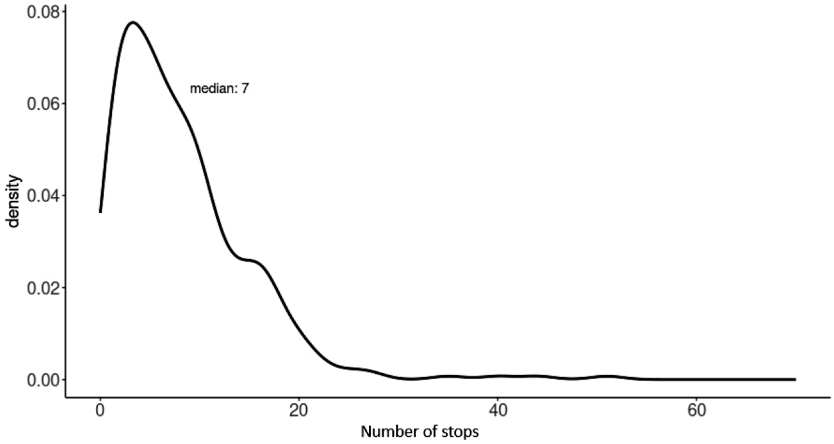

Fig. 2. Kernel density - Number of stops.

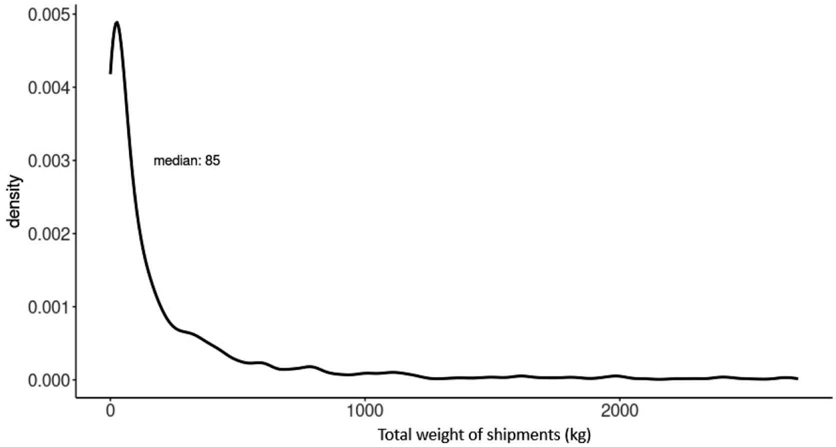

Fig. 3. Kernel density - Total weight of shipments (highly skewed, extending to ~ 25 tons).

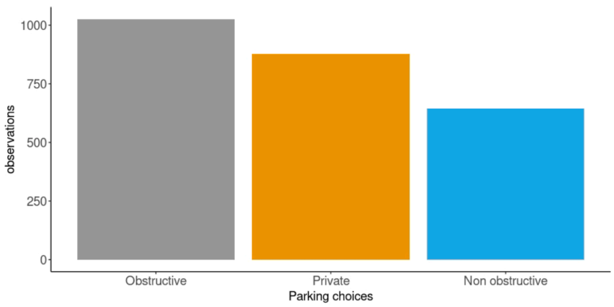

Fig. 4. Parking choice (total).

Fig. 5 shows the number of observations for each of the three parking alternatives by type of carrier, period, type of shipper or receiver, type of vehicle, and zone. In particular, it illustrates the specificity of Paris within the Île de France Region with regard to parking behavior of commercial vehicle drivers : widespread obstructive parking (more than 70 % of the observations in Paris). Given the limited availability of parking infrastructure in the city center, as well as the time pressure placed on delivery drivers, the cumbersome nature of goods handling and the low level of fines for double parking in Paris in 2010, the high level of obstructive parking by urban freight vehicles is hardly surprising (Béziat, 2021).

Parking choice is influenced by other factors, such as the characteristics of both the freight round and the shipper or recipient. Larger establishments are more likely to provide private parking lots, and stops performed with a truck are more likely to require space and take time, hence requiring such private spots (depending on availability). Despite representing a small number of observations

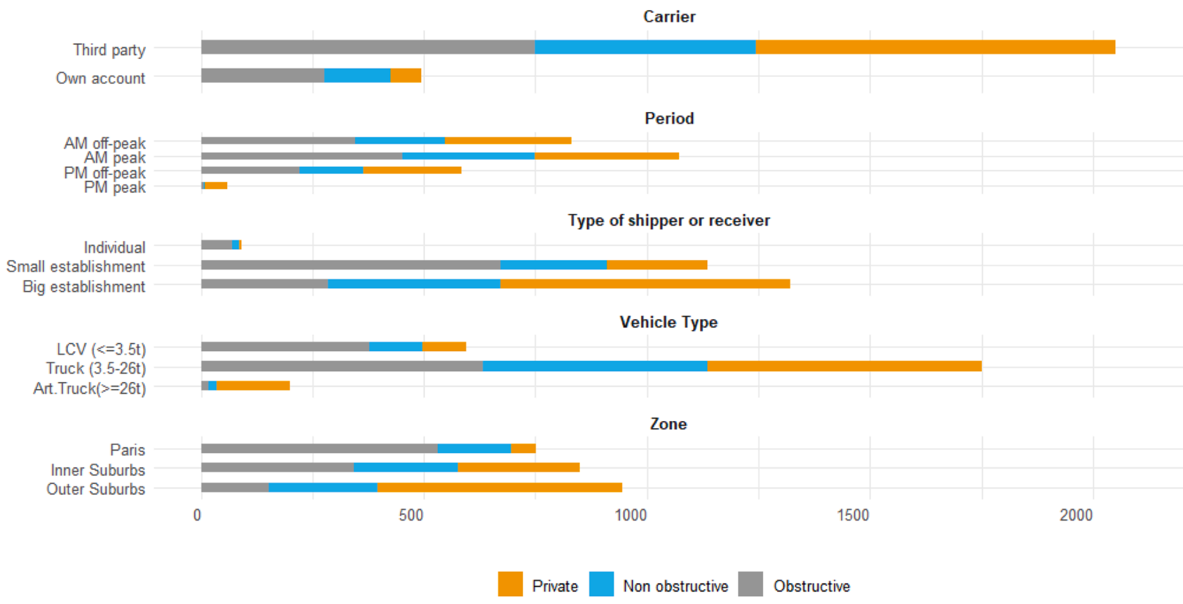

Fig. 5. Parking choice (observations).

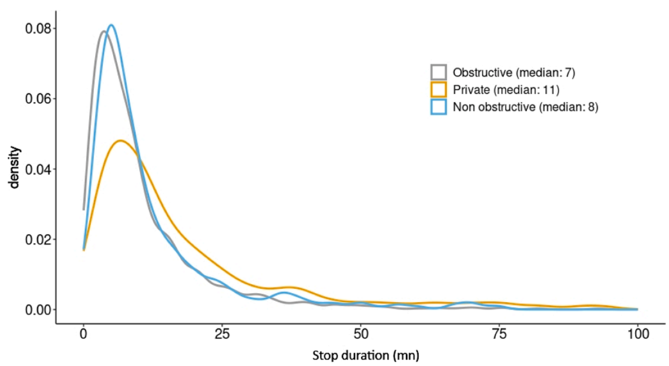

Fig. 6. Kernel density - Stop duration.

(due to the fact that the sample was collected in 2010), B2C shipments (for individual recipients) are obviously not associated with private parking. Interestingly, own-account transport carriers rely heavily on public parking, whether obstructive or non-obstructive.

Fig. 6 illustrates the variability in stop duration depending on parking choice. Private parking stop duration is significantly longer than that for public parking stops, thus reflecting the correlation with the use of large vehicles for heavy shipments. In addition, stops performed at obstructive parking locations appear on average to be marginally faster than those in non-obstructive public parking contexts.

4. Modeling work

The decision-making process for delivery drivers with respect to parking location and duration raises the question of whether this is a joint decision or an action taken in anticipation. This is a significant modeling challenge, as drivers are uncertain about the time required to complete specific stops prior to their completion. Hybrid choice models assume that attitudes and anticipations are latent hidden factors influencing decision outcomes. Therefore, indicators measuring these latent attitudes should not be treated as dependent variables but rather as explanatory variables. Hybrid choice models exhibit the notable feature of proposing an approach that simultaneously models choices and indicators, which are generally but not exclusively responses to attitudinal questions (Abou-Zeid and Ben-Akiva, 2014).

We adopt this framework to jointly model parking choice and stop duration. Crucially, we introduce a latent variable informed by a number of explanators related to task characteristics, including shipment weight, nature, packaging, required handling tools, and additional tasks. These variables capture the effort-level required to complete a stop. We also include variables related to the number of remaining stops, which can affect how long a given driver spends on each task and how she/he decides to park. We argue that this framework captures a form of anticipation effect, where expected efforts jointly affect parking choice and stop duration.

Our approach is different from Choudhury et al. (2017), who also proposed hybrid choice models to capture anticipations. Their models are particularly useful when examining the complex interplay between choices made at different points in time. For instance, the authors used them to study whether the decision to purchase a car at time t is influenced by anticipating a child's birth at time $t+1$. In our case, anticipations do not take the form of lag and lead variables, but are inferred through our interpretation of the different model components. A typical hybrid choice model features three components: a structural equation component, a measurement model component and a choice model component (Vij and Walker, 2014). We first introduce the choice model component.

4.1. Choice model component

The choice model component is rooted in the well-known random utility maximization framework, according to which drivers are assumed to choose the most suitable parking alternative given the task at-hand, as well as its location and scheduling. The model accounts for several layers of heterogeneity. In what follows, we build our model step-by-step, adding one layer at a time before presenting the other hybrid choice model components.

4.1.1. Observed heterogeneity

We start with a simple model where choices are solely explained by observed factors such as shipment weight, geographical location or driver status (self-employed or not). In what follows, “obst” stands for “obstructive”, while “priv” and “n-obst” stand for “private” and “non-obstructive”, respectively.

$$\begin{cases} U_{obst,n,t} &= \beta'_{obst} x_{obst,n,t} + \epsilon_{obst,n,t} \\ U_{priv,n,t} &= \beta'_{priv} x_{priv,n,t} + \epsilon_{priv,n,t} \\ U_{n-obst,n,t} &= \epsilon_{n-obst,n,t} \end{cases} \tag{1}$$

where a driver n associates utility U to parking alternative i ($obst$, $priv$, or $n-obst$) for stops t (with $t=1,\dots,T$ and T corresponding to the total number of stops on a given day). Moreover, β_{obst} and β_{priv} are vectors of parameters to be estimated (including alternative specific constants), while $x_{i,n,t}$ is a vector of independent variables. Finally, $\epsilon_{obst,n,t}$, $\epsilon_{priv,n,t}$ and $\epsilon_{n-obst,n,t}$ are type 1 extreme value error terms, which are identically and independently distributed across alternatives and observations with mean zero, variance $\pi^2/6$ and the scale set to unity, as commonly found in the literature (Train, 2009). Non-obstructive parking is the reference alternative, for which the utility is set to zero. Under this specification, the probability that driver n chooses alternative i in choice situation t corresponds to the multinomial logit formula:

$$P_{i,n,t} = \frac{exp(\lambda V_{i,n,t})}{\sum_{j=1}^{J} exp(\lambda V_{j,n,t})} \tag{2}$$

with $\lambda V_{i,n,t} = U_{i,n,t} - \epsilon_{i,n,t}$, that is, the modeled part of utility. The model accounts for differences in scale across geographical zone through the vector λ. Scale measures choice determinism. When scale increases, choices become more deterministic. When scale decreases, choices become more random for the point of view of the analyst. Our approach can be justified by the fact that the variance of the error term can be assumed to be different between different segments of the data, and in our instance Paris versus the inner and outer suburbs. Not accounting for differences in scale may lead to biased estimates and issues with model interpretation. This is in line with Train (2009), who states that “the variance of the error term can differ over geographic regions, data sets, time, or other factors”. The product of λ and β is not separately identified, so for the inner and outer suburbs, the scale is specified as constant and equal to 1, meaning that we measure the relative scale for Paris with respect to the other two zones. We propose $\lambda = \exp(\lambda_{Paris} x_{Paris,n,t})$, where λ_{Paris} is a parameter to be estimated and $x_{Paris,n,t}$ is a dummy variable that takes the value 1 if delivery task t performed by driver n takes place in Paris. This ensures that the scale is equal to 1 for the inner and outer suburbs and that the scale parameter λ_{Paris} is positive.

The multinomial logit model presented in this section is limited, in that it can only measure systematic taste variations. In substantially simpler words, it can only capture the effect of the explanatory variables that are included in the model, which are described in Table 1 (deterministic heterogeneity). The use of mixed logit models to overcome this limitation is pervasive in the transportation research literature and the freight literature. In the context of our paper, this allows to consider that not all drivers are the same, even after accounting for their main observables characteristics. In addition, the model in its current form assumes that all parking space alternatives are available in all choice situations. This may not be the case in practice, and in some circumstances drivers may only face a choice between *obstructive* and *non-obstructive* for example, rather than *obstructive*, *private* and *non-obstructive*. Whether a given parking alternative i is available at time t for driver n is not observed in the data.

Two additional layers of heterogeneity are hence introduced. We account for random heterogeneity in parking preferences across drivers by the means of error components, and we use a latent class approach to infer parking space availability in each choice situation. We first introduce the error component structure.

4.1.2. Random heterogeneity in preference across drivers

Many different error component structures can be found in the literature. In this study, we assume normally distributed error components associated with alternatives, or nests of alternatives. This class of models are referred to as *normal error component* *logit mixture* models (NECLM). The cases that are relevant to our study are discussed in Walker et al. (2007), and in particular the alternative-specific variance and nesting cases, which both allow to capture correlation across choices for the same driver, as well as correlation between alternatives. A thorough specification search was carried out[2], and the following alternative-specific variance structure was chosen for the model based on goodness-of-fit:

$$\begin{cases} U_{obst,n,t} & = \beta'_{obst} x_{obst,n,t} + \sigma_{obst}\eta 1_n + \epsilon_{obst,n,t} \\ U_{priv,n,t} & = \beta'_{priv} x_{priv,n,t} + \sigma_{priv}\eta 2_n + \epsilon_{priv,n,t} \\ U_{n-obst,n,t} & = \sigma 1_{n-obst}\eta 1_n + \sigma 2_{n-obst}\eta 2_n + \sigma 3_{n-obst}\eta 3_n + \epsilon_{n-obst,n,t} \end{cases} \tag{3}$$

where the parameters labeled as σ are error component parameters, while $\eta 1_n$, $\eta 2_n$ and $\eta 3_n$ are three sets of standard normal draws. Note that we introduce correlation between the normally distributed error components for $obst$ and $n-obst$ in one hand (on-street alternatives), and $priv$ and $n-obst$ on the other (legal alternatives) by the means of a Cholesky decomposition. The probability for driver n to choose alternative i in choice situation t now becomes:

$$P_{i,n,t} = \int_\sigma \frac{exp(\lambda V_{i,n,t})}{\sum_{j=1}^{J} exp(\lambda V_{j,n,t})} f(\sigma|\Omega) d\sigma \tag{4}$$

with $f(\sigma|\Omega)$ describing the distribution function of the error components and where Ω is a vector of parameters of this distribution. In the remainder of the paper, we simplify this notation for convenience, and simply write $f(\sigma)$ (the same applies to other distribution functions throughout the paper). The integral is solved by the means of simulation methods as it does not have any closed form solution.

4.1.3. Latent availability of parking space alternatives

A common challenge with revealed preference data is that the set of available alternatives is not observed, which contrasts with stated preference data where choice scenarios are under the control of the analyst (see Chaniotakis and Pel, 2015 for an example). Calastri et al. (2019) proposed a modeling framework for inferring choice availability. Their approach is based on a latent class model (Greene and Hensher, 2003) where, differently from a large body of studies, classes do not define different categories of respondents but different categories of choice situations where specific choice alternatives can be available or not. Model parameters are the same across all classes. Class allocation is probabilistic and intervenes at the choice task level. Class allocation probabilities can be specified as a function of relevant variables, zone and destination (type of establishment) in our case. We incorporate this new layer of heterogeneity in our model by first reformulating Eq. (5), where the probability for driver n to choose alternative i from a set of I alternatives available in choice situation t corresponds to:

$$P_{i,n,t}(G_{n,t}) = \int_\sigma \frac{exp(\lambda V_{i,n,t})}{\sum_{j=1}^{I} exp(\lambda V_{j,n,t})} f(\sigma) d\sigma \tag{5}$$

with $j \in G_{n,t}$ and where $G_{n,t}$ is a set of available alternatives. The set of available alternatives is defined by the researcher for each latent class. The model can feature S classes, and each driver has a probability to belong to each class at time t. It comes that the probability that driver n belongs to class s with class-specific choice set G_{n,t_s} corresponds to $\pi_{n,t,s}$, where restrictions ensure that $0 < \pi_{n,t,s} < 1$ and $\sum_{s=1}^{S} \pi_{n,t,s} = 1$.

Our model features two classes. In the first class, all parking space alternatives are available. In the second class, the $private$ space alternative is not available. Other specifications were tested with a different number of classes, or different restrictions on availability, but results were not found to be significant. The probability for a driver to belong to the full availability class at time t (i.e. $s = 1$) is given by a class allocation model and corresponds to:

$$\pi_{n,t,s=1} = \frac{1}{1 + exp(q_{n,t})} \tag{6}$$

Conversely, the class membership probability for the class where the $private$ space alternative is not available (i.e. $s = 2$) corresponds to:

$$\pi_{n,t,s=2} = \frac{exp(q_{n,t})}{1 + exp(q_{n,t})} \tag{7}$$

with $q_{n,t} = \gamma z_{n,t}$, where $z_{n,t}$ is a vector of variables while γ is a vector of parameters that are estimated jointly with the rest of the choice model, and includes a constant. More precisely:

$$\begin{aligned} q_{n,t} = {} & \gamma_{constant} \\ & + \gamma_{individual} z_{individual,n,t} + \gamma_{small\ estab} z_{small\ estab,n,t} \\ & + \gamma_{outer\ suburbs} z_{outer\ suburbs,n,t} + \gamma_{inner\ suburbs} z_{inner\ suburbs,n,t} \end{aligned} \tag{8}$$

As a result, class membership probabilities are a function of variables related to destination (type of establishment) and zone (Paris, inner suburbs and outer suburbs). This is an important point as we aim to capture heterogeneity in parking supply. Small

[2] The different specifications that we tested are reported in Appendix, while detailed outputs are available as supplementary material.

establishments and individuals are far less likely to provide private parking spaces for delivery drivers compared to big establishments. Moreover, the supply of private parking spaces is likely to be substantially lower in a dense urban environment such as Paris compared to the inner and outer suburbs. It is worth noting that we also account for the effect of destination and zone in the choice model. However, the variables only enter the utility for *obstructive*, as opposed to *obstructive* and *private*, given that the variables already influence whether *private* is chosen through the class allocation model.

The log-likelihood of the model now corresponds to:

$$LL = \sum_{n=1}^{N}\left[\ln \int_{\sigma}\left(\prod_{t=1}^{T}\left(\sum_{s=1}^{S}\left(\pi_{n,t,s}\ \frac{exp(\lambda V_{i,n,t})}{\sum_{j=1}^{I} exp(\lambda V_{j,n,t})}(G_{n,t_s})\right)\right)\right)f(\sigma)d\sigma\right] \tag{9}$$

The last remaining layer of heterogeneity to be introduced is brought in by the other components of the hybrid choice model. We first describe the structural equation and the measurement model, before laying out the final specification for the choice model utilities and the log-likelihood for the overall model.

4.2. Structural equation

The meaning of the latent variable is derived from the model components it interacts with. As previously stated, the latent variable is specified as having a joint effect on both parking choice and stop duration. As such, it measures the difficulties anticipated by the driver for completing her/his task, and the efforts required by the drivers as a result. It is specified as a function of the characteristics of the undertaken task, and encompasses factors such as shipment weight, quantity of packaging unit, and procedural requirements. The latent variable is hence refereed to as 'task-level effort', which is denoted as $\alpha_{n,t}$ in the model. The structural equation is specified as follows:

$$\begin{aligned}
\alpha_{n,t} = {} & \\
& \alpha_{log(weight)}x_{log(weight)} + \alpha_{weight_NA}x_{weight_NA} + \alpha_{fragile}x_{fragile} + \alpha_{food}x_{food} \\
& + \alpha_{food-fresh}x_{food-fresh} + \alpha_{chemicals}x_{chemicals} + \alpha_{specialized}x_{specialized} + \alpha_{type_NA}x_{type_NA} \\
& + \alpha_{parcels}x_{parcels} + \alpha_{pallets}x_{pallets} + \alpha_{bulk}x_{bulk} + \alpha_{pack_other}x_{pack_other} + \alpha_{pack_NA}x_{pack_NA} \\
& + \alpha_{manual\ forklift}x_{manual\ forklift} + \alpha_{handcart}x_{handcart} + \alpha_{roll}x_{roll} \\
& + \alpha_{tailgate/motor.\ forklift}x_{tailgate/motor.\ forklift} + \alpha_{handling_NA}x_{handling_NA} \\
& + \alpha_{misc\ pick-up}x_{misc\ pick-up} + \alpha_{control}x_{control} + \alpha_{add.tasks_other}x_{add.tasks_other} \\
& + \alpha_{add.tasks_NA}x_{add.tasks_NA} + \alpha_{log(remain.stops)}x_{log(remain.stops)} + \alpha_{log(tot.stops)}x_{log(tot.stops)} \\
& + \varphi_n
\end{aligned} \tag{10}$$

where φ_n is a disturbance term that follows a standard normal distribution (which is a common assumption in the hybrid choice model literature). While most variables are described in Table 1, some clarifications are needed. Most variables are dummy variables, except for $log(weight)$, $log(tot.stops)$ (total number of stops) and $log(remain.stops)$ (remaining stops), which are continuous. They refer to the log of total shipment weight, the log of the total number of stops that a driver must complete throughout their round, and the log of the number of remaining stops to complete at time t, respectively. Dummy variables controlling for the effect of missing data are labeled with the "NA" ("not available") suffix. Note that we have omitted the suffixes n and t for all the variables for clarity.

4.3. Measurement model

The measurement model consists of a log-linear regression of parking time modeled as a function of the task-level effort variable. More precisely, the probability of observing the log-transformed parking duration y for respondent n at time t is derived from the corresponding log-normal density function:

$$D_{y_{n,t}} = \frac{1}{\sqrt{2\pi\delta^2}}exp(-\frac{(y_{n,t} - \zeta\alpha_{n,t})^2}{2\delta^2}) \tag{11}$$

in which ζ is an estimated parameter measuring the impact of the latent variable $\alpha_{n,t}$ on parking duration and δ corresponds to an estimated standard deviation. Crucially, $\alpha_{n,t}$ is also specified as an explanator of parking choice in the choice model component of the hybrid model. See Dalla Chiara and Goodchild (2020), Dalla Chiara et al. (2022) and Wang and Osaragi (2024) for other applications of a log-normal probability density function for modeling durations.

4.4. Final model specification

As a final step, we introduce the latent variable described in Eq. (10) in the choice model utilities:

$$\begin{cases}
U_{obst,n,t} & = \beta'_{obst}x_{obst,n,t} + \sigma_{obst}\eta 1_n + \theta_{obst}\alpha_{n,t} + \epsilon_{obst,n,t} \\
U_{priv,n,t} & = \beta'_{priv}x_{priv,n,t} + \sigma_{priv}\eta 2_n + \theta_{priv}\alpha_{n,t} + \epsilon_{priv,n,t} \\
U_{n-obst,n,t} & = \sigma 1_{n-obst}\eta 1_n + \sigma 2_{n-obst}\eta 2_n + \sigma 3_{n-obst}\eta 3_n + \epsilon_{n-obst,n,t}
\end{cases} \tag{12}$$

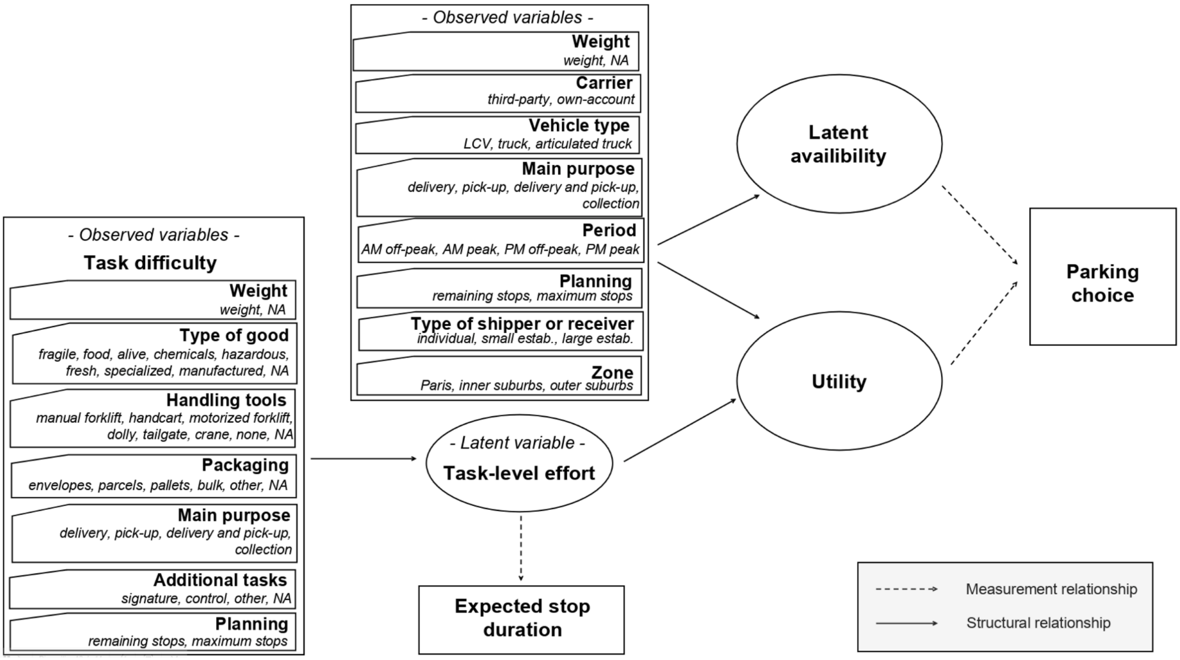

Fig. 7. Parking hybrid choice model.

where θ_{obst} and θ_{priv} are estimated parameters capturing the impact on the task-level effort latent variable on parking choice probabilities. It is crucial to note that some of the variables entering the structural equation are also introduced directly in the choice model utilities. This means for example that shipment weight has a direct effect on $U_{obst,n,t}$ through $\beta_{obst,\log(weight)}$ as presented in the results further below, as well as an indirect effect through the latent variable. The same applies to $x_{log(tot.stops)}$ and $x_{log(remain.stops)}$ and the variables capturing the main purpose of each stop. The choice model component also features additional variables which are not considered in the structural equation as they mostly affect parking choice. These variables, also introduced in Table 1, include geographical zone, time period, transport carrier, vehicle type, and type of establishment.

We now present the final likelihood function of the hybrid choice model, which corresponds to the joint probability of observing a given parking choice subject to availability along with a given stop duration for each driver and stop. This specification is also described in Fig. 7 for clarity purposes.

$$LL_{hybrid} = \sum_{n=1}^{N} \left[\ln \int_{\varphi} \int_{\sigma} \left(\prod_{t=1}^{T} \left(\sum_{s=1}^{S} \left(\pi_{n,t,s} \frac{exp(\lambda V_{i,n,t})}{\sum_{j=1}^{I} exp(\lambda V_{j,n,t})} (G_{n,t_s}) \right) D_{y_{n,t}} \right) \right) f(\varphi) f(\sigma) d\varphi d\sigma \right] \tag{13}$$

The hybrid choice model has been estimated on 2543 stops with 2000 Sobol draws. All models, including those presented in the Appendix, have been estimated using the Apollo package for R (Hess and Palma, 2019) and the BGW algorithm (Bunch, 2024).

5. Modeling results

The results of each model component are presented in Tables 2, 3 and 5, respectively. A number of preliminary models were estimated, leading to a confident assertion that the final results discussed in this section are indeed robust. In particular, we tested whether to estimate a pooled model on the three different zones while accounting for differences in scale, as opposed to estimating separate models for Paris, the inner suburbs and the outer-suburbs, respectively. Test results are detailed in the appendix section and suggest that it is adequate to estimate a single, pooled model, while also accounting for scale heterogeneity between the three geographic zones. Moreover, alternative error component structures and models with and without accounting for latent availability are also reported. Starting values for the hybrid choice model were obtained from estimating a multinomial logit model, for which detailed results are also available in appendix. The log-likelihood at convergence for the final model is -4505.62, while the AIC and BIC are 9157.24 and 9583.64. The results for the measurement model will be presented first, before examining the determinants of task-level effort (structural equation), parking space availability (the latent class component) and finally, parking choice (i.e. the choice model). Given that certain variables such as shipment weight are present in both the structural equation and the choice model, it is important to also look at the marginal effects presented in the remainder of this paper to fully assess the effect of each variable on parking choice with all else being equal.

Table 2
Results - Measurement model and scale.

Category	Parameter	Coeff.	Rob.Std.Err.	Rob.T-ratio
θ (effect of α on choices)	*obstructive*	0.48	0.18	2.60
	private	0.34	1.6	0.21
Measurement model	ζ	0.29	0.03	11.24
	δ	0.7	0.02	42.17
Error component	$\sigma_{obstructive}$	−5.87	3.1	−1.89
	$\sigma_{private}$	4.4	3.43	1.28
	$\sigma 1_{non-obstructive}$	−6.45	2.89	−2.23
	$\sigma 2_{non-obstructive}$	−1.02	0.79	−1.3
	$\sigma 3_{non-obstructive}$	−0.55	1.19	−0.46
Scale	λ_{Paris}	−0.7	0.22	−3.17

5.1. Hybrid choice model estimation

5.1.1. Measurement model

The parameters included in the measurement model indicate how parking choice and stop duration vary simultaneously based on the latent variable related to expected task difficulty. The parameter estimates for the measurement model are reported in Table 2.

Our results indicate that $\theta_{obstructive}$ and ζ have been found to be both positive and significant, while $\theta_{private}$ is also positive yet not significant (Rob.T. = 0.21). This finding means that an increase in the latent variable α related to expected task difficulty increases the chances that a driver parks in an obstructing location, slightly increases the chances of parking in a private location (although the effect is small and inconclusive according to the model), and decreases the chances of parking in a non-obstructing location. At the same time, the expected stop duration increases. We interpret these results as follows : drivers more likely to expect a difficult task, leading to longer stop durations, are also more likely to attempt to compensate for this by reducing parking search time. Moreover, in anticipation of a difficult task, delivery drivers may be encouraged to park as close as possible to their clients, even in an obstructive manner if necessary. This result might be in part driven by the fact that *stop duration* and *shipment weight* have been log-transformed. As a result, extreme observations (long stop durations and extremely heavy shipments) do not influence model outcomes as much as if they were specified as linear. In reexamining Figs. 2, 3 and 6, we find that the distributions for number of stops, shipment weights and stop duration are all highly skewed to the right, thus justifying our choice. This approach also means that the share of heterogeneity in behavior captured by the latent variable applies more to the average driver than to extreme cases. Our findings are further enriched by investigating the determinants of α, whereby a positive parameter should be interpreted as increasing expected task difficulty (and a negative parameter as decreasing it).

5.1.2. Determinants of task difficulty

Table 3 lists the hybrid model results for the structural equation. We first observe that $\alpha_{log(weight)}$ is positive and significant, in line with expectations. Heavier shipments increase the perceived effort, leading to a higher probability for a driver to expect a longer stop duration, on the one hand, and parking in an obstructing location on the other.

A substantial number of variables included in the structural equation were not found to be significant but were still kept in the model to account for their effect regardless. Variables related to the type of goods were not found to be significant, except for non-hazardous chemical substances, which $\alpha_{chemicals}$, was found to be negative (rob. T-ratio = −2.52). The variables related to handling tools reveal that the use of more sophisticated tools, such as a tailgate, a motorized forklift, a handcart or a roll substantially increase task difficulty. Variables related to packaging and additional tasks were not found to affect the perceived level of difficulty. Lastly, we found that the total number of stops ($\alpha_{log(tot.stops)}$) and number of remaining stops, $\alpha_{log(remain.stops)}$, were both highly significant ($p < 0.01$ and 0.05, respectively) and negative. More precisely, drivers with more tasks to perform overall and before the end of their shift perceive each stop as less difficult than drivers with fewer tasks left to perform. This constitutes a clear $lead$ effect, as drivers are seen to adjust their perception of task difficulty (hence their behavior), as also based on the number of stops yet to be performed. While these results do provide new insights into driver behavior, they do not imply that overall higher shipment weights increase the chance for a driver to park in a given parking location. The results of the structural equation need to be compared and contrasted with those of the choice model, while the “net” effect of the main variables is given by the marginal effect measurements.

5.1.3. Latent class model for private parking space availability

Results for the class allocation model are reported in Table 4 below. The four variables entering the class allocation model are all found to be strongly significant. Results indicate that it is less likely that a private parking space is available when the destination is a small establishment or an individual. Indeed, $\gamma_{small\ estab.}$ and $\gamma_{individual}$ are both positive, which in turns increases the class membership probability of the non-availability class (see Eq. (7) for details). This result is in line with expectation, as individuals and small businesses are less likely to propose a dedicated space for deliveries compared to big establishments. Moreover, we find that γ_{inner} and γ_{outer} are negative. This means that it is more likely that a private parking space is available if a delivery takes place in the inner or outer suburbs, as opposed to Paris. This is again in line with expectations, as the supply of private parking space for delivery drivers is expected to be lower in a dense urban environment such as Paris.

Table 3
Results - Structural equation.

Category	Parameter	Coeff.	Rob.Std.Err.	Rob.T-ratio
Weight	$\alpha_{log(weight)}$	0.65	0.08	8.64
	α_{weight_NA}	3.61	0.49	7.34
Type of good (ref = manufactured)	$\alpha_{fragile}$	0.09	0.31	0.28
	α_{food}	0.3	0.26	1.16
	$\alpha_{food-fresh}$	−0.07	0.36	−0.21
	$\alpha_{chemicals}$	−0.83	0.33	−2.52
	$\alpha_{specialized}$	0.67	0.5	1.32
	α_{type_NA}	−0.4	0.25	−1.59
Handling tools (ref = none)	$\alpha_{manual forklift}$	0.25	0.2	1.24
	$\alpha_{handcart}$	0.4	0.19	2.07
	α_{roll}	1.65	0.65	2.53
	$\alpha_{tailgate\ or\ motor.forklift}$	0.82	0.28	2.96
	$\alpha_{handling\_NA}$	0.07	0.45	0.15
Packaging (ref = envelopes)	$\alpha_{parcels}$	−0.45	0.31	−1.45
	$\alpha_{pallets}$	−0.18	0.34	−0.52
	α_{bulk}	0.16	0.46	0.34
	α_{pack_other}	−0.12	0.79	−0.15
	α_{pack_NA}	−1.3	0.64	−2.03
Main purpose (ref = delivery)	$\alpha_{misc\ pick-up}$	0.81	0.22	3.58
Additional tasks (ref = none)	$\alpha_{control}$	−0.38	0.27	−1.42
	$\alpha_{add.tasks\_other}$	0.37	0.38	0.96
	$\alpha_{add.tasks\_NA}$	−0.22	0.21	−1.05
Planning	$\alpha_{log(remain.stops)}$	−0.19	0.09	−2.16
	$\alpha_{log(tot.stops)}$	−1.04	0.15	−6.77

Table 4
Results - Class allocation model.

Category	Parameter	Coeff.	Rob.Std.Err.	Rob.T-ratio
Class allocation parameter	$\gamma_{constant}$	0.23	0.49	0.46
	$\gamma_{small\ estab.}$	1	0.26	3.9
	$\gamma_{individual}$	4.13	0.67	6.18
	$\gamma_{outer\ suburbs}$	−3.03	0.47	−6.51
	$\gamma_{inner\ suburbs}$	−2.2	0.44	−4.96

Finally, we present the results for the choice model component.

5.1.4. Choice model results

Table 5 reports the results of the choice component of the model. We first focus on the observed heterogeneity. In line with expectations, shipment weight is found to significantly decrease the chance of selecting obstructive parking locations ($\beta_{obstructive,log(weight)}$). At the same time, $\beta_{private,log(weight)}$ has not been found to be significant, (and the parameter value is substantially lower than what is found for $\beta_{obstructive,log(weight)}$). Given that shipment weight also affects parking choice via the latent variable related to expected task level effort, assessing the effect of shipment weight on parking choice should not be conducted based on Table 5 alone. The overall effect of shipment weight is presented in Table 7 in the form of pseudo-marginal effects derived through sampling enumeration, as introduced further below. Vehicle size has also been found to directly influence private parking choice given that $\beta_{obstructive,art.truck}$ and $\beta_{private,art.truck}$ where found to be significant at the 5 % level. Again, the overall effect is better captured through marginal effects, given that the interaction between articulated truck and number of stops ($\beta_{private,truck \times \log(tot.stops)}$) is also found to be significant. Carrier' status also affects parking choice. Drivers who are employed by a third-party carrier are less likely to use private locations since the effect of $\beta_{private,third-party}$ was found to be strong (-5.23) and significant. Regarding the influence of round scheduling, drivers are substantially more likely to park on a private location during the PM peak compared to the other time periods considered (AM off-peak, AM peak, PM off-peak) given that $\beta_{private,PMpeak}$ equals to 5.3 ($p < 0.01$). The number of remaining stops was not found to have a direct effect on parking choice, unlike the total number of stops ($\beta_{obstructive,\log(tot.stops)}$). Drivers required to stop many times during a given round are more likely to park in an obstructing location. Also, the type of shipper or receiver, and global geographic factors are found to exert an influence on parking choice, even after accounting for choice availability. Drivers have a higher probability to select an obstructive parking location when the recipient is a small business ($\beta_{obstructive,small\ estab.} = 1.19$) or an individual ($\beta_{obstructive,individual} = 1.54$) as opposed to a large business. The parameters capturing zonal effects (outer suburbs and inner suburbs vs. Paris) were both

Table 5
Results - Choice model component.

Category	Parameter	$\beta_{obstructive}$			$\beta_{private}$		
		Coeff.	Rob.Std.Err.	Rob.T-ratio	Coeff.	Rob.Std.Err.	Rob.T-ratio
Constant	*ASC*	2.06	0.97	2.13	8.9	4.03	2.21
Weight	*log(weight)*	−0.52	0.15	−3.42	−0.19	1.15	−0.16
	weight_NA	−2.35	0.9	−2.62	1.65	6.63	0.25
Carrier (ref = own-account)	*third-party*	−0.86	0.46	−1.86	−5.23	2.72	−1.92
Vehicle type (ref = truck)	*LCV*	−0.93	0.49	−1.9	−2.79	2.05	−1.36
	LCV × log(weight)	0.27	0.12	2.16	1.11	0.56	2
	LCV × weight_NA	2.62	1.31	1.99	4.93	3.35	1.47
	art. truck	2.22	0.98	2.26	−9.81	4.49	−2.18
	art. truck × log(tot.stops)	−0.47	0.83	−0.57	9.86	3.31	2.98
Main purpose (ref = delivery)	*misc pick-up*	−0.75	0.37	−2.02	0.29	1.24	0.24
Period (ref = AM peak)	*AM off-peak*	0.22	0.21	1.04	1.17	0.67	1.73
	PM off-peak	0.01	0.28	0.04	0.88	0.86	1.02
	PM peak	2.07	0.89	2.31	5.3	1.52	3.48
Planning	*log(remain.stops)*	−0.06	0.14	−0.4	0.81	0.48	1.68
	log(tot.stops)	0.98	0.31	3.13	−3.77	2.77	−1.36
Type of shipper or receiver (ref. = large establishment)	*small estab*	1.19	0.18	6.57	.	.	.
	individual	1.54	0.46	3.38	.	.	.
Zone (ref = Paris)	*outer suburbs*	−2.62	0.69	−3.81	.	.	.
	inner suburbs	−1.57	0.63	−2.5	.	.	.

found to be significant at the 1 % level. Drivers operating in zones further away from Paris (outer suburbs) were less likely to select obstructing locations ($\beta_{obstructive,outer\ suburbs} = -2.62$). The inner suburban zone exhibited similar albeit weaker effects.

In examining the error components, we have found a significant level of unobserved heterogeneity between drivers given that more than half of the parameters labeled as σ are significant.

5.2. Predictions

5.2.1. Marginal effects

Marginal effects (MFX) assess the impact of specific parameter estimates on the predicted probabilities of drivers choosing each parking alternative. Marginal effects are calculated for the shipment weight, the type of carrier, the geographic location, the type of truck, the type of shipper or recipient (small business, large business, individual), the total number of stops, and number of remaining stops. Marginal effects and choice predictions (introduced below) have been computed by means of sampling enumeration (see Hess et al., 2018; Beaumais and Crastes dit Sourd, 2024 for methodological insights and other applications, respectively). More precisely, and in the context of computing marginal effects, this approach consists of predicting the likelihood, for each stop included in the model, that drivers choose a given parking alternative while keeping all variables at their respective values, except one. For example, the marginal effects for the geographic zone are obtained by making a prediction assuming that all stops in the sample take place in Paris, all else being equal. This process is then repeated, and new predictions are derived, this time in assuming that all stops occur in the outer suburbs and lastly, the inner suburbs. The difference between choice probabilities under these three scenarios gives rise to (pseudo) marginal effects. For each observation in the sample, 200 predictions are produced, with each one corresponding to a set of draws taken from a multivariate normal distribution, whose means equal the hybrid choice model estimates, along with a variance-covariance equal to the robust variance-covariance matrix of the model parameters at convergence. Making multiple predictions using different draws allows computing standard errors for the marginal effects; in fact, the enumeration sampling process is very similar to the Krinsky and Robb approach (Krinsky and Robb, 1986, 1990). We first start with the marginal effects for the class allocation model.

Table 6 should be interpreted as follows: the probability that a private spot is available when delivering to an individual is 71.39 percentage points (%pt) lower than when delivering to a big establishment, while the difference between a small establishment and a big establishment is 8.96 points. Zone effects are also strongly significant. The probability that a private parking spot is available in Paris is 43.64 points lower compared to the inner suburbs, and 50.29 points lower compared to the outer suburbs. Altogether, these results confirm the importance of accounting for latent availability for private spaces, and show that in certain cases and particularly in Paris, drivers only face a restricted number of choices.

Table 6
Marginal effects - class allocation model - private spot availability.

		Mean (%pt)	Std.Err.	T-ratio
Establishment (destination)	Individual w.r.t. Big	71.39	0.11	6.52
	Small w.r.t. Big	8.96	0.04	2.54
	Small w.r.t. Individual	−62.42	0.11	−5.52
Geographical location (zone)	Inner w.r.t. Paris	−43.64	0.11	−4.06
	Outer w.r.t. Paris	−50.29	0.11	−4.48
	Outer w.r.t. Inner	−6.64	0.03	−2.53

Table 7
Marginal effects - Shipment weight.

Weight	MFX (%pt)	All alternatives available			Private not available
		Obstructive	Private	Non-Obstructive	Obstructive
1st quartile	Mean	2.83	−2.23	−0.61	2.33
w.r.t.	Std. Err.	0.01	0.01	0.01	0.01
2nd quartile	T-ratio	3.13	−2.16	−0.82	2.39
1st quartile	Mean	5.29	−4.18	−1.11	4.43
w.r.t.	Std. Err.	0.02	0.02	0.01	0.02
3rd quartile	T-ratio	3.20	−2.13	−0.80	2.39
1st quartile	Mean	12.78	−10.21	−2.57	11.47
w.r.t.	Std. Err.	0.04	0.05	0.03	0.05
4th quartile	T-ratio	3.52	−2.07	−0.73	2.47
2nd quartile	Mean	2.46	−1.95	−0.50	2.10
w.r.t.	Std. Err.	0.01	0.01	0.01	0.01
3rd quartile	T-ratio	3.28	−2.11	−0.78	2.40
2nd quartile	Mean	9.95	−7.99	−1.96	9.14
w.r.t.	Std. Err.	0.03	0.04	0.03	0.04
4th quartile	T-ratio	3.63	−2.04	−0.70	2.49
3rd quartile	Mean	7.49	−6.03	−1.46	7.05
w.r.t.	Std. Err.	0.02	0.03	0.02	0.03
4th quartile	T-ratio	3.74	−2.02	−0.67	*2.51*

Note: 1st quartile = 20 kg; 2nd quartile = 88.5 kg; 3rd quartile = 325 kg; 4th quartile = 25,000 kg

Table 8
Marginal effects - Remaining stops.

Stops	MFX (%pt)	All alternatives available			Private not available
		Obstructive	Private	Non-Obstructive	Obstructive
First stop	Mean	−6.71	7.22	−0.52	−3.36
w.r.t.	Std. Err.	0.03	0.04	0.03	0.04
Last stop	T-ratio	−2.00	1.83	−0.17	−0.88

As for shipment *weight*, we have proceeded with four sets of predictions, first assuming that the shipment weight corresponds to the 1st quartile of the sample for all stops, with the same process then being repeated for the 2nd, 3rd and 4th quartiles. For the number of remaining stops (*log(remain.stops)*), the choice predictions at the beginning of the round (when the number of remaining stops equals to the total number of stops) are compared with those at the end of the round (i.e. just one stop remaining). Regarding the type of carrier, two sets of predictions are compared (*third-party* vs. *own-account*). A similar approach has been adopted to compute the marginal effects for *Zone*, *Vehicle type*, and *Shipper or Recipient type*, as described above. These results are reported in Tables 7–10.

The results in Table 7 should be interpreted as follows: for the lighter shipments considered (1st quartile) the chances of a driver parking in an obstructing spot are 2.83 points higher than that found for the 2nd shipment weight quartile. Chances are also 2.23 points lower that the driver parks in a private location and 0.61 points lower for a non-obstructing location. All results are found to be significant at various levels of confidence (ranging from 1 % to 10 %) expect for the non-obstructive alternative. Naturally, the largest differences are found when comparing the 1st quartile with the 4th quartile, which yields a higher chance of parking in an obstructing location (+12.78 points) for the scenario assuming lighter shipments. The last column shows the marginal effects for $obstructive$ (with respect to $non-obstructive$) when $private$ is not available. We find that the results are similar across the two latent classes, for example, looking again at the difference between the 1st quartile and the 4th, we find that the marginal effect is +11.47 points for $obstructive$ (and so -11.47 points for $non-obstructive$). Subsequent results should be interpreted in a similar way.

Table 9
Marginal effects - Carrier.

Carrier	MFX (%pt)	All alternatives available			Private not available
		Obstructive	Private	Non-Obstructive	Obstructive
Third-party	Mean	−3.41	16.22	−12.81	10.03
w.r.t.	Std. Err.	0.06	0.09	0.06	0.06
Own-account	T-ratio	−0.61	1.77	−2.11	1.78

Table 10
Marginal effects - Zone.

Zone	MFX (%pt)	All alternatives available			Private not available
		Obstructive	Private	Non-Obstructive	Obstructive
Outer suburbs	Mean	−10.20	2.57	7.63	−14.97
w.r.t.	Std. Err.	0.03	0.01	0.02	0.04
Inner suburbs	T-ratio	−3.30	2.86	3.17	−3.40
Outer suburbs	Mean	−21.43	8.58	12.85	−24.08
w.r.t.	Std. Err.	0.06	0.03	0.03	0.05
Paris	T-ratio	−3.79	2.89	3.62	−4.69
Inner suburbs	Mean	−11.23	6.01	5.22	−9.11
w.r.t.	Std. Err.	0.04	0.02	0.02	0.04
Paris	T-ratio	−2.73	2.40	2.41	−2.55

Table 11
Marginal effects - Establishment (destination).

Establishment	MFX (%pt)	All alternatives available			Private not available
		Obstructive	Private	Non-Obstructive	Obstructive
Small	Mean	10.54	−3.02	−7.52	14.79
w.r.t.	Std. Err.	0.02	0.01	0.02	0.03
Large	T-ratio	4.30	−3.29	−4.17	5.07
Small	Mean	−2.95	0.99	1.96	−3.48
w.r.t.	Std. Err.	0.07	0.05	0.06	0.07
Individual	T-ratio	−0.44	0.20	0.33	− 0.51
Large	Mean	−13.49	4.01	9.47	−18.27
w.r.t.	Std. Err.	0.07	0.04	0.05	0.07
Individual	T-ratio	−2.05	0.98	1.95	−2.77

Interestingly, the aforementioned *lead* effect captured by the number of remaining stops a driver must perform is only found to be significant when $private$ is available. We find that drivers are less likely to park on an $obstructive$ spot at the beginning of their tour compared to the end.

Regarding the type of carrier, we find that when $private$ is available, third-party transport service providers are 16.22 points more likely to park in a private location compared to a own-account supplier, again with all else being equal (-3.41 points and not significant for Obstructive vs. -12.81 points for Non-Obstructive). Interestingly, we also find that third-party transport service providers are 10.03 points more likely to park in an obstructive location when a private location is not available.

Zone factors are found to be significant in determining parking choices, even after accounting for these variables in the class allocation model. As an example, a driver asked to perform a stop in the outer suburbs (or inner suburbs, respectively) is 21.43 points (or 11.23 points) less likely to park in an obstructing space than a driver in Paris. This finding could suggest that private parking spots are not only less likely to be available in Paris, but also less convenient than in the inner and outer suburbs (with narrower entrances and longer waiting times), and the same applies to non-obstructive spots. Drivers may have to park further away from where the delivery must take place because the best spots are taken, but other spots are nevertheless available (Table 11).

Finally, we can report from the model that the type of shipper or receiver has a strong and significant effect on parking choice, again even after accounting for these factors in the class allocation model. A driver is more likely to park in an obstructing location when the establishment is labeled as small compared to a large establishment (10.54 points higher, T-ratio = 4.3). The effect is equal to +14.79 points when a private space is not available. A possible interpretation is that big establishments have well-established delivery protocols, while other establishments are more flexible.

Table 12
Choice probabilities for four different tour profiles.

Outer suburbs			
Profile	Obstructive	Private	Non-obstructive
1	0.839	0.021	0.140
2	0.461	0.122	0.417
3	0.287	0.414	0.298
4	0.089	0.844	0.066
Inner suburbs			
Profile	Obstructive	Private	Non-obstructive
1	0.929	0.008	0.063
2	0.659	0.085	0.255
3	0.459	0.352	0.189
4	0.182	0.771	0.047
Paris			
Profile	Obstructive	Private	Non-obstructive
1	0.908	0.001	0.091
2	0.774	0.022	0.204
3	0.686	0.145	0.169
4	0.555	0.359	0.086

5.2.2. *Profiles*

To further highlight the value of our results, especially in the context of integrating them into an agent-based model, we have performed predictions for various driver profiles. This approach is also based on sample enumeration, and closely resembles the method followed to compute the marginal effects presented above. However, we had set the values for the different variables at the same time before making predictions, with all else being equal (as opposed to only one at the same time for the marginal effects). Results are reported in Table 12, while the various profiles considered are described below. Note that unlike marginal effects, the differences in choice probabilities have not been computed based on the value of a given variable, but instead and more simply as the parking choice probabilities for the different scenarios.

Four distinct profiles have been considered herein, representing archetypal freight delivery tours in urban contexts. They are defined as follows:

1. Home delivery of a 1 kg parcel of manufactured goods, delivered without handling equipment, using an LCV, from a third-party transport provider, as part of a 150-stop round.
2. Delivery of 300 kg of drinks in open crates to a small HoReCa (Hotel - Restaurant - Catering) establishment, using a handcart and an HGV, carried out by a supplier on his own-account, as part of a 20-stop round.
3. Delivery of a 35 kg parcel of manufactured goods to a large office building, using a handcart with an LCV, from a third-party transport provider on a 30-stop round.
4. Delivery of 3 tons of pallets of manufactured goods to a large retail outlet, using a manual forklift, with an articulated truck, from a third-party transport provider, as part of a 6-stop round.

Table 12 reports parking choice predictions for each of the four profiles. These results further describe how parking choice is substantially influenced by the zone in which the stops need to be performed (i.e. in comparing the three tables), as well as by the characteristics of the delivery tour (i.e. in comparing the rows in the same table). For all profiles, the probability of obstructive parking is higher in Paris than that for the inner suburbs, which in turn is higher than that for the outer suburbs. Profile 2 shows a higher probability of parking in a non-obstructive manner for all three zones. There is a higher likelihood of private parking for Profiles 3 and 4, where stops are performed for large office buildings or supermarkets. Profile 1 exhibits a very high probability of parking in an obstructing spot regardless of the zone considered, but especially in the city of Paris. This result is partially due to the limited number of observations in the database regarding shipments to private individuals (approximately 90 out of 2,543; see data limitation in Section 6). However, we have opted to retain this profile due to topical nature of parcel home-delivery services, plus the fact that our results suggest these services generate a disproportionate level of obstructive parking.

6. Discussion and conclusion

Our findings provide valuable insights into the behavior of delivery drivers. The research herein sheds a light on their decision-making processes and the factors influencing their choices. These findings are consistent with expected behavioral patterns, thus indicating that the research has effectively captured the real-world dynamics of stops to deliver or pickup goods, in particular the dynamic change of preferences for obstructive parking.

Our results may help local authorities to design more efficient parking strategies, and suggest that some parking locations should be dedicated to freight vehicles, not only in proximity to large business establishments, but also near firms that receive small shipments. In the same vein, we have shown that drivers performing home deliveries are substantially more likely to double park, thus highlighting the need of dedicated parking spots near residential areas, especially given the growth of e-commerce. In addition, model estimates suggest that a broader implementation of dynamic parking spot use might be relevant, especially in Paris. Parking spots could be reserved for deliveries between certain hours, for example peak versus off-peak, as a way of mitigating the negative effects of obstructive parking on businesses, travel time, as well as air quality and carbon emissions. Finally, delivery area booking might also be an effective strategy if properly implemented, given the awareness and anticipative nature of strategies adopted by delivery drivers when parking in the context of a long, uncertain urban freight round.

Other important findings suggest that delivery drivers anticipate whether a task is going to require substantial efforts or not, and this influences where they park. These effects can significantly impact the effectiveness and broader impact of delivery stops. The study highlights that delivery drivers are acutely aware of the attributes defining their tasks, such as weight, packaging and procedural requirements. This allows them to make informed decisions about how to approach each task and evaluate the efforts required for each delivery, leading to better resource management and enhanced operational efficiency, sometimes at the expense of other road users. Lastly, the concept of task-level effort has been introduced as a latent variable, that serves as a critical link between where drivers choose to park and how long it takes them to perform a given task. Recognizing the interplay between these factors is essential for delivery optimization.

The research contributes to a body of well-established evidence that choice models serve as a useful tool for gaining a deeper understanding of the decisions made by delivery drivers. Various approaches can be employed to investigate this issue; each one provides a unique perspective on the intricate dynamics of parking choice. Some models may oversimplify the choice process by assuming that the duration of a delivery task is solely determined by where the driver has parked. Other more sophisticated techniques such as Heckman's discrete-continuous model, consider the hidden variables affecting parking choice and duration instead. Adding to this literature, our article demonstrates that the hybrid choice model framework is also useful for tackling this intricate issue.

This study does have certain limitations, in particular a lack of information on the availability of parking infrastructure and the impact this may exert on parking search time. In addition, the precise schedule of drivers is unknown, although it could help informing stop duration. For instance, delivery drivers may feel compelled to expedite a delivery if they are behind schedule. Similarly, as is common in the literature (Ghizzawi et al., 2024), we have modeled the parking decision as being solely the choice of the delivery driver and have not consider the potential influences of other stakeholders (shippers, receivers, etc.). Moreover, a limitation placed on the data is the small number of observations of home deliveries, which in 2010 was a less developed segment. As a result, recent developments linked to the growth of e-commerce such as Cheng et al. (2024) cannot be tracked. Nonetheless, these observations have been retained to provide a point of comparison for future studies.

More generally, while the data used in this paper is not recent, some of the empirical findings can help shaping agent-based models. In addition, the possibility of finely tuning the profile of delivery drivers would also benefit urban traffic simulations. We are also the first revealed-preferences based study to include net shipment weight in an urban freight choice model and stress out the importance of accounting for this factor, which is strongly significant even after accounting for vehicle size. While the effect of weight on parking choice could have marginally changed between 2010 and 2024, it is still very likely to be a major factor which other studies should account for, as further supported by the magnitude of the marginal effects reported in the paper. Moreover, methodological insights include how hybrid choice models can link expected delivery time and parking choice to derive behavioral insights when parking time for the non-chosen alternatives is unknown. We argue that this is an interesting alternative to a more common attribute-based approach, where each parking alternative (obstructive, non-obstructive, private) would be defined by a specific stop duration value (similarly to what is found in many revealed preferences and stated preferences applications). However, in the context of our data, this would raise endogeneity concerns as the stop duration values/levels for the non-chosen alternatives would be data driven (inferred from the rest of the sample, or from a hold-out sample). While this would be an interesting comparison for future urban freight research, we have not attempted this in our paper.

Finally, we acknowledge that the presence of an observer may influence parking behavior, and may result in underestimating obstructive practices. Nevertheless, certain studies within the transportation literature have demonstrated that the presence of an observer does not necessarily result in a significant alteration of driver behavior (e.g. Quimby et al., 1999; Hjälmdahl and Várhelyi, 2004; Amado et al., 2014). Furthermore, in-vehicle observation methods have been shown to be both reliable and valid. It is worth noting that other data collection approaches, including the UGMS survey of economic establishments, as well as an ad-hoc on-street data collection effort on parking behavior (performed respectively in 2010 in the Paris Region, and in 2014 in the city of Paris) have yielded very similar results in terms of share of obstructing parking for these zones (Béziat, 2017). While this strengthen our confidence that observer bias is likely limited, we recognize that there is a possibility that it plays a role, thus emphasizing the need for further investigation and data collection.

In conclusion, recent advancements in big-data, open-data and AI-driven analytics have rapidly expanded the scope of transport analysis and urban-mobility research (Gao et al., 2023; Xiao and Xu, 2024). However, there is still a significant need for fine-grained observational datasets. This study has highlighted the significance of collecting observational data to provide more detailed analyses of delivery driver behavior, which in turn facilitates the implementation of more effective public policies to mitigate the externalities associated with commercial vehicle parking in urban areas. Our findings have confirmed the expected behavioral patterns of delivery drivers, and found significant anticipatory effects. By including task-level effort as a latent variable, we uncovered patterns of behavior that can inform policy making. From a research point of view, the parking profiles derived from the type of analyses carried out may prove to be useful in the context of a multi-agent simulation of urban freight movements, e.g. by assigning different obstructive parking probabilities to the simulated vehicles depending on delivery location, which is a promising area for future work.

Acknowledgment

The authors acknowledge and thank the Ile-de-France Region, the DGITM, LAET, and ADEME for access to the Paris Region Urban Goods Movement Survey. We are also grateful to the three reviewers for their careful reading and valuable suggestions, which have significantly improved this manuscript. All remaining errors and omissions are our own.

CRediT authorship contribution statement

Romain Crastes dit Sourd: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization; **Pascal Gastineau:** Writing – review & editing, Writing – original draft, Visualization, Funding acquisition, Data curation, Conceptualization; **Adrien Beziat:** Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Funding acquisition, Data curation, Conceptualization; **Martin Koning:** Writing – review & editing, Writing – original draft, Validation, Resources, Funding acquisition, Data curation, Conceptualization.

Data availability

Data will be made available on request.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Mixed multinomial logit model (MMNL) estimation

(Table A.5).

Table A.1
Results - Pooled mixed multinomial logit model.

Category	Parameter	$\beta_{\text{obstructive}}$			β_{private}		
		Coeff.	Rob.Std.Err.	Rob.T-ratio	Coeff.	Rob.Std.Err.	Rob.T-ratio
Constant	ASC	1.52	0.72	2.12	0.08	1.12	0.07
Weight	*log(weight)*	−0.16	0.06	−2.62	0.05	0.08	0.54
	weight_NA	−0.46	0.48	−0.96	1.26	0.72	1.76
Carrier (ref = own-account)	*third-party*	−0.39	0.36	−1.10	−1.99	0.75	−2.64
Vehicle type (ref = truck)	*LCV*	−0.64	0.44	−1.47	−1.61	0.80	−2.00
	LCV × log(weight)	0.20	0.12	1.73	0.61	0.19	3.28
	LCV × weight_NA	1.94	1.14	1.70	2.56	1.32	1.95
	art. truck	1.88	0.98	1.93	−3.11	1.64	−1.90
	art. truck × log(tot.stops)	−0.23	0.74	−0.30	3.76	1.12	3.37
Main purpose (ref = delivery)	*misc pick-up*	−0.33	0.28	−1.19	0.41	0.29	1.40
Period (ref = AM peak)	*AM off-peak*	0.21	0.20	1.04	0.63	0.33	1.89
	PM off-peak	−0.04	0.27	−0.16	0.36	0.44	0.82
	PM peak	1.76	0.95	1.86	3.95	1.02	3.88
Planning	*log(remain.stops)*	−0.12	0.13	−0.92	0.23	0.22	1.05
	log(tot.stops)	0.38	0.19	2.03	−1.40	0.40	−3.45
Type of shipper or receiver (ref. = large establishment)	*small estab*	1.16	0.18	6.38	−0.20	0.25	−0.82
	individual	1.50	0.46	3.29	−3.08	1.11	−2.76
Zone (ref = Paris)	*outer suburbs*	−1.96	0.42	−4.72	3.12	0.68	4.60
	inner suburbs	−1.24	0.40	−3.08	2.31	0.63	3.68
Error component (all aternatives)	$\sigma_{obstructive}$	2.75	0.31	8.75	.	.	.
	$\sigma_{private}$	−0.34	0.24	−1.43	.	.	.
	$\sigma 1_{non-obstructive}$	0.63	0.20	3.11	.	.	.
	$\sigma 2_{non-obstructive}$	−0.70	0.12	−6.04	.	.	.
	$\sigma 3_{non-obstructive}$	3.75	0.36	10.56	.	.	.
Scale (all alternatives)	λ_{Paris}	−0.60	0.17	−3.55	.	.	.

Table A.2
Results - Outer suburbs - Mixed multinomial logit model.

Category	Parameter	$\beta_{\text{obstructive}}$			β_{private}		
		Coeff.	Rob.Std.Err.	Rob.T-ratio	Coeff.	Rob.Std.Err.	Rob.T-ratio
Constant	ASC	2.74	1.44	1.91	6.22	1.88	3.31
Weight	*log(weight)*	−0.25	0.12	−2.16	0.13	0.13	1.04
	weight_NA	−1.25	0.84	−1.49	1.46	0.98	1.49
Carrier (ref = own-account)	*third-party*	−0.88	0.84	−1.05	−4.27	1.33	−3.22
Vehicle type (ref = truck)	*LCV*	−2.04	1.07	−1.90	−0.52	1.32	−0.40
	LCV × log(weight)	0.62	0.40	1.56	0.78	0.46	1.68
	art. truck	−0.41	1.64	−0.25	−8.42	2.63	−3.20
	art. truck × log(tot.stops)	0.44	1.14	0.39	5.73	1.67	3.44
Main purpose (ref = delivery)	*misc pick-up*	−0.33	0.49	−0.67	0.13	0.44	0.31
Period (ref = AM peak)	*AM off-peak*	0.18	0.34	0.53	0.87	0.43	2.04
	PM off-peak	0.33	0.48	0.69	0.92	0.65	1.43
	PM peak	3.70	1.41	2.63	4.97	1.57	3.17
Planning	*log(remain.stops)*	0.43	0.22	1.92	0.64	0.36	1.78
	log(tot.stops)	−0.94	0.49	−1.92	−2.71	0.80	−3.40
Type of shipper or receiver (ref. = large establishment)	*small estab*	0.78	0.35	2.22	−0.67	0.37	−1.83
	individual	2.36	0.88	2.68	−2.96	1.43	−2.07
Error component (all aternatives)	$\sigma_{obstructive}$	2.53	0.45	5.58	.	.	.
	$\sigma_{private}$	0.78	0.19	4.04	.	.	.
	$\sigma 1_{non-obstructive}$	−0.65	0.21	−3.11	.	.	.
	$\sigma 2_{non-obstructive}$	1.37	0.45	3.06	.	.	.
	$\sigma 3_{non-obstructive}$	3.72	0.50	7.40	.	.	.

Table A.3
Results - Inner suburbs - Mixed multinomial logit model.

Category	Parameter	$\beta_{\text{obstructive}}$			β_{private}		
		Coeff.	Rob.Std.Err.	Rob.T-ratio	Coeff.	Rob.Std.Err.	Rob.T-ratio
Constant	ASC	−0.57	0.85	−0.67	2.55	1.32	1.92
Weight	*log(weight)*	−0.05	0.08	−0.61	−0.10	0.12	−0.84
	weight_NA	1.03	0.78	1.33	2.42	1.11	2.18
Carrier (ref = own-account)	*third-party*	−0.30	0.50	−0.61	−2.27	0.97	−2.34
Vehicle type (ref = truck)	*LCV*	0.53	0.59	0.90	−1.78	1.38	−1.29
	LCV × log(weight)	0.02	0.16	0.14	0.82	0.30	2.74
	LCV × weight_NA	−0.69	1.78	−0.39	1.91	1.83	1.04
	art. truck	1.82	2.01	0.91	1.65	2.53	0.65
	art. truck × log(tot.stops)	0.22	1.29	0.17	2.17	1.68	1.29
Main purpose (ref = delivery)	*misc pick-up*	−0.33	0.36	−0.91	0.64	0.51	1.27
Period (ref = AM peak)	*AM off-peak*	0.24	0.31	0.75	0.21	0.64	0.34
	PM off-peak	−0.12	0.41	−0.29	−0.50	0.72	−0.69
	PM peak	1.37	1.31	1.04	3.33	1.81	1.84
Planning	*log(remain.stops)*	−0.26	0.21	−1.22	−0.03	0.31	−0.10
	log(tot.stops)	0.50	0.26	1.92	−1.00	0.51	−1.96
Type of shipper or receiver (ref. = large establishment)	*small estab*	1.37	0.27	5.15	0.01	0.44	0.02
	individual	0.72	0.47	1.54	−2.28	1.90	−1.21
Error component (all aternatives)	$\sigma_{obstructive}$	1.54	0.40	3.85	.	.	.
	$\sigma_{private}$	2.03	0.37	5.50	.	.	.
	$\sigma 1_{non-obstructive}$	−0.52	0.16	−3.13	.	.	.
	$\sigma 2_{non-obstructive}$	0.47	0.20	2.37	.	.	.
	$\sigma 3_{non-obstructive}$	2.59	0.43	6.04	.	.	.

Table A.4
Results - Paris - Mixed multinomial logit model.

Category	Parameter	$\beta_{\text{obstructive}}$			β_{private}		
		Coeff.	Rob.Std.Err.	Rob.T-ratio	Coeff.	Rob.Std.Err.	Rob.T-ratio
Constant	ASC	−0.22	0.64	−0.34	−1.56	1.51	−1.03
Weight	*log(weight)*	0.02	0.07	0.29	0.29	0.19	1.55
	weight_NA	0.33	0.42	0.80	1.04	1.28	0.81
Carrier (ref = own-account)	*third-party*	−0.51	0.34	−1.49	0.37	0.86	0.42
Vehicle type (ref = truck)	*LCV*	0.00	0.25	-0.01	0.29	0.83	0.36
Main purpose (ref = delivery)	*misc pick-up*	0.14	0.48	0.29	0.49	0.78	0.63
Period (ref = AM peak)	*AM off-peak*	0.14	0.29	0.49	1.02	0.63	1.62
	PM off-peak	−0.01	0.33	−0.03	1.30	0.77	1.69
	PM peak	−1.66	1.44	−1.15	1.56	2.11	0.74
Planning	*log(remain.stops)*	−0.30	0.15	−2.05	0.22	0.37	0.60
	log(tot.stops)	0.65	0.21	3.02	−1.14	0.54	−2.12
Type of shipper or receiver (ref. = large establishment)	*small estab*	0.65	0.18	3.55	−0.06	0.47	−0.13
	individual	1.16	0.58	1.98	−0.62	1.55	−0.40
Error component (all aternatives)	$\sigma_{obstructive}$	0.51	1.12	0.45	.	.	.
	$\sigma_{private}$	1.66	0.31	5.31	.	.	.
	$\sigma 1_{non-obstructive}$	−0.20	0.17	−1.17	.	.	.
	$\sigma 2_{non-obstructive}$	0.47	0.27	1.72	.	.	.
	$\sigma 3_{non-obstructive}$	0.75	0.82	0.92	.	.	.

Table A.5
Goodness-of-fit.

Model	Log-likelihood	Number of parameters
Pooled (Table A.1)	−1687.23	44
Outer suburbs (Table A.2)	−550.75	37
Inner suburbs (Table A.3)	−589.6	39
Paris (Table A.4)	−529.25	31

Likelihood-ratio test: test-stat = 35.26, DoF = 63, p-value = 0.997.

Appendix B. Multinomial logit model (MNL) estimation

(Table B.1).

Table B.1
Results - Pooled multinomial logit model.

Category	Parameter	$\beta_{\text{obstructive}}$			β_{private}		
		Coeff.	Rob.Std.Err.	Rob.T-ratio	Coeff.	Rob.Std.Err.	Rob.T-ratio
Constant	*ASC*	0.45	0.83	0.54	−0.61	0.81	−0.76
Weight	*log(weight)*	−0.09	0.05	−1.76	0.09	0.05	1.82
	weight_NA	0.43	0.45	0.96	2.30	0.48	4.79
Carrier (ref = own-account)	*third-party*	−0.16	0.32	−0.51	−1.69	0.42	−4.00
Vehicle type (ref = truck)	*LCV*	0.13	0.37	0.36	−0.46	0.63	−0.73
	LCV × log(weight)	0.09	0.09	1.05	0.25	0.15	1.68
	LCV × weight_NA	0.49	1.08	0.46	0.19	1.07	0.18
	art. truck	2.03	0.81	2.51	−2.51	0.83	−3.01
	art. truck × log(tot.stops)	−0.74	0.57	−1.28	2.12	0.49	4.28
Main purpose (ref = delivery)	*misc pick-up*	−0.28	0.24	−1.15	0.24	0.21	1.11
Period (ref = AM peak)	*AM off-peak*	0.16	0.19	0.84	0.11	0.24	0.50
	PM off-peak	−0.05	0.25	−0.24	−0.06	0.38	−0.18
	AM peak	1.11	0.96	1.16	2.09	0.86	2.41
Planning	*log(remain.stops)*	−0.06	0.11	−0.51	0.12	0.14	0.83
	log(tot.stops)	0.49	0.17	2.82	−0.84	0.24	−3.49
Type of shipper or receiver (ref. = large establishment)	*small estab.*	1.31	0.16	8.03	0.16	0.17	0.97
	individual	1.86	0.40	4.59	−1.73	0.66	−2.60
Zone (ref = Paris)	*outer suburbs*	−2.40	0.70	−3.42	2.42	0.65	3.69
	inner suburbs	−1.80	0.72	−2.50	1.81	0.63	2.88
Scale (all alternatives)	λ_{Paris}	− 0.70	0.28	−2.47	.	.	.

Log-likelihood = −2049.63.

Appendix C. Model selection

In what follows, we report the specification of the error component structures for a series of benchmark models. This protocol aimed at ensuring that the alternative specific variance structure fitted the data best. Each benchmark model has been estimated with and without accounting for latent availability for the *private* spot alternative (Table C.1).

C.1. Restricted alternative specific variance model

$$\begin{cases} U_{obst,n,t} & = \beta'_{obst} x_{obst,n,t} + \sigma_{obst}\eta 1_n + \theta_{obst}\alpha_{n,t} + \epsilon_{obst,n,t} \\ U_{priv,n,t} & = \beta'_{priv} x_{priv,n,t} + \sigma_{priv}\eta 2_n + \theta_{priv}\alpha_{n,t} + \epsilon_{priv,n,t} \\ U_{n-obst,n,t} & = \epsilon_{n-obst,n,t} \end{cases} \tag{C.1}$$

C.2. Nesting model

$$\begin{cases} U_{obst,n,t} & = \beta'_{obst} x_{obst,n,t} + \sigma_{nest1}\eta_{nest1,n} + \theta_{obst}\alpha_{n,t} + \epsilon_{obst,n,t} \\ U_{priv,n,t} & = \beta'_{priv} x_{priv,n,t} + \sigma_{nest2}\eta_{nest2,n} + \theta_{priv}\alpha_{n,t} + \epsilon_{priv,n,t} \\ U_{n-obst,n,t} & = \sigma_{nest1}\eta_{nest1,n} + \sigma_{nest2}\eta_{nest2,n} + \epsilon_{n-obst,n,t} \end{cases} \tag{C.2}$$

We find that the best fitting model corresponds to the alternative specific variance specification with a latent availability component. The nesting specification is found to be the worst specification in all cases. Detailed results are available in supplementary material.

Table C.1
Benchmark models - Results.

Model	Error component structure	Log-likelihood	Number of parameters	AIC	BIC
With latent availability	Alternative specific variance	−4505.62	73	9157.24	9583.64
	Nesting	−4532.32	70	9204.63	9613.52
	Restricted alternative specific variance	−4526.79	71	9195.6	9610.30
Without latent availability	Alternative specific variance	−4513.68	72	9171.36	9591.92
	Nesting	−4545.15	69	9228.31	9631.34
	Restricted alternative specific variance	−4532.77	70	9205.53	9614.42

References

Abou-Zeid, M., Ben-Akiva, M., 2014. Handbook of choice modelling. Edward Elgar Publishing, Cheltenham. chapter Hybrid Choice Models. pp. 383–412.
Amado, S., Arıkan, E., Kaça, G., Koyuncu, M., Turkan, B.N., 2014. How accurately do drivers evaluate their own driving behavior? An on-road observational study. Acc. Anal. Prev. 63, 65–73.
Amaya, J., Encarnación, T., Delgado-Lindeman, M., 2023. Understanding delivery drivers' parking preferences in urban freight operations. Transp. Res. Part A 176, 103823.
Ambrosini, C., Patier, D., Routhier, J.-L., 2010. Urban freight establishment and tour based surveys for policy oriented modelling. Procedia-Social Behav. Sci. 2 (3), 6013–6026.
Beaumais, O., Crastes dit Sourd, R., 2024. Modeling quality and price perception in the choice of drinking water in france: a hybrid choice model approach. Water Resour. Res. 60 (2), e2023WR034803.
Béziat, A., 2017. Approche des liens entre transport de marchandises en ville, formes urbaines et congestion: Le cas de l'Ile-de-France. Ph.D. thesis. Université Paris-Est.
Béziat, A., 2021. Spatialiser l'offre et la demande de stationnement pour la logistique urbaine à paris. Transp. Urbains 138, 29–33.
Bunch, D.S., 2024. Numerical methods for optimization-based model estimation and inference. In: Handbook of Choice Modelling. Edward Elgar Publishing, pp. 594–629.
Calastri, C., Hess, S., Choudhury, C., Daly, A., Gabrielli, L., 2019. Mode choice with latent availability and consideration: theory and a case study. Transp. Res. Part B 123, 374–385.
Castrellon, J.P., Sanchez-Diaz, I., Kalahasthi, L.K., 2023. Enabling factors and durations data analytics for dynamic freight parking limits. Transp. Res. Rec. 2677 (2), 219–234.
Chaniotakis, E., Pel, A.J., 2015. Drivers' parking location choice under uncertain parking availability and search times: a stated preference experiment. Transp. Res. Part A 82, 228–239.
Cheng, R., Fessler, A., Nielsen, O.A., Larsen, A., Jiang, Y., 2024. Assessing the potential impacts of public transport-based crowdshipping: a case study in a central district of copenhagen. Front. Eng. Manag. 11 (4), 697–709.
Choudhury, C., Hess, S., Villas, L., Place, L., Oakil, A.T., 2017. A peek at the future: capturing anticipation effects in discrete choice models.
Coulombel, N., Dablanc, L., Gardrat, M., Koning, M., 2018. The environmental social cost of urban road freight: evidence from the paris region. Transp. Res. Part D 63, 514–532.
Dalla Chiara, G., Cheah, L., Azevedo, C.L., Ben-Akiva, M.E., 2020. A policy-sensitive model of parking choice for commercial vehicles in urban areas. Transp. Sci. 54 (3), 606–630.
Dalla Chiara, G., Goodchild, A., 2020. Do commercial vehicles cruise for parking? Empirical evidence from seattle. Transp. Policy 97, 26–36.
Dalla Chiara, G., Krutein, K.F., Ranjbari, A., Goodchild, A., 2021. Understanding urban commercial vehicle driver behaviors and decision making. Transp. Res. Rec. 2675 (9), 608–619.
Dalla Chiara, G., Krutein, K.F., Ranjbari, A., Goodchild, A., 2022. Providing curb availability information to delivery drivers reduces cruising for parking. Sci. Rep. 12 (1), 19355.
Gao, Z., Huang, H., Yang, L., Guo, J., Wu, J., 2023. Future urban transport management. Front. Eng. Manag. 10, 534–539.
Gavaud, O., Douet, M., 2012. The deployment of river freight terminals: the example of the concrete industry in Île de France. Procedia-Social Behav. Sci. 48, 2272–2283.
Ghizzawi, F., Galal, A., Roorda, M.J., 2024. Modelling parking behaviour of commercial vehicles: a scoping review. Transp. Rev. 44 (4), 743–765.
Gouriéroux, C., Laferrère, A., 2009. Managing hedonic housing price indexes: the French experience. J. Hous. Econ. 18 (3), 206–213.
Greene, W.H., Hensher, D.A., 2003. A latent class model for discrete choice analysis: contrasts with mixed logit. Transp. Res. Part B 37 (8), 681–698.
Hess, S., Palma, D., 2019. Apollo: a flexible, powerful and customisable freeware package for choice model estimation and application. J. Choice Model. 32, 100170.
Hess, S., Polak, J.W., 2004. An analysis of parking behaviour using discrete choice models calibrated on SP datasets.
Hess, S., Spitz, G., Bradley, M., Coogan, M., 2018. Analysis of mode choice for intercity travel: application of a hybrid choice model to two distinct US corridors. Transp. Res. Part A 116, 547–567.
Hjälmdahl, M., Várhelyi, A., 2004. Validation of in-car observations, a method for driver assessment. Transp. Res. Part A 38 (2), 127–142.
Holguín-Veras, J., Sánchez-Díaz, I., 2016. Freight demand management and the potential of receiver-led consolidation programs. Transp. Res. Part A 84, 109–130.
Jaller, M., Holguín-Veras, J., Hodge, S.D., 2013. Parking in the city: challenges for freight traffic. Transp. Res. Rec. 2379 (1), 46–56.
Kalahasthi, L.K., Sánchez-Díaz, I., Castrellon, J.P., Gil, J., Browne, M., Hayes, S., Sentís, R.C., 2022. Joint modeling of arrivals and parking durations for freight loading zones: potential applications to improving urban logistics. Transp. Res. Part A 166, 307–329.
Kauf, S., 2016. City logistics–a strategic element of sustainable urban development. Transp. Res. Procedia 16, 158–164.
Kim, W., Wang, X., 2022. Double parking in New York City: a comparison between commercial vehicles and passenger vehicles. Transportation 49 (5), 1315–1337.
Krinsky, I., Robb, A.L., 1986. On approximating the statistical properties of elasticities. Rev. Econ. Stat., 715–719.
Krinsky, I., Robb, A.L., 1990. On approximating the statistical properties of elasticities: a correction. Rev. Econ. Stat. 72 (1), 189–190.
Lopez, C., Gonzalez-Feliu, J., Chiabaut, N., Leclercq, L., 2016. Assessing the impacts of goods deliveries' double line parking on the overall traffic under realistic conditions. In: Information Systems Logistics and Supply Chain: ILS Conference 2016: Building a Resilient Future.
Lopez, C., Zhao, C.-L., Magniol, S., Chiabaut, N., Leclercq, L., 2019. Microscopic simulation of cruising for parking of trucks as a measure to manage freight loading zone. Sustainability 11 (5), 1276.
Marcucci, E., Gatta, V., Scaccia, L., 2015. Urban freight, parking and pricing policies: an evaluation from a transport providers' perspective. Transp. Res. Part A 74, 239–249.
Morillo, C., Campos, J.M., 2014. On-street illegal parking costs in urban areas. Procedia-Social Behav. Sci. 160, 342–351.
Nguyen, T.C., Kim, J., 2024. Exploring resource-efficient urban mobility for sustainable low emission solutions: a case study of Île-de-France, France. Sci. Total Environ. 955, 176968.
Norwood, F.B., Lusk, J.L., 2011. Social desirability bias in real, hypothetical, and inferred valuation experiments. Am. J. Agric. Econ. 93 (2), 528–534.
Nourinejad, M., Wenneman, A., Habib, K.N., Roorda, M.J., 2014. Truck parking in urban areas: application of choice modelling within traffic microsimulation. Transp. Res. Part A 64, 54–64.

Quimby, A., Maycock, G., Palmer, C., Grayson, G.B., 1999. Drivers' speed choice: an in-depth study. TRL Report 326 .
Ramirez-Rios, D.G., Kalahasthi, L.K., Holguín-Veras, J., 2023. On-street parking for freight, services, and e-commerce traffic in US cities: a simulation model incorporating demand and duration. Transp. Res. Part A 169, 103590.
Routhier, J.-L., Toilier, F., 2007. FRETURB V3, a policy oriented software of modelling urban goods movement. In: 11th WCTR.
Savadogo, I., Beziat, A., 2021. Evaluating the potential environmental impacts of a large scale shift to off-hour deliveries. Transp. Res. Part D 90, 102649.
Schmid, J., Wang, X.C., Conway, A., 2018. Commercial vehicle parking duration in New York City and its implications for planning. Transp. Res. Part A 116, 580–590.
Soto, J.J., Márquez, L., Macea, L.F., 2018. Accounting for attitudes on parking choice: an integrated choice and latent variable approach. Transp. Res. Part A 111, 65–77.
Train, K.E., 2009. Discrete Choice Methods with Simulation. Cambridge University Press.
Vij, A., Walker, J.L., 2014. Hybrid choice models: the identification problem. In: Handbook of Choice Modelling. Edward Elgar Publishing, pp. 519–564.
Walker, J.L., Ben-Akiva, M., Bolduc, D., 2007. Identification of parameters in normal error component logit-mixture (NECLM) models. J. Appl. Econom. 22 (6), 1095–1125.
Wang, W., Osaragi, T., 2024. Lognormal distribution of daily travel time and a utility model for its emergence. Transp. Res. Part A 183, 104058.
Xiao, L., Xu, W., 2024. Urban spatial cluster structure in metro travel networks: an explorative study of wuhan using big and open data. Front. Eng. Manag. 11, 231–246.
Yang, Z., Liu, Y., Wu, L., Martinet, S., Zhang, Y., Andre, M., Mao, H., 2020. Real-world gaseous emission characteristics of Euro 6b light-duty gasoline-and diesel-fueled vehicles. Transp. Res. Part D 78, 102215.
Yin, B., Liu, L., Coulombel, N., Viguié, V., 2018. Appraising the environmental benefits of ride-sharing: the Paris region case study. J. Clean. Prod. 177, 888–898.