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A Policy-Sensitive Model of Parking Choice for Commercial Vehicles in Urban Areas

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Abstract. Understanding factors that drive the parking choice of commercial vehicles at delivery stops in cities can enhance logistics operations and the management of freight parking infrastructure, mitigate illegal parking, and ultimately reduce traffic congestion. In this paper, we focus on this decision-making process at large urban freight traffic generators, such as retail malls and transit terminals, that attract a large share of urban commercial vehicle traffic. Existing literature on parking behavior modeling has focused on passenger vehicles. This paper presents a discrete choice model for commercial vehicle parking choice in urban areas. The model parameters were estimated by using detailed, real-world data on commercial vehicle parking choices collected in two commercial urban areas in Singapore. The model analyzes the effect of several variables on the parking behavior of commercial vehicle drivers, including the presence of congestion and queuing, attitudes toward illegal parking, and pricing (parking fees). The model was validated against real data and applied within a discrete-event simulation to test the economic and environmental impacts of several parking measures, including pricing strategies and parking enforcement.

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Keywords: discrete choice modeling • parking • urban logistics • freight transportation • discrete-event simulation

1. Introduction

With the growth in urban populations and the rise of online shopping, commercial vehicles (delivery and service trucks and vans) take on an increasingly relevant role in modern urban societies. On the one hand, they are necessary to sustain cities’ economies and their dwellers’ lives. On the other hand, they compete for transport infrastructure with private and public vehicles, aggravate the state of already congested urban transport systems, and generate negative externalities for the environment and society.

An increasingly relevant problem in urban areas is related to the very last meters of a delivery: finding available parking near the destination. Parking availability in urban areas is usually limited due to the lack of available space, high land values and opportunity costs of space, and high parking demand. This

is true for any type of vehicle, but it is especially true for commercial vehicles delivering/picking up goods or performing a service in urban areas. First, in comparison with passenger cars, they often require more space to park, not only because they are generally larger in size, but also because they require more space to load/unload goods and maneuvering (Jaller, Holguín-Veras, and Hodge 2013; Chen and Conway 2016). Second, commercial vehicles need to park closer to their destination than cars, as walking while carrying goods is difficult (Amer and Chow 2017). Third, they often cannot afford to spend time searching for available parking, as they usually run on a tight delivery schedule. In the absence of available parking, commercial vehicle drivers usually choose to either wait for available space or park illegally on the curbside or in the travel lane. The consequences of

commercial vehicle drivers parking behaviors are far-reaching, affecting the urban transport system, environment, economy, and society. Han et al. (2005) found that commercial vehicles stopping in travel lanes is the third major cause of nonrecurrent urban congestion, after crashes and construction. They estimated the total annual cost of delays caused by illegally parked commercial vehicles to be \$10 billion in the United States. Moreover, the lack of parking spaces consistently ranks among the top 10 issues for transport and logistics company executives and among the top three issues for commercial drivers (American Transportation Research Institute 2018). Parking fines paid annually by private carriers can amount to millions of dollars: for instance, carriers paid \$8.2 million in 2011 in Chicago (Kawamura et al. 2014) and \$2.5 million in 2009 in Toronto (Nourinejad et al. 2014) in penalties.

These impacts can be magnified near large urban freight traffic generators. Such facilities produce and attract a large number of daily truck trips either individually or collectively. For instance, the ports of New York and New Jersey generate approximately 9,000 truck trips per day (Brom et al. 2009), which represent approximately 5.8% of Manhattan's daily truck traffic, or 2.6% of New York City's (NYC) total truck trips. Similarly, in a study by Jaller, Wang, and Holguín-Veras (2015), 56 selected large buildings hosting businesses and services including shopping malls were identified as large urban freight traffic generators and were associated with approximately 4% of NYC total freight trips generated. Furthermore, a recent study of parking requirements for freight activity in NYC found that the largest occupancy rates of on-street parking also corresponded to these locations (Jaller, Holguín-Veras, and Hodge 2013). As a result, carriers are, in most cases, forced to park illegally and to pay large amounts of money in parking fines (USD\$500 to USD\$1,000 per truck per month; Holguín-Veras et al. 2008). Such experiences are not unique to NYC and are similar in other large cities such as Paris (Dablanc and Beziat 2015), where illegal parking was estimated at approximately 62%; Singapore (Dalla Chiara and Cheah 2017), where unauthorized parking in dense commercial urban areas reached 60% of total vehicle arrivals, and vehicles queued on average five minutes to access private loading/unloading bay areas; Southampton (Triantafyllou, Cherrett, and Browne 2014), where the increasing observed freight congestion and intramodal conflicts around a large mall motivated an assessment study on urban consolidation center; and Dhaka (Zannat et al. 2013), where commercial vehicles occupy most of the space allocated for private vehicles.

Several parking policies to handle such impacts have been proposed and deployed around the world with

different results. Capacity extension, parking and loading bay management, access and time restrictions, pricing, and enforcement all rely on significant changes in demand and behavior to influence policy effectiveness. Modeling frameworks to evaluate potential measures for large urban freight traffic generators will ultimately rely on better understanding of the changes in commercial vehicle drivers' parking behaviors.

1.1. Understanding Urban Parking Behaviors

In the past few decades, researchers have dedicated considerable effort to studying passenger vehicles' parking behaviors in urban areas. The results of these studies have had a twofold contribution. First, they have identified externalities caused by passenger vehicles parking in urban areas. Shoup (2006) estimated that 95% of a car's lifetime is spent parked. For cars, parking duration is relatively long (several hours), and a lack of parking spaces causes drivers to cruise around a neighborhood in search of available parking, increasing congestion and causing excess travel, air pollution, and greenhouse gas (GHG) emissions (Millard-Ball, Weinberger, and Hampshire 2014). Researchers found that, on average, 30% of road traffic is caused by vehicles cruising (Shoup 2006). Second, the quantitative analyses of passenger vehicle drivers' parking behaviors have revolutionized parking and travel demand policymaking in many cities around the world, contributing to reductions in cruising and double parking, and improving cities' livability. Examples include data-driven parking pricing (e.g., Ottosson et al. 2013) and real-time parking information systems (e.g., San Francisco Municipal Transportation Agency 2011).

Although the parking literature has focused on passenger vehicles, little is known about commercial vehicles' parking behaviors. As with passenger cars, parking is also a major time component for commercial vehicles, with vehicles parked 60% to 70% of their total operating time (Dalla Chiara and Cheah 2017). However, commercial vehicles stop more frequently, with an average parking duration of between 10 and 20 minutes (Dalla Chiara and Cheah 2017). Moreover, they lack flexibility in their activity scheduling; whereas individual travelers can modify their trip and destination according to the state of road and parking congestion, commercial vehicles are often committed to preplanned stop locations in order to meet delivery time windows.

As a consequence, commercial vehicle drivers adopt parking behaviors different from those of passenger vehicle drivers. Therefore, travel and parking policies that target only passenger vehicles might have unexpected consequences for the urban logistics system, causing delays, illegal parking, increased vehicle miles traveled, and higher delivery costs in urban areas.

1.2. Research Objectives

Several cities have implemented policies targeted to commercial vehicles. Common examples include banning commercial vehicles from traveling and parking in central areas or during certain times of the day, or imposing vehicle size limitations for carriers.

Another policy issue is the amount of urban space that should be allocated to commercial vehicle parking. Minimum parking requirements have been adopted by many cities around the world, imposing on real estate developers a minimum number of loading and unloading bays per unit of space dedicated to commercial activities. However, no guidance is given on how to manage these spaces, for example, whether they should be free of charge or priced, and how much they should cost.

With the increase in freight parking demand and the lack of parking supply, city planners are called upon to update their freight parking policies and find new solutions. Examples include centralized receiving services in multitenant buildings, public urban consolidation centers, and parking information systems.

To estimate the impacts of these initiatives and to better inform freight parking policies, we need to better understand commercial vehicle drivers parking behaviors.

Our goal was to empirically investigate commercial vehicle drivers' parking behaviors in urban areas by formulating and estimating the first (to our knowledge) random utility model of commercial vehicle driver parking choice. We modeled a driver's choice between authorized parking (i.e., parking in a loading/unloading bay) and unauthorized parking (i.e., parking in the travel lane or in spaces dedicated to passenger vehicles), and analyzed the impacts of several factors affecting this choice, including the level of the parking fee and the parking fine, the level of parking enforcement, and the impact of parking congestion. The model parameters were estimated by using data on real-life commercial vehicle parking and delivery operations collected in two dense urban commercial areas in Singapore.

We then used the estimated model to assess the economic and environmental impacts of several parking management strategies, including changes in the number of loading/unloading bays and their parking fee, change in enforcement level, and the introduction of a centralized receiving service.

Results obtained from the current modeling effort can better inform decision makers, including city planners, real estate developers, building managers, and private carriers, on how to account for drivers' behaviors to better manage commercial vehicle parking in large freight traffic generators, such as shopping malls, transit nodes, and dense urban commercial areas.

Because of the context in which the data were collected, the results from the current modeling effort are less applicable to areas that do not attract a large number of freight vehicle trips and are served only by curbside parking (e.g., residential areas or low-rise commercial buildings).

The next section summarizes the literature on parking choice and commercial vehicle driver parking behaviors and parking policies. Section 3 introduces a behavioral framework for commercial vehicle driver parking choice. Section 4 describes the data collection and processing methods, the context in which the data were collected, and the sample used for model estimation. Section 5 describes the formulation and estimation of the parking choice model, and Section 6 contains the empirical model results and model validation. The parking choice model was then used within the simulation framework, which is described in Section 7. Section 8 concludes the paper and discusses policy implications.

2. Relevant Literature

2.1. Parking Choice Modeling

Most disaggregate parking models proposed in the literature have focused on passenger vehicle drivers. Table 1 lists the most relevant works and summarizes their modeling approaches.

Parking measures can represent powerful tools to manage travel demand in urban areas. Consequently, researchers and practitioners have developed data-driven models to better understand travelers' responses to parking policies, such as changes in pricing or parking access restrictions.

Early studies focused on modeling individuals' choice of parking location by dividing a study area into clusters of geographically close parking places, which then represented the alternatives of the universal choice set. Gillen (1978) and Lambe (1996) studied parking location choice alone; Van Der Goot (1982) and Hunt and Tepley (1993) studied jointly parking location and parking type; Hensher and King (2001) studied jointly parking location and travel mode.

Gillen (1978) was among the earliest to model the parking location choices of individual drivers. In his model, each parking location is considered as a separate good, characterized by a monetary cost component (parking fee) and a time cost component (walking time to the final destination, which we refer to as "egress time"). A driver will park at the location that minimizes these cost components. By modeling the trade-off between parking cost and egress time, it is possible to estimate the "re-location" effect, that is, the shift in parking demand from urban to suburban areas, caused by the introduction of different parking measures.

Table 1. Studies on Passenger Vehicles Parking Choice Modeling

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

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

Hunt and Teply (1993) used a Nested Logit (NL) model to simultaneously represent the choice of parking location and type, considering on-street, off-street, and employer-arranged parking (for commuters). Similarly, Hensher and King (2001) used an NL model to represent the choice of parking location and travel mode, including as alternatives the possibility to switch from private to public transport and to forego the trip.

A shift in paradigm in the modeling of parking choice occurred when researchers acknowledged the inefficiency generated by on-street parking: drivers generally prefer to park on-street rather than off-street because they are closer to the final destination; this causes on-street parking congestion, which consequently generates the phenomenon of “cruising.” Cruising was described by Shoup (2006, p. 479) as “a mobile queue of cars that are waiting for curb vacancies.” Cruising was estimated to contribute to a considerable amount of urban road traffic (Shoup 2006). Therefore, later studies on parking shifted from modeling the location choice to the choice between on-street and off-street parking.

Axhausen and Polak (1991) were among the first to use Stated parking Preferences (SP) data to model the choice among free/paid on-street, off-street, and illegal parking types. They also introduced in the utility formulation time-specific variables other than egress time: access time (travel time from the origin to the parking location) and search time (time spent searching and queueing for parking).

In recent work, Qin et al. (2017) used an NL model to analyze the parking choice behavior of air travelers at airports. At the upper level of the nested model, the choice between off-site and on-site parking was modeled, whereas at the lower level the choice between different connection models from the parking facility to the airport terminals was modeled.

The attitude toward attributes of parking alternatives such as price, fine, search time, and egress time varies across drivers. A thorough exploration of individual preference heterogeneity was performed by Hess and Polak (2004), who found that, although deterministic preference heterogeneity can be captured by segmenting the population into groups of individuals sharing common characteristics, there exists “random” taste variation among individuals within segments. This variation, if not properly accounted for, might cause potential bias and poor model fit. The Mixed Logit (ML) model can represent both deterministic and random taste variation. Hess and Polak (2004) found significant random taste variation for both time-related attributes (access time, search time, and egress time) and cost attributes. In particular, parking cost was modeled separately for legal and illegal parking, with the latter showing significant taste variation across individuals. One conclusion from the study was that drivers behave as risk-takers: one dollar spent in (legal) parking cost brings about more disutility than one dollar of an expected parking fine.

After Hess and Polak (2004), the use of the ML model framework with SP data became the state-of-the-art in parking choice modeling (Anderson, Das, and Tyrrell 2006; Hilvert, Toledo, and Bekhor 2012; Ibeas et al. 2014; Chaniotakis and Pel 2015).

Several papers have also explored the effects of parking congestion. Among these, Hilvert, Toledo, and Bekhor (2012) found that drivers who need longer parking durations are more willing to spend time searching for parking and queueing. Ibeas et al. (2014) found that drivers have a higher value of access time than the value of egress time. Chaniotakis and Pel (2015) found that, after parking cost, the uncertainty of finding a vacant parking lot is the second most important variable explaining the parking type choice.

The duration of parking plays a key role in determining parking choice. Although previous works had generally treated parking duration as an exogenous explanatory variable, more recent works by Kobus et al. (2013) and Habib, Morency, and Trépanier (2012) have explored its endogeneity with parking choice. To estimate the effect of parking fees on the choice between on- and off-street parking, Kobus et al. (2013) used a large data set of individuals' parking duration and accounted for variable endogeneity using an Instrumental Variable (IV) approach. Habib, Morency, and Trépanier (2012) integrated the choice of parking with activity-scheduling decisions such as trip departure time and parking duration, estimating a Discrete-Continuous (DC) model for parking choice, duration, and departure time.

Although most of the literature described analyzed the effects of observable factors on the parking choice, Soto, Márquez, and Macea (2018) explored the inclusion of individual attitudes (risk-averse attitude and positive-car attitude) in the modeling of parking choice by using a Hybrid Discrete Choice (HDC) model. The introduction of latent attitudes was found to improve the model fit and influence time valuations.

2.2. Parking Policies

We found three main classes of modeling approaches used to evaluate ex-ante the impact of commercial vehicle parking policies in the literature: analytic, simulation, and discrete choice models.

Analytic parking models have been used to evaluate the effects of changes in parking price and parking space allocation (Arnott and Inci 2006, Lam et al. 2006). However, these studies have usually not distinguished between freight and passenger vehicles, and often have not represented parking behaviors. One exception was the study by Amer and Chow (2017), which extended the on-street parking model developed by Arnott and Inci (2006) and analyzed the

impact of allocating more curb space for loading/unloading of commercial vehicles. In their model, trucks' parking behavior differed from that of cars, as cars were found to cruise for parking whenever there were no available parking lots, whereas commercial vehicles parked illegally and did not cruise for parking.

Agent-based simulation models have been used to evaluate parking policies, mostly from the perspective of private cars and not of commercial vehicles (Benenson, Martens, and Birfir 2008; Waraich and Axhausen 2012). Moreover, illegal parking has not often been modeled. The few studies that have simulated commercial vehicle parking (Gao and Ozbay 2016, Iwan et al. 2018) have focused on testing policies related to different curb allocation to load/unload zones, but they have not simulated policies such as pricing and parking enforcement, which require the modeling of drivers' parking behaviors.

Marcucci, Gatta, and Scaccia (2015) and Gatta and Marcucci (2016) collected stated preference data from transport and logistics companies to evaluate their sensitivity toward the number of loading bays, parking congestion, and road pricing. Dell'Olio et al. (2017) focused on receivers, studying their willingness to adopt off-hours delivery strategies and urban distribution centers. Although these papers contributed to a better understanding of the impacts of urban logistics and parking policies from a strategic point of view, they did not carry out an operational analysis of such changes. Quak and de Koster (2009) employed a two-step methodology in which strategic responses to delivery time windows and vehicle access restrictions were analyzed, and their environmental and financial performances were evaluated by simulation. However, this approach did not incorporate the behavior of truck drivers.

To the knowledge of the authors, the work by Nourinejad et al. (2014) has been the only disaggregate modeling of parking for truck drivers. In this study, truck parking events were observed, and data were used to estimate a binary logit model of the parking location. A driver's acceptance or rejection of a specific parking lot was modeled as a function of two variables: distance from final destination and parking type (on-street vs. loading/unloading bay). The model was implemented within an agent-based simulation software to evaluate different allocations of parking spaces. The combination of discrete parking choice model and simulation model resulted in a powerful tool to simulate parking policies. However, this study had some limitations: (i) the model did not estimate the effects of parking pricing or parking enforcement on parking choice; (ii) no vehicle or activity-specific variables were collected; (iii) in collecting the data used to estimate the parking choice

model, the authors assumed that the rejected parking locations were available, although no data were collected on the actual parking occupancy and congestion; (iv) no data were collected on illegal parking; and (v) the model was not policy-sensitive, that is, it could not be used to simulate behavioral responses to policy changes.

2.3. Research Gaps and Contributions of the Current Work

This paper builds upon the previous work on parking choice modeling for passenger vehicle drivers and addresses a critical research gap in the area of commercial vehicle parking behavior in urban areas. The model developed in the rest of the paper is based on a unique data set of revealed preferences and models commercial vehicle parking choice.

Although several works have provided empirical evidence that commercial vehicles behave differently than passenger vehicles, none of these works have attempted to incorporate these differences into a behavioral model. The current work contributes to the empirical parking literature by analyzing several aspects of commercial vehicle drivers' parking behaviors, including their willingness to pay for parking, the effects of parking congestion and their queueing behavior, and their attitude toward illegal parking.

Finally, few studies have simulated the impacts of parking policies for commercial vehicles, and the models currently available allow the study of only a limited number of policies, such as changes in curb allocation to loading/unloading zones. So far, no simulation framework has been developed to test "soft-policies" such as parking pricing and parking enforcement.

We address these research gaps in the rest of the paper, developing a behavioral framework for modeling commercial vehicle parking choice and a simulation model to test different commercial vehicle parking policies.

3. Behavioral Framework

3.1. Decision Makers and Parking Alternatives

In this study, we modeled the parking choice of a commercial vehicle driver delivering goods, picking up goods, or performing a service in an urban area. In this section, we define who is the decision maker, the choice considered, and the alternatives the decision maker faces.

The action of parking is performed by commercial vehicle drivers, who, upon arrival at a location, choose where to park the vehicle while performing the designated activity. Although different stakeholders influence the parking choice (e.g., city authorities, building managers, carrier managers, etc.), the decision-makers

considered here were commercial vehicle drivers alone. Chatterjee and Cohen (2004, p. 3-1) defined commercial vehicles as "any vehicle used for commercial purposes" and categorized them into commercial passenger vehicles (e.g., private shuttles and buses), commercial freight vehicles, and commercial service vehicles. In this study, only the latter two types were considered: freight vehicles used to deliver and collect core goods of the commercial establishments served; service vehicles used to transport ancillary goods and to perform several retail support functions (e.g., maintenance and repair, cleaning and hygienic services, safety, and security).

The decision a driver makes upon arrival at a delivery location is where to park the vehicle (the *parking choice*) among a set of possible alternatives. Table 2 classifies parking alternatives across two dimensions: whether the parking alternative is considered legal or illegal and whether the parking occurs on-street or off-street. Among the four combinations identified, we restrict our attention to three of them:

- the *loading/unloading bay area* (LB) is a space reserved for commercial vehicles, comprising one or more loading/unloading bays, and often suited for parking of larger trucks (heavy goods vehicles or HGVs) and for the loading/unloading of a large amount of goods;
- the *passenger carpark* (CRP) is primarily intended for passenger vehicles, but smaller commercial vans can also park;
- *illegal on-street parking* (STR), such as double-parking, is a form of parking that involves the risk of being fined if a vehicle is caught by traffic police. We did not consider on-street legal parking (curbside parking), given our focus on large freight traffic generators in urban areas and the study areas observed (see Section 4.2), in which curbside parking was not available.

The provision of designated LB parking is often regulated by the city authorities, who provide guidelines and regulations on the minimum parking capacity of these facilities. However, because of land constraints and high land values, such facilities are often not well suited to accommodate the growing demand for large commercial vehicle parking and are often congested. Consequently, vehicle drivers face a choice of whether to park at the LB (and potentially wait in a

Table 2. Classification of Parking Alternatives for Commercial Vehicles

	Legal	Tolerated/illegal
On-street	• Curbside parking	• Double parking (STR)
Off-street	• Loading/unloading bay area (LB)	• Public carpark (CRP)

queue if all the parking slots are busy) or to choose alternative parking locations. In the following section, we discuss which factors influence this choice.

3.2. Determinants of Parking Choice

Commercial vehicle drivers do not operate in isolation, as they are part of a supply chain, linking shippers with receivers (Holguín-Veras, Aros-Vera, and Browne 2015). Their actions and behaviors are usually constrained within a “freight activity schedule,” a plan listing the daily sequence of pick-up and delivery locations and, for each location, the activity to be performed and the expected arrival time. Very often receiving businesses prefer to have the goods delivered during their operating times, which often overlap with peak hour traffic. Therefore, it is common for commercial vehicles to face parking congestion upon arrival, especially at the LB. The driver then chooses between waiting in a queue to access the LB, or park elsewhere (STR or CRP). We expected that the longer the queue to access the LB, the more likely a driver will choose an alternative parking location.

Another important determinant is the parking cost, which often increases with the parking duration. We considered a vehicle’s parking duration as deterministic and known in advance, such that a driver is able to correctly estimate and compare the costs of different parking alternatives. We considered this to be a reasonable assumption, given that such duration often depends on the type of activity to be performed (e.g., by the type of commodities and volumes to be handled) and by the time at which the next consignment is scheduled, both of which are determined by the freight activity schedule. The parking duration is also an indirect measure of how much time the driver is willing to spend at a given destination, considering how tight is his/her daily schedule.

We grouped the attributes influencing the parking choice into three general categories:

- *alternatives-specific attributes* are factors that characterize the parking alternatives, usually comprising time-invariant variables such as the parking cost and the parking capacity, as well as time-variant factors such as the current state of congestion;
- *vehicle-specific attributes* are factors that describe the vehicle used, as well as other characteristics such as the number of workers (which might comprise not only the vehicle driver but also one or more helpers) and the vehicle ownership (e.g., whether the vehicle is owned by a retailer, supplier, or a transport and logistics company);
- *activity-specific attributes* describe the activity to be performed at a given location, including the activity purpose (e.g., whether it is a pick-up, delivery, or service), the type of commodity handled and its volume, and the parking duration.

There are other possible factors that also might explain the parking choice as well. One is the individual drivers’ attitudes toward illegal parking, which might be influenced by personal traits, previous history of being fined by traffic police, the driver’s employer attitude, and internal company policies.

3.3. A Random Utility Model of Parking

In this section, we introduce a random utility model (RUM) of parking choice for commercial vehicles (for further discussion on RUM we refer to Train (2003) and Ben-Akiva and Lerman (1985)).

Consider a commercial vehicle n arriving at time t in the vicinity of a destination where an activity (delivery/pick-up/service) should be performed. A vehicle is characterized by a vehicle type v_n (light or heavy goods vehicle, LGV or HGV), a parking duration d_n (exogenous and known by the driver before making a parking choice), and by a set of other vehicle- and activity-specific attributes Z_n .

A destination is served by a universal set of parking alternatives C , which we assumed consisting of $C = \{LB, CRP, STR\}$, as defined.

We assumed that the individual set C_n of feasible parking alternatives faced by a vehicle n only depends on its vehicle type:

$$C_n = \begin{cases} \{LB, STR, CRP\} & \text{if } v_n = LGV \\ \{LB, STR\} & \text{if } v_n = HGV. \end{cases}$$

We assumed that a driver is free to choose any parking location desired, considering as constraint only whether the parking location is physically accessible (generally HGVs are too large to access car parks suited for passenger cars and vans).

Vehicle n driver chooses a parking alternative $i \in C_n$ considering the following alternative-specific attributes: the state of congestion q_{it} , which we assumed to be time- and alternative-variant, and the parking cost $c_{ni}(d_n, v_n)$, which we assumed to be a function of the parking duration and the vehicle type, as well as varying across alternatives. We introduce the notation $x_{nit} = h(q_{it}, c_{ni}, Z_n)$, where h is any vector-valued function, such that alternative-specific attributes can interact nonlinearly with any other vehicle- and activity-specific attribute.

Vehicle n driver perceives utilities $\{U_{ni}\}_{i \in C_n}$ for each alternative and will choose the alternative i , which provides him or her with the highest utility in comparison with the other alternatives in the individual choice set. We modeled utilities as random variables being a linear combination of (i) deterministic components V_{ni} , often referred to as the “representative” part of the utilities and (ii) unobserved factors captured by random error terms ε_{ni} . The representative utility was modeled as a function of the observed

attributes $V_{ni} = \beta' x_{nit}$, where β is a vector of parameters to be estimated describing the effect of covariates x_{nit} on the utilities. The utilities can be written as follows:

$$U_{ni} = \beta' x_{nit} + \varepsilon_{ni}$$

Assuming the error terms ε_{ni} to be independent, and identically and extreme-value distributed with location parameter $\eta = 0$ and scale parameter $\mu = 1$, we can compute the Multinomial Logit (MNL) choice probabilities P_{ni} as follows:

$$P_{ni} = \frac{e^{\beta' x_{nit}}}{\sum_{j \in C_n} e^{\beta' x_{njt}}} \quad (1)$$

In order to obtain estimates of the parameters $\hat{\beta}$ and choice probabilities \hat{P}_{ni} , we collected disaggregate data of commercial vehicles parking and delivering goods at several urban retail malls in Singapore.

4. Data Description

Detailed data on real-world commercial vehicle parking and delivery operations were collected in commercial urban areas in Singapore between 2015 and 2017. The following sections describe the context and specific sites in which the data were collected, the data collection method, and describe the sample obtained.

4.1. Context

Singapore is a city-state and island country located in Southeast Asia and characterized by one of the highest population densities in the world (almost 8,000 people per km^2). As the country experienced a growing population and economy amid land constraints, traffic congestion soon became a major concern.

Commercial vehicles in Singapore account for 17% of the motor vehicle population (162,712 commercial

vehicles in 2017), travel more than private cars (a commercial vehicle travels on average 35,200 km/year vs. 17,400 km/year for a car), and are usually older (approximately 36% 10 years or older vs. the 13% for cars) (Singapore Land Transport Authority 2015, 2017).

Approximately 94% of retail sales are store-based, and retail outlets are commonly found within urban shopping malls, multistory buildings operated by a mall operator (Euromonitor International 2016). Singapore has 212 malls (as of 2017), hosting 24,375 in-mall stores. An average mall hosts approximately 120 stores and has a floor area of 35,000 m^2 (authors' data). The geographical distribution of large retail malls in Singapore is displayed in Figure 1a.

These malls contribute to a large share of the city's vehicle traffic, attracting large numbers of both passenger and commercial vehicles. On an average weekday, the estimated number of total freight trips generated by all malls in Singapore is 48,750 freight trips (authors' data). This high number of freight trips translates into a high demand for freight parking. However, because of limited land availability, high land values, and the high opportunity costs of land usage in urban centers, malls often lack adequate parking and logistics infrastructure to meet demand. As a consequence, the burden of freight parking is often shared with the neighboring streets, where vehicles park on the curb, illegally on-street, and in passenger-reserved parking lots.

4.2. Sites Description

We monitored vehicle arrivals at two commercial urban areas, each hosting a large shopping mall, thereafter named mall A and mall B. Table 3 reports their main features. The two malls were expected to generate similar parking demand because they hosted a similar number of stores and had a similar retail mix. However, their parking facilities were different:

Figure 1. (Color online) (a) Map of Retail Malls in Singapore (Size of Circle and Color Indicate the Number of Stores per Mall) and (b) Distribution of Number of Stores per Retail Mall in Singapore, as of 2018

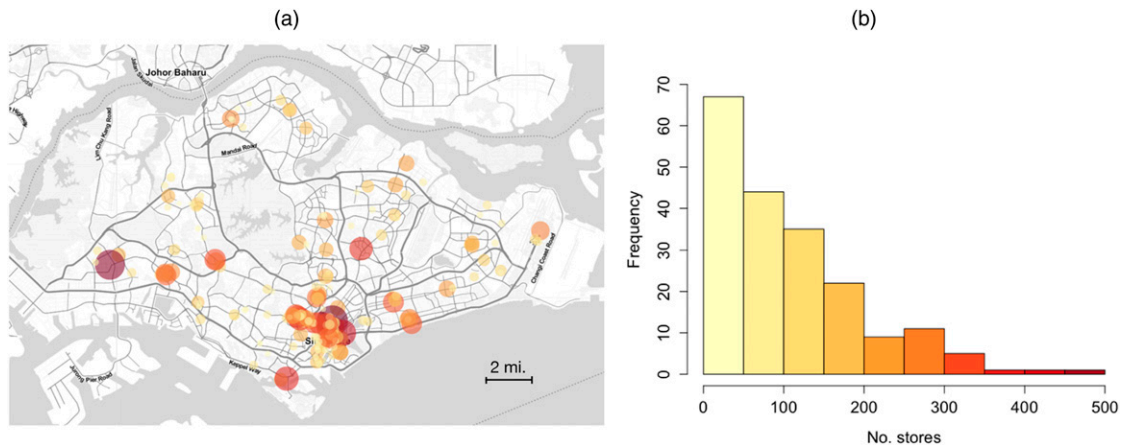


Table 3. Comparison Between Case Study Areas

Attribute	Mall A	Mall B
Commercial activities		
Retail floor area	21,800 m^2	29,200 m^2
No. of floors	6	7
No. of stores	162	170
Retail mix	- Dining: 26% - Electronics: 19% - Fashion: 30% - Others: 25%	- Dining: 32% - Electronics: 6% - Fashion: 31% - Others: 31%
No. of anchor tenants ^a	3	5
Parking infrastructure		
LB parking capacity	6 parking lots	16 parking lots
LB price	Free-of-charge	1 SG\$ per 30 minutes
CRP price	1.2 SG\$ (first hour), 0.8 SG\$ per subsequent 30 minutes	1.07 SG\$ (first hour), 0.32 SG\$ per subsequent 30 minutes

^aStores that are larger in size and tends to produce a large amount of freight trips (e.g., supermarkets, department stores, etc.).

mall A's LB area had a smaller parking capacity of six parking lots, while mall B's LB area hosted 16 parking slots for commercial vehicles. The management of mall A shared that commercial vehicle illegal parking was perceived to be a significant problem. The two malls also differed in their parking management: the LB area at mall A was free-of-charge, whereas mall B cost SG\$1 for every 30 minutes of parking or part thereof (SG\$1 = US\$0.75 as of 2018). In the streets surrounding both malls, double continuous yellow lines mandated no parking at all times on each roadside (Singapore Government 1995). Moreover, no curb space was allocated to any type of vehicle parking. Therefore, any on-street parking in the study areas was considered to be illegal. However, because no parking enforcement cameras were in operation, the only enforcement in the study areas was performed by patrolling traffic police vehicles.

4.3. Data Collection Method and Data Processing

The roads and parking infrastructure surrounding malls A and mall B were monitored for three and four weekdays, respectively, from 7:00 a.m. to 5:00 p.m. The observed days were distant from holidays or sales periods. The data collection times were chosen for the following reasons: (i) they included peak hours (respectively at 10:00–11:00 a.m. and 2:00–3:00 p.m.); (ii) on average, 80% of total arrivals to the loading/unloading bay occurred during these times (Dalla Chiara and Cheah 2017); and (iii) stores opening times were usually at 10:00 a.m., and most deliveries occurred when shopkeepers were present. The data collection took place between 2015 and 2017.

Data were simultaneously obtained from two sources at each site: automatic road-side video recordings and intercept driver survey. We describe both data sources in the rest of this section.

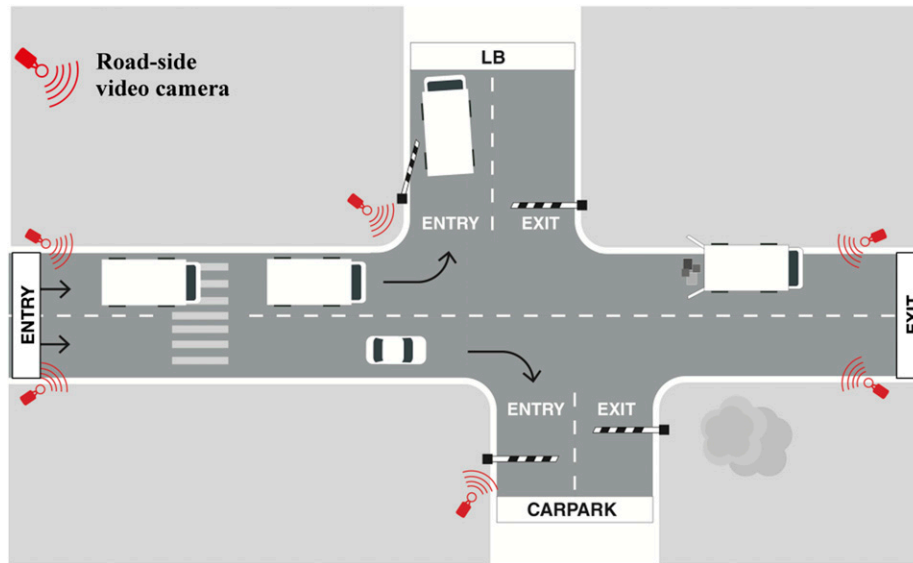
Figure 2 depicts a hypothetical study area characterized by three main elements: an LB area, a public carpark, and a road network. At each site, several video cameras were deployed to monitor vehicle movements. Video cameras were placed at the entrances and exits of the sites' road networks, as well as at the entrances of the different parking facilities.

The videos were subsequently analyzed using a license plate recognition algorithm to obtain, for each vehicle passing through a camera location, its license plate number (used as a vehicle's unique identifier), and a timestamp (refer to Sun et al. (2017) for details on the license plate recognition algorithm developed). By tracking a vehicle across different cameras, we obtained a set of timestamps that corresponded to the boxes in Figure 3: (1) vehicles arriving at the study area, (2) parking, (3) leaving the parking lot, and (4) exiting.

The raw data points collected by the video recordings were postprocessed to obtain the variables described as follows:

- *Dwell time* is the total time a vehicle spent in the study area.
- *Queue length* is the number of vehicles waiting for a parking spot in the LB to become available; it was estimated by using the historical records of vehicles' arrival and departure times (the queue length estimation algorithm is described in Appendix B in the online supplemental material).
- *Queueing time* is the time a vehicle waited to access the LB, and was estimated as follows: (1) for all vehicles entering the LB, the difference between the time at which a vehicle parked and the time a vehicle entered the study area was calculated (respectively, timestamps 2 and 1 in Figure 3); (2) the mean of this time interval for those vehicles that did not queue (i.e., for which, at the time of arrival to the study area,

Figure 2. (Color online) Parking System with a One-Way Road, Two Off-Street Parking Facilities (a Loading Bay Area and a Carpark) and Road-Side Video Cameras Deployed



at least one parking slot in the LB was available) was obtained and used as the estimated travel time through the road; (3) the estimated travel time was subtracted from the previously computed time difference for those vehicles that did queue to access the LB, hence obtaining an estimate of their queueing time; (4) the queueing time was set to zero for those vehicles that did not queue.

- *Parking duration* is the time interval a vehicle was parked and was estimated as the difference between the time at which a vehicle left and arrived at the parking slot (respectively, timestamps 3 and 2 in Figure 3).

- Parking choice is either LB, CRP, or STR. Although alternatives LB and CRP were directly observed, we distinguished between vehicles transiting the study area and STR parked vehicles according to their dwell time: if a vehicle was not observed entering any off-street parking facilities, and its dwell time exceeded four minutes, then it was classified as STR; if instead its dwell time was below four minutes, then it was classified as in-transit. The four-minute boundary was the minimum dwell time of the illegally parked vehicles, which were recorded manually.

Simultaneously with the video recordings, we conducted intercept driver surveys. A pure “choice-based” sampling protocol was used; interviewed drivers were randomly selected within each of the three possible parking locations. We strove to achieve a uniform sampling rate over time. Interviews were performed after each vehicle driver was about to leave the parking area, with each interview lasting approximately two to three minutes.

In addition to a vehicle plate and parking choice, the variables recorded in the survey include activity purpose (delivery/pick-up or service), type and

volume of commodities handled, and the number of workers (Appendix A in the online supplemental material describes all the variables collected in the surveys). Data from the manually collected survey were matched with the data automatically collected from the road-side video cameras using the license plates.

4.4. Sample Description

Table 4 reports the total number of commercial vehicle trips observed at each mall, by data source and parking location.

Using road-side video cameras, a total of 4,339 commercial vehicle-trips were observed arriving and parking. We observed approximately 500 arrivals per day at mall A, and 700 at mall B. The larger number of vehicles parking at mall B was expected, given that mall B hosted more stores and more anchor (larger) tenants. Figure 4a compares the hourly arrival rates for mall A and B. We noted two peak hours: the first around 10:00 a.m. and the second one around 2:00–3:00 p.m.

Figure 3. Baseline Process Flow of Commercial Vehicle Parking Operations

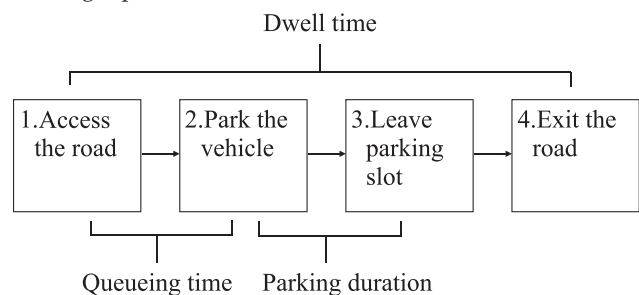


Table 4. Data Collection Summary

Statistic	Mall A	Mall B
No. days monitored	3 days	4 days
Total vehicle trips recorded by video	1,536	2,803
No. (share) vehicle trips observed parking at:		
Loading/unloading bay area (LB)	498 (0.32)	1,720 (0.61)
Carpark (CRP)	504 (0.33)	671 (0.24)
On-street (STR)	534 (0.35)	412 (0.15)
No. (share ^a) vehicle drivers interviewed	374 (0.24)	381 (0.14)
Mean parking duration	23.3 minutes	27.5 minutes
Mean queueing time ^b	6.2 minutes	5.2 minutes

^aShare of vehicles interviewed over the total vehicles detected by video recordings.

^bAveraged over the queueing times of vehicles that parked at the LB only.

We observed a different parking distribution across the two malls: mall A arrivals distributed equally across different parking types, whereas mall B arrivals seemed to favor the loading/unloading bay area, followed by the carpark and on-street parking. This was also expected, given mall B's larger LB in comparison with that of mall A. The mean parking duration and LB queueing time were similar across the two malls. Figure 4b shows the histogram of parking duration, combining data from both malls. We observed a right-skewed empirical distribution, similar to a log-normal distribution. For a detailed analysis of the data obtained, we refer to Dalla Chiara and Cheah (2017).

Of the vehicles tracked by video cameras, 740 drivers (17% of all arrivals) were interviewed.

Several difficulties were encountered during the interviews. In particular, vehicles illegally parked on STR were generally reluctant to participate in the survey. Moreover, it was not always possible to survey carparks, as mall operators were less willing

to give permission. This resulted in sampling bias, which was taken into account during the modeling.

Table 5 analyzes the sample composition described by the vehicle- and activity-specific attributes observed. Of the drivers interviewed, 60% used light goods vehicles (LGVs) and, for a similar share of vehicles, the driver alone performed the activity. Most of the vehicles were owned by businesses classified as “wholesale trade” (according to the Singapore Standard Industrial Classification), followed by transport and logistics, manufacturing, and retailing businesses.

Regarding the activity performed, most vehicles were observed carrying out only deliveries (84%), 8% carried out a service activity, and another 8% were involved in a pick-up. Although 44% delivered small quantities of goods (less than $0.5 m^3$), a considerable share (20%) moved large quantities ($> 2m^3$). A large share of vehicles carried fresh and frozen food, whereas the remaining share distributed all other commodity type categories. This was expected,

Figure 4. (Color online) (a) Average Commercial Vehicle Arrival Rates (Vehicles/Hour); (b) Empirical Distribution of Parking Duration (Minutes)

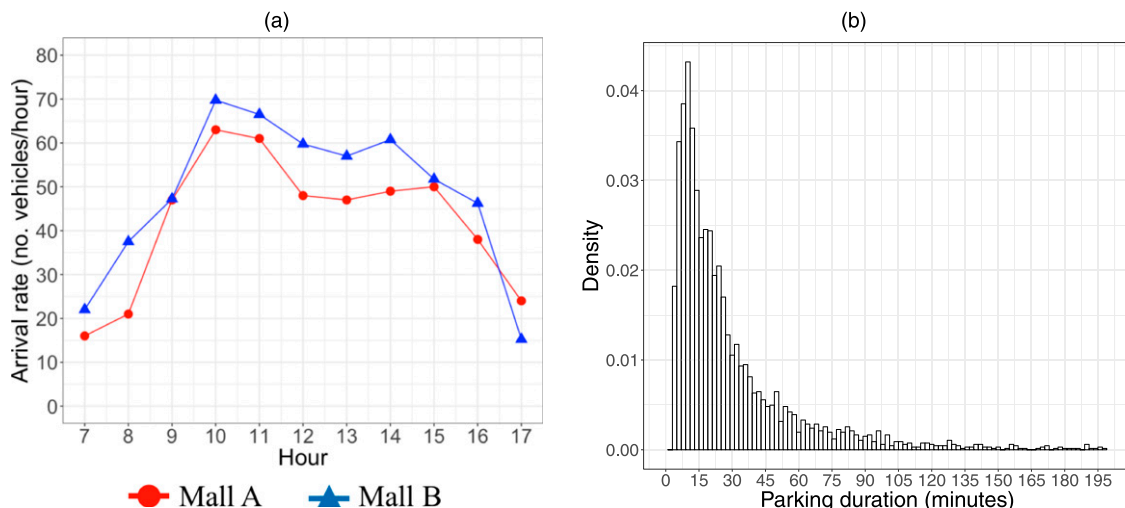


Table 5. Sample Composition

Attribute	Level	Share
Vehicle attributes		
Vehicle type	Light goods vehicle (LGV)	0.61
	Heavy goods vehicle (HGV)	0.39
Number of passengers	1 passenger (driver only)	0.62
	> 1 passengers	0.38
Vehicle owner type	Wholesale	0.39
	Transportation and logistics	0.17
	Manufacturing	0.12
	Retail	0.11
	Others	0.05
	Unknown	0.16
Activity attributes		
Activity purpose	Delivery only	0.84
	Service activity	0.08
	Delivery and pick-up	0.06
	Pick-up only	0.02
Volume	$[0, 0.5]m^3$	0.44
	$(0.5, 1]m^3$	0.22
	$(1, 2]m^3$	0.17
	$> 2m^3$	0.17
	Commodity type	Fresh and frozen food
	Nonperishable food	0.15
	Prepared food	0.12
	Service vehicles	0.08
	Clothing and accessories	0.07
	Recreational goods and stationeries	0.07
	Optics, photography and electronics	0.07
	Cosmetics, cleaning, pharmaceutical	0.05
	Household goods	0.02
	Unknown	0.12

as both case study areas presented a uniform retail mix with different kinds of stores and services sold.

5. Model Specification

Consider the case of a commercial vehicle driver n who, upon arrival at time t at the vicinity of the destination, chooses parking alternative i . In the initial formulation of the behavioral model of parking choice, we assumed the following:

- the driver knows the parking duration d_n ;
- the driver knows (or can estimate, in the case of illegal parking) the total parking cost, given the parking duration;
- the driver is able to observe the queue length q_{it} , the number of vehicles waiting in the queue outside a parking facility i .

The basic model specification of the representative utility is as follows:

$$V_{ni} = \beta_i + \beta_i^c c_i(d_n) + \beta_i^q q_{it}, \quad i \subseteq \{LB, CRP, STR\}, \quad (2)$$

where β_i , β_i^q , and β_i^c are alternative specific unknown parameters to be estimated representing, respectively, the mean of the unobserved factors, the marginal effect of queueing, and the marginal effect of parking cost, on

the respective parking utilities. We expect both β_i^q and β_i^c to be negative. Moreover, we will normalize $\beta_{LB} = 0$ for identification purposes.

In the following sections, we discuss different formulations of the effects of cost and queueing on the parking choice, as well as behavioral heterogeneity among drivers.

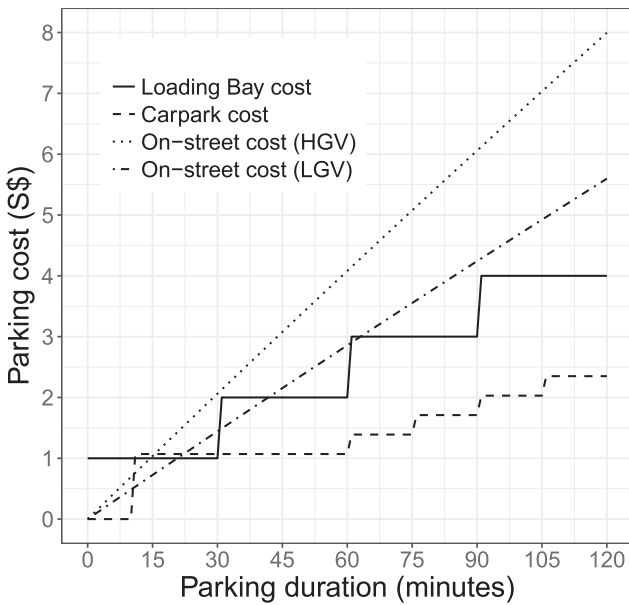
5.1. Effect of Parking Cost

Different parking alternatives have different parking costs. Off-street parking (LB and CRP) are priced according to a parking tariff, a fixed price per unit of parking time or part thereof. These costs (c_{LB} and c_{CRP}) are an increasing nonlinear function of parking duration. Figure 5 displays the total cost of parking at mall B (mall A's cost functions are similar) for varying levels of parking duration. The cost function for off-street parking appears as a step function.

In this study, on-street parking was considered to be a form of illegal parking, which involved a cost that equals to the parking fine only if a parked vehicle was caught by a patrolling traffic police car. This (c_{STR}) was modeled as an expected cost:

$$c_{STR} = \mathbb{E}[fine] = fine(v_n) \times p_{fine}, \quad (3)$$

Figure 5. Total Cost (Singapore Dollars) of Parking by Parking Duration and Parking Choice (at Mall B)



where $\text{fine}(v_n)$ is the level of the parking fine as a function of vehicle type (in Singapore the fine level for LGVs is SG\$70, for HGVs is SG\$100), and p_{fine} is the probability of getting fined, which increases with the parking duration and with the level enforcement. Let's assume a traffic police car patrols the area according to a Poisson process with rate λ (arrivals per minute). Because of the memory-less property of the Poisson distribution, the time interval T between the arrival of vehicle n that parks illegally and the time of arrival of the next patrolling car is exponentially distributed with parameter λ . Then, given that the vehicle stays time d_n minutes on-street, and assuming a patrolling rate λ , the probability of being fined is

$$p_{\text{fine}} = P(T \leq d_n) = 1 - e^{-\lambda d_n}, \quad (4)$$

and therefore, the expected cost of on-street parking is

$$c_{\text{STR}} = \text{fine}(v_n) \times (1 - e^{-\lambda d_n}). \quad (5)$$

Different values for λ were tried, and the enforcement level of two visits per day resulted in the highest model goodness-of-fit. Hence, in the rest of the study, we assumed two visits per day, which corresponds to $\lambda = 2/(24 \times 60) = 0.0014$ per minute.

The expected fine cost for on-street parking is plotted in Figure 5 separately for LGVs and HGVs and for varying levels of parking duration. We observe the following: (i) for HGVs, the STR alternative is the most expensive parking option for parking durations of longer than 15 minutes; (ii) for LGVs, the expected cost of STR follows the cost of CRP and becomes increasingly more expensive with longer durations;

(iii) for vehicles with parking durations of shorter than 15 minutes, the expected cost of STR is lower than the cost of LB.

We tested for nonlinearity for both the effects of on-street and off-street parking and found no significant improvement in the model goodness-of-fit.

5.2. Effect of Parking Congestion

Although CRP parking capacity is very large and STR parking can take place virtually anywhere on a road, the LB parking capacity is limited. At any point in time, there is a probability that the LB capacity is fully utilized, and arriving vehicles might have to queue to access the LB. A driver who observes a long queue upon arrival might choose to park elsewhere. Therefore, parking congestion is an important variable that influences parking choice. We explored (i) how a driver estimates the queueing time, (ii) potential nonlinearity, and (iii) endogeneity problems of parking congestion affecting parking choice.

At arrival, a vehicle driver observes the queue length q_t to enter the LB, measured as the number of vehicles waiting on-street to access the facility. A "naïve driver" estimates the waiting time by looking at q_t alone. However, different LBs might have different parking capacity, and therefore an "informed driver" is able to better estimate the expected queueing time by considering both the queue length and the parking capacity: for a given queue length, a queue is expected to deplete faster at a larger LB than at a smaller one.

Previous studies that analyzed consumers' queueing behaviors (Lu et al. 2013; Conte, Scarsini, and Sürücü 2016) found two types of individuals: those who consider only the queue length and those who consider both queue length and its speed in estimating the expected queueing time. In general, the effect of queueing seems to be context-dependent. In our specific case, we expected commercial vehicle drivers to have knowledge of the system (hence of the parking capacity at a given location) and to therefore be able to estimate correctly the expected queueing time.

In Table 6 we show eight different tested specifications of a choice model (I) and compare their goodness-of-fit. In specifications I–IV the state of the queue was a function of queue length alone (q_t), whereas in specifications V–VIII it was entered as fraction q_t/N , where N is the parking capacity. The specifications that took into account parking capacity performed better than those that considered queue length alone. We concluded that in our case the commercial vehicle drivers behave as informed drivers who use not only queue length but also parking capacity to estimate queueing time.

Table 6. Goodness-of-Fit Comparison for Different Specifications of the Effect of Queue on Parking Choice

Model	Attribute	Functional form	No. param. ^a	(-) Log-likelihood	Akaike Information Criterion (AIC)	Bayesian Information Criterion (BIC)
I	q_t	Linear	1	365.043 (8) ^b	742.085 (8) ^b	769.725 (7) ^b
II	q_t	Quadratic	2	363.412 (7)	740.823 (7)	773.070 (8)
III	q_t	Box-Cox	2	359.055 (5)	732.110 (4)	764.356 (5)
IV	q_t	Piecewise l.	3	358.064 (4)	732.128 (5)	768.981 (6)
V	q_t/N	Linear	1	360.421 (6)	732.842 (6)	760.481 (3)
VI	q_t/N	Quadratic	2	354.591 (1)	723.182 (1)	755.428 (1)
VII	q_t/N	Box-Cox	2	354.635 (2)	723.270 (2)	755.516 (2)
VIII	q_t/N	Piecewise l.	3	355.034 (3)	726.067 (3)	762.920 (4)

^aNumber of parameters estimated.

^bRanking from 1 (best) to 8 (worst) model goodness-of-fit.

We also tested for nonlinearity in the effect of queueing on parking choice. Three nonlinear formulations of queue length were tested: quadratic, Box-Cox, and piecewise linear transformation. In the quadratic transformation, an extra term multiplied the square of queue length. The Box-Cox transformation was formulated as follows:

$$\frac{(q_t)^\delta - 1}{\delta}, \quad (6)$$

where δ is the unknown transformation parameter to be estimated. Finally, the piecewise transformation tested whether different queue lengths influence the parking choice differently, in particular, we tested separately for short (only one vehicle in the queue), medium (two to three vehicles in the queue), and long (four-plus vehicles in the queue) lengths.

In Table 6, among the models accounting for parking capacity (models V–VIII), those with the best goodness-of-fit were model VI, in which the term q_t/N entered both as linear and as quadratic; and model VII, in which the term q_t/N was transformed according to the Box-Cox transformation. In comparison with the quadratic form, the Box-Cox transformation has several advantages: it avoids potential collinearity between the linear and the quadratic terms, and it is a more flexible functional form. Figure 6 compares the effect of different functional forms for the term q_t/N on the utility. Note that, in the quadratic functional form, utility seemed to improve whenever $q_t/N > 0.61$. This is explained by the fact that less than 5% of the observed vehicles experienced such long queues (> 4 in mall A, and > 10 in mall B). The Box-Cox transformation did not show such behavior and, therefore, was the preferred transformation.

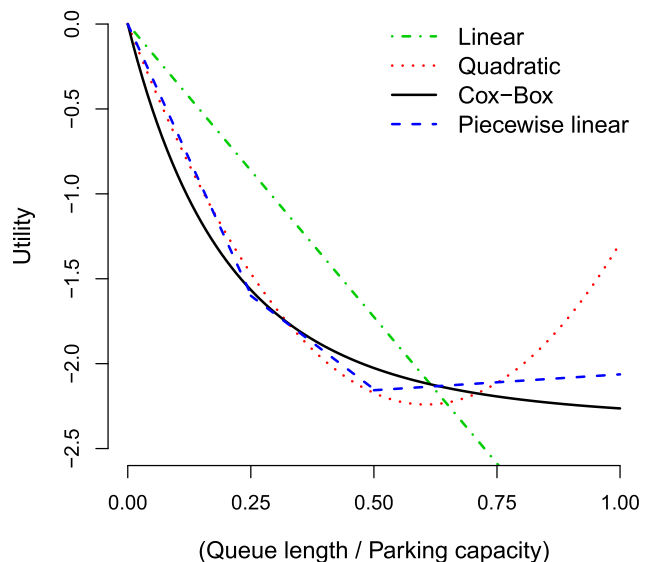
5.2.1. Endogeneity of Queue Length. One necessary condition to obtain unbiased estimates of the unknown parameters is the exogeneity of the explanatory variables. Whenever an observable covariate is correlated with unobserved factors contained in the

error term (hence its endogeneity), its coefficient estimate will capture not only the effect of the variable itself but also the effect of the correlated unobserved factors on the utility (Train 2003).

In the parking situation analyzed, an arriving vehicle driver who observes a long queue might choose to not join it and park elsewhere. However, other factors such as a temporary closure of a road lane or the passage of a police car might also influence the vehicle driver, who would then be willing to join queues that were unacceptable in a normal situation. Therefore, we suspected that the queue length is positively correlated with unobserved factors that make the LB a more attractive alternative, introducing a bias toward zero.

A Control Function (CF) approach was used to correct the coefficient bias of the queue coefficient due to the endogeneity of queue length. The CF consists of a two-step procedure (Guevara and Ben-Akiva 2006,

Figure 6. (Color online) Comparison of Different Specifications of Queue Length Effect on the Utilities of Different Parking Alternatives



Petrin and Train 2010). First, an auxiliary regression of the queue length on an instrumental variable is estimated:

$$q_{nt} = \alpha_0 + \alpha_1 arr_t + \mu_{nt}, \quad (7)$$

where arr_t represents the number of arrivals to the LB in the time interval $(t, t - 1h)$, α_0 and α_1 are unknown coefficients to be estimated, and μ_{nt} is a random error term. arr_t is a good instrumental variable if it is correlated with the queue length and uncorrelated with other factors that positively affect the utility of LB. Then the error term μ_{nt} captures the factors that induce correlation between the queue length and the error term ε_{ni} in Equation (2). Next, we compute the regression residuals of Equation (7), denoting them as $\hat{\mu}_{nt}$. These fitted residuals are then included as an explanatory variable in the utility function 2.

5.3. Preference Heterogeneity

The effect of cost, expected fine, and queuing on the parking choice might vary across drivers. These differences might be related to observable characteristics of the decision makers. For instance, we expected LGV drivers to differ from HGV drivers in their attitudes toward parking fines, given that their choice set is larger and the parking fine is lower. We also expected drivers with a larger volume of goods to be delivered to prefer the LB, because it is often equipped with freight elevators and elevated platforms.

Systematic taste variation was tested by segmenting the population into different groups using the vehicle- and activity-specific variables listed in Table 5. First, each of these variables was entered alone in the model, hence testing their influence on each alternative's alternative-specific constant (ASC). Then, the variable was interacted with alternative-specific variables, thus testing whether the effects of parking cost, expected fine, or queuing differ across groups. The model addition is retained only if it provides a significant improvement to the model goodness-of-fit.

An additional, purely random variation in taste might exist as a result of unobserved population segments or simply due to individuals' differences. The presence of such random taste variation can be tested by using the Mixed Logit (ML) model framework. We assumed that the coefficient of the alternative-specific variables varied according to a random continuous distribution, with unknown distribution parameters to be estimated. Both normal and lognormal distributions were tested. Although it is not recommended to assume a normal distribution for parameters that are expected to be negative, the use of a lognormal distribution resulted in extremely large estimates for standard deviations. Moreover, by assuming normally distributed parameters, we obtained

a small (below 2%) cumulative probability of the coefficients to be positive. We, therefore, assumed normally distributed parameters for the alternative-specific variables and tested whether the estimated standard deviations were significantly different from zero.

5.4. Final Model Specification

The final model specification is reported below (we omit the subscript n to simplify notations):

$$\begin{aligned} U_{LB} &= \beta_{LB}^c c_{LB}(d) + \beta_{LB}^{c, serv} c_{LB}(d) \mathbb{1}_{[service]} \\ &\quad + \beta_{LB}^q \left(\frac{(q_t/N)^\delta - 1}{\delta} \right) + \beta_{LB}^{vol} \left(\frac{volume}{workers} \right) + \lambda \hat{\mu} + \varepsilon_{LB} \\ U_{CRP} &= \beta_{CRP} + \beta_{CRP}^c c_{CRP}(d) + \varepsilon_{CRP} \\ U_{STR} &= \beta_{STR} + \beta_{STR}^f c_{STR}(d) + \beta_{STR}^{f, hgv} c_{STR}(d) \mathbb{1}_{[HGV]} \\ &\quad + \beta_{STR}^{help} \mathbb{1}_{[workers \geq 1]} + \beta_{STR}^{tl} \mathbb{1}_{[TL]} + \varepsilon_{STR}, \end{aligned} \quad (8)$$

where

- β_{CRP} , β_{STR} are unknown Alternative Specific Constants (ASC) for carpark (CRP) and on-street (STR) parking alternatives; the ASC for LB parking is normalized to zero for identification purposes;
- β_{LB}^c is the unknown parameter that multiplies the LB parking cost c_{LB} ; whenever the activity purpose is service, then an additional effect of LB cost is $\beta_{LB}^{c, serv}$, which multiplies the LB cost and dummy variable $\mathbb{1}_{[service]}$ that takes a value of 1 whenever the vehicle is a service vehicle;
- β_{CRP}^c is the unknown parameter that multiplies $c_{CRP}(d)$, the total cost of CRP;
- β_{STR}^f is the unknown parameter that multiplies the STR cost; whenever the vehicle is HGV, an additional effect of STR cost is $\beta_{STR}^{f, hgv}$, which multiplies the STR cost and dummy variable $\mathbb{1}_{[HGV]}$;
- β_{LB}^q is the unknown parameter representing the effect of congestion at the LB; it multiplies the Box-Cox transformation of the queue length;
- β_{LB}^{vol} is the unknown parameter for the effect of volume of goods handled per worker, which multiplies the total volume of goods ($volume$) divided by the total number of workers ($workers$);
- λ is the unknown parameter that multiplies the control function fitted residuals (μ), to correct for the endogeneity of queue length;
- β_{STR}^{help} is the unknown parameter multiplying dummy variable $\mathbb{1}_{[workers \geq 1]}$, which takes a value of 1 whenever the driver has one or more helpers, and 0 otherwise;
- β_{STR}^{tl} is the unknown parameter multiplying dummy variable $\mathbb{1}_{[TL]}$, which takes a value of 1 whenever the vehicle owner is a transport and logistics company; and
- ε_{LB} , ε_{CRP} , ε_{STR} are random error terms.

We noted that the effect of parking duration was indirectly captured in the model, as parking cost is a function of duration. However, the direct effect of duration on the parking choice was not included in the final model. Several variants of the model here formulated are estimated and compared in the next section.

6. Empirical Results

Parameters of model 8 were estimated by using the sample of commercial vehicles observed at mall A and B, described in Section 4.4.

We compared three nested formulations of model 8:

- Model I is an MNL model with alternative-specific variables only;
- Model II uses the same formulation as model I, but additionally it segments the population of commercial vehicle drivers into segments showing significantly different parking behaviors;
- Model III is an ML model that, in addition to model II, includes random taste variation.

Estimation was performed by using PythonBiogeme, an open-source free-ware for maximum likelihood estimation (Bierlaire 2016). The model coefficients were first estimated by Exogenous Sample Maximum Likelihood (ESML). A correction to the model alternative-specific constants was then applied to account for sampling bias (following Manski and Lerman 1977) due to difficulties encountered in collecting data at STR and CRP locations (explained in Section 4.4). Appendix C in the online supplemental material describes the estimation procedure and the bias correction method.

Table 7 reports, for each model, the estimates of the coefficients, their asymptotic robust standard deviations, and the p -values of the individual coefficients' t -tests, which describes whether a coefficient is significantly different from zero.

The estimated coefficients have the following implications.

- Parking cost has a negative effect on both alternatives CRP and LB. By dividing the coefficient for LB parking cost by the coefficient for the CRP cost, we obtained a ratio of 0.795 (using the estimates from model III) for freight vehicles and a ratio of 1.114 for service vehicles. Hence, service vehicles are more willing to pay for CRP than for the LB, whereas freight vehicles are more willing to pay for LB than CRP.

- The sign of the coefficient of the expected parking fine is negative. However, its magnitude varies for LGVs and HGVs. Interestingly, one dollar of expected fine generates more disutility to LGV drivers than to HGV drivers, even if the fine is larger for HGVs. This might be explained by the fact that LGV drivers can choose among more parking alternatives than HGVs. Consequently, HGVs are less flexible and

more willing to accept the payment of higher parking fines. Moreover, the coefficient for the expected fine is the only parameter that showed random taste variation. We compared the effect of expected fine with the cost of parking at the LB by dividing the two respective coefficients. We obtained, for both freight and service vehicles, and for both LGVs and HGVs, ratios below one. This means that a single dollar paid in LB parking fees carries less disutility than one dollar paid in parking fine. However, considering the distribution of the expected fine, we can compute the percentage of vehicles for which this ratio is above one. Although less than 10% of LGVs have a ratio above one, this percentage increases to 20% for HGVs, indicating that HGVs are more prone to illegal parking than to LGVs. However, in comparing the results with that from a similar analysis carried out for passenger vehicles (see tables 3–5 in Hess and Polak 2004), we noted that passenger vehicle drivers are more risk-prone than commercial vehicle drivers. One reason could be that it is a common practice for logistics companies to pay for parking fees, whereas parking fines are charged to the driver.

- The parameter capturing the effect of parking congestion is negative, and its Box-Cox transformation parameter δ is not significantly different from zero. However, δ is significantly different from 1 at a 0.01 significance level for all three models. Therefore, queue length has a nonlinear effect on the choice of LB, and the relationship is approximately logarithmic. The effect of congestion on the attractiveness of LB seemed to decrease in magnitude as congestion increases. This is counter-intuitive, but it might be explained by the fact that drivers arriving during peak hours might expect longer queues, which make the presence of congestion less important to their parking choice. On the other hand, "unexpected congestion" in the form of smaller queues forming occasionally might deter drivers arriving during off-peak hours, who perhaps do not expect congestion at all. Moreover, as discussed in Section 5.2, the model goodness-of-fit improved when parking congestion was modeled as the fraction of queue length by parking capacity, instead of queue length alone, which might indicate that drivers are well informed of the parking capacity and use this information to better predict queueing time. Finally, the parameter λ multiplying the control function residuals is significantly different from zero. When added to the model, the effect of queue length increases in magnitude, which might be interpreted as a correction of the endogeneity of queue length.

- Preference for a certain parking type varies with vehicle- and activity-specific characteristics. The larger the volume of goods handled per worker,

Table 7. Estimation Results

Coefficient	Explanatory variable	Coefficient estimates (robust standard error)		
		Model I	Model II	Model III
LB-specific attributes				
β_{LB}^c	LB park cost	-0.428*** (0.118)	-0.816*** (0.193)	-1.049*** (0.294)
$\beta_{LB}^{c, serv}$	LB park cost × Dummy: service vehicle	/	-0.514** (0.185)	-0.421 (0.243)
β_{LB}^q	Queue length / LB capacity	-1.510** (0.559)	-2.340* (1.070)	-2.495* (1.100)
δ	Box-Cox transformation parameter	-0.357 (0.448)	-0.891 (0.706)	-0.668 (0.608)
β_{LB}^{vol}	Total volume/No. passengers	/	0.526*** (0.179)	0.584*** (0.205)
λ	Control function residuals	/	-0.133*** (0.037)	-0.121* (0.051)
CRP-specific attributes				
β_{CRP}	CRP alternative specific constant	-1.005*** (0.343)	-2.425*** (0.727)	-2.505*** (1.010)
β_{CRP}^c	CRP park cost	-0.121 (0.307)	-1.140*** (0.374)	-1.319*** (0.424)
STR-specific attributes				
β_{STR}	STR alternative specific constant	-0.760*** (0.286)	-3.170*** (0.762)	-2.170* (1.290)
β_{STR}^f	Mean expected fine	-0.682*** (0.151)	-1.380*** (0.289)	-3.076*** (1.090)
σ^f	Standard deviation of expected fine	/	/	1.103* (0.506)
$\beta_{STR}^{f, hgv}$	Expected fine × Dummy: HGV	/	0.759*** (0.224)	1.125*** (0.396)
β_{STR}^{help}	Dummy: ≥ 1 helper	/	1.380*** (0.269)	1.776*** (0.378)
β_{STR}^l	Dummy: transport and logistic sector	/	0.555 (0.306)	1.009* (0.483)

Note. CRP, carpark; HGV, heavy goods vehicle; LB, loading/unloading bay area; STR, on-street.

*** $p \leq 0.001$; ** $p \in (0.001, 0.01]$; * $p \in (0.01, 0.05]$; · $p \in (0.05, 0.1]$.

the more likely a vehicle is to park at the LB. This result is expected, because the LB is often equipped with freight elevators and ramps, making it easier for workers to carry larger quantities of goods. On the other hand, whenever there are one or more helpers, the driver is more likely to park illegally. One explanation for this behavior is that whenever there are helpers, the driver is able to stay in the vehicle while the other performs the delivery/pick-up, with the advantage of being able to move the vehicle whenever traffic police are seen arriving. Finally, there is a tendency for vehicles owned by transport and logistics companies (e.g., couriers) to be more willing to park illegally on-street. This might be explained by the fact that these vehicles may be more in of a “hurry” than vehicles owned by manufacturers, suppliers, or retailers because they may have to perform more deliveries in a single day, hence the tendency to resort to illegal forms of parking. Finally, we did not observe any significant improvement of the model

goodness-of-fit by adding the type of commodity as a set of binary variables to the model, and therefore they were not added to the final model formulation.

Table 8 reports the summary statistics of each model’s goodness-of-fit. A large decrease in the final log-likelihood can be seen when vehicle- and activity-specific variables were added to the model (going from model I to II). However, the inclusion of random taste variation in model III did not bring about much further decrease in the final log-likelihood, with only the coefficient for the expected fine being randomly distributed.

6.1. Model Validation

The predictive abilities of the models derived above were tested on out-of-sample data by leave- d -out cross-validation (see Appendix D in the online supplemental material). We iteratively partitioned the original sample into test and training sets K times, each time random sampling without replacement d

Table 8. Model Estimation Summary Statistics

Statistics	Model I	Model II	Model III
No. parameters	7	13	14
Sample size	740	740	740
Initial log likelihood	-613.079	-613.079	-613.079
Final log likelihood	-354.635	-296.753	-292.075
ρ^2	0.422	0.516	0.524
$\bar{\rho}^2$	0.410	0.495	0.501
Akaike Information Criterion (AIC)	723.270	619.506	612.149
Bayesian Information Criterion (BIC)	755.516	679.392	676.642
No. draws	/	/	100,000

observations, leaving them out as a test set, and using the remaining as a training set. At each iteration, the model coefficients were estimated by using the training set, and the choice probabilities were computed for each observation in the test set. Then, a Monte Carlo simulation was performed on each observation in the test set B times, each time predicting a parking choice. We then computed the “hit rate” by assigning a score of 1 whenever the predicted choice corresponded to the observed choice, and 0 otherwise. The mean hit rate and its standard deviation were reported for different model formulations. The higher the mean hit rate, the higher is the model predictive capability to predict the parking choices for the test set. We compared four different model formulations: a constant-only MNL model, whose estimation required only observing the parking shares without any need of disaggregated data at the level of individual vehicle arrivals; and models *I-III*, described in Section 6. Table 9 reports the means and standard deviations of the hit rates for each model formulation. Twenty percent of the observations were used as a test set, and parameters K and B were set equal to 100. Moreover, because the parameter representing the effect of the expected parking fine in model *III* (ML model) was randomly distributed, individuals faced different values for this parameter, randomly sampling it from the estimated distribution.

The mean hit rate was computed for all individuals, as well as separately for individuals choosing LB, CRP, and STR. All models, including the base model,

showed a good predictive ability for LB parking, because this was the preferred choice. In comparison with the base model, by adding the alternative-specific variables in model *I*, the prediction improved slightly for LB, CRP prediction largely improved, and STR parking was still poorly predicted. By adding vehicle- and activity-specific variables (model *II* and *III*), the largest improvement in prediction was seen for STR parking. Finally, models *II* and *III* had similar predictive performance, with model *III* showing a slightly larger standard deviation than model *II*.

7. Policy Simulation

The parking choice model (model *II* described in Section 6) was used to assess the operational impacts of different parking policies. In this section, we discuss a method to simulate a hypothetical parking system, such as the one described in Figure 2. Historical records of the 4,400 commercial vehicles collected at the urban malls described in Section 4.3 were used as input to a discrete-event simulation, which tracked vehicles as they arrived and made their way through the network of parking facilities. The choice of parking was simulated for each vehicle arrival by Monte Carlo simulation using the probability distributions over the choice sets obtained from the parking choice model. In addition to individuals’ parking choices, the model also outputs the resulting system congestion.

We simulated different policies: changes in loading/unloading parking capacity, changes in parking tariffs and parking fines, and the introduction of a centralized receiving policy, in which helpers staged at the loading/unloading bays area (LB) would reduce individuals’ parking duration by helping drivers performing the delivery/pick-up.

The simulated policies were compared in their ability to reduce the mean delivery cost, and carbon dioxide emissions, which we will refer to, respectively, as financial and environmental impacts.

7.1. Simulation Model

A mall can be described as a queueing system in which the system arrivals are commercial vehicles and the system resources are its road and parking

Table 9. Hit Rate Means and Standard Deviations

Model	Description	Mean (standard deviation) hit rate			
		All	LB	CRP	STR
Base	Constants-only MNL model	0.649 (0.036)	0.787 (0.039)	0.252 (0.127)	0.144 (0.077)
I	MNL model without segmentation	0.704 (0.034)	0.825 (0.035)	0.402 (0.143)	0.235 (0.093)
II	MNL model with segmentation	0.759 (0.032)	0.854 (0.032)	0.494 (0.144)	0.407 (0.103)
III	ML model	0.763 (0.076)	0.856 (0.112)	0.532 (0.154)	0.406 (0.183)

Note. CRP, carpark; LB, loading/unloading bay area; MNL, multinomial logit; STR, on-street; ML, mixed logit.

infrastructures. Each resource is characterized by a given number of servers (number of spaces that can be occupied by one vehicle at a time). When all the servers are busy, vehicle arrivals have to wait in a queue until a server becomes available. In order for a vehicle to successfully perform its activity (delivery, pick-up, or service), it has to occupy a parking server for a given parking duration.

A Discrete-Event Simulation (DES) model was used to simulate such a queueing system (Law 2015). Figure 7 depicts the DES model implemented, which is characterized by three types of resources (represented as circles):

- STR resources represent a road, which is virtually split into three segments: an ingress segment (STR-I); a parking segment (STR-P), which illegally parked vehicles occupy; and an egress segment (STR-E). STR-types of resources are characterized by an infinite number of servers (no queue forms). Each vehicle spends a random amount of time at the STR-I and STR-E, representing the travel time in and out of the system;

- the LB resource represents the loading/unloading bays area and is characterized by a finite number of servers;

- the CRP resource represents a public carpark and is characterized by an infinite number of servers.

Resources are linked by arrows representing different vehicle trajectories. After accessing the system by occupying a server at the STR-I, a vehicle driver would choose where to park among LB, STR-P, or CRP. The parking choice was simulated by using the choice model presented. The choice model took as inputs a vehicle's parking duration, activity, and vehicle-specific characteristics (deterministic inputs except the parking duration in the case of the centralized receiving policy scenarios); the number of vehicles waiting in queue to access the LB at the time of the vehicle arrival (output of the DES model); and the characteristics of the parking alternatives (fixed by the researcher according to the desired policy scenario). The choice model estimated a vehicle's

choice probabilities, and a Monte Carlo simulation was performed to choose a parking resource. We assumed that (i) once a parking resource had been chosen, the driver would not change his or her mind, and (ii) a vehicle would not leave the system until its parking duration had been completed.

The DES model takes two sets of inputs: parking supply and parking demand inputs. Parking supply inputs are a set of parameters whose values are fixed by the researcher, describing the main features of the parking infrastructure and its management. Each combination of parking supply input values determines a "scenario." These parameters were as follows:

- LB parking capacity (we assumed all other nodes had infinite capacity);
- LB and CRP parking cost (SG\$ per unit of time);
- fine level for LGVs and HGVs (SG\$); and
- parking enforcement level (number of traffic police visits per day).

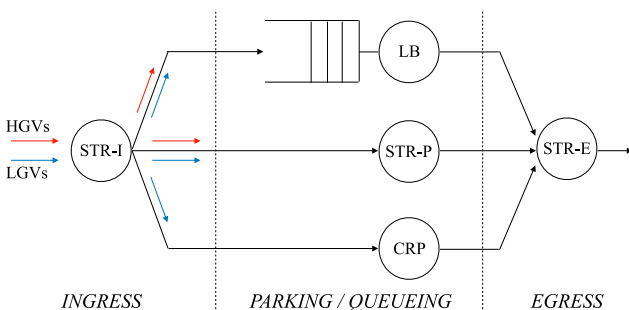
The parking demand consisted of the complete record of historical arrivals and departures of approximately 4,400 commercial vehicle trips, collected at mall A and mall B (described in Section 4.3). Each vehicle's real arrival and departure time, parking duration, and type were used as fixed inputs to the model. However, because to simulate the parking choice, the full set of individual attributes was needed, and these were available only for a subset of the arrivals (those manually surveyed), we artificially input the missing values by using a Random Forest regression method (Stekhoven and Buhlmann 2012), trained using the arrivals for which the complete set of attributes is available (approximately 750 observations).

For each vehicle arrival, the DES model records the simulated parking choice and the time spent queueing (if any).

The model was calibrated against the real observed parking demands and queueing time distribution. We calibrated two sets of parameters: the STR-I travel time was adjusted to reflect the observed travel time distribution; and the alternative-specific constants (ASC) of the choice model were adjusted to reflect site-specific parking demands by iteratively adding the term $\log(M_i/\hat{M}_{ik})$ in the respective utility functions, where M_i is the observed share of vehicle choosing alternative i and \hat{M}_{ik} the simulated share for i at iteration k . We iteratively (i) simulated, (ii) computed the parking demand shares, and (iii) adjusted the model ASCs, until the observed and simulated shares were close enough (Train 2003).

Appendix E in the online supplemental material compares the observed parking demands and average queueing time with the respective quantities obtained by simulating the system using the actual parking supply inputs ("baseline" scenario) after

Figure 7. (Color online) Discrete-Event Simulation Model Framework



calibration. The derived model was found to closely replicate real parking behaviors and parking congestion. In the next section, we describe policy scenarios tested.

7.2. Policy Scenarios

The current state of the system, reflected in the data collected at mall A and mall B, is referred to as the baseline scenario, for which parking supply inputs are described in Table 3. Each “parking policy” deviated from the baseline scenario by changing one attribute (e.g., the parking price or the parking capacity). For each policy, we identified two scenarios: one associated with a “positive” change, and the other related to a “negative” change. Table 10 describes the parking policy scenarios we were interested in simulating. The attributes’ values were chosen to reflect actual changes that might take place in the observed context.

The Centralized Receiving (CR) policy consists of placing at the LB specialized personnel to help vehicle drivers perform deliveries/pick-ups. We simulated the effect of this policy by assuming that these helpers would reduce a vehicle parking duration d to a given level \bar{d} as follows:

$$d_{CR} = \min(d, \bar{d}), \quad (9)$$

where d_{CR} is the parking duration of a vehicle that parked at the LB under the CR policy regime. We tested two scenarios of such a policy: an “efficient” CR regime with $\bar{d} = 15$ minutes, and an “inefficient” CR regime with $\bar{d} = 30$ minutes. We further assumed that all vehicles choosing LB would be served by CR at a cost of SG\$4 per m^3 of goods handled on top of the parking cost (service vehicles would not be affected by this policy).

7.3. Impact Metrics and Policy Classification

Three types of policy impacts were obtained from the simulation: operational, financial, and environmental

impacts. In the following paragraphs, we describe how these metrics were computed (for more details, we refer to Dalla Chiara 2018).

Operational impact metrics were the aggregate demands for the different parking alternatives and the mean time that vehicles parking at the LB spent queueing.

The financial impact was measured as the average generalized cost (in SG\$) incurred by a carrier to park and perform a delivery/pick-up or a service. We considered three cost components: labor, parking, and fuel cost. Labor cost was defined as the product of a vehicle’s dwell time (which included queueing and parking duration) and its value of time. Parking cost consisted of the parking fee or the expected parking fine (according to whether a vehicle was parked legally or illegally). Fuel cost was computed by multiplying the total fuel consumed while idling on-street (either queueing or on-street parking) by the fuel cost.

The environmental impact was measured as the total amount of carbon dioxide (CO_2) emitted by all vehicles transiting and parking in the system. There were two types of emitting agents: (on-street) idling vehicles and in-transit vehicles. Commercial vehicles idle on-street (usually leaving the engine on) either waiting to park or parking illegally. Transiting vehicles are those that do not intend to park but whose travel speeds through the area are negatively affected by the idling vehicles. Idling emissions were computed simply by multiplying the total time spent on-street by appropriate emission factors, which converted the idling time into CO_2 emissions. To compute the driving emissions, we used the formulas derived in Hickman (1999), in which the amount of CO_2 emitted by a vehicle traveling a road segment is a function of the vehicle type (LGV, HGV, or passenger car), the length of the road segment, and the average travel speed. The latter one depends on the current traffic conditions and on the number of vehicles idling on-street, which is an output of our DES model. We computed the effects of idling vehicles on the average

Table 10. Parking Policies and Scenarios Description

Policy	Scenario	Description
Parking capacity	PC-1	Increase loading bay capacity (add 2 lots)
	PC-2	Decrease loading bay capacity (remove 2 lots)
Loading bay pricing	PRL-1	Free loading bay parking
	PRL-2	Expensive loading bay parking (1.5 SG\$/15 minutes)
Carpark pricing	PRC-1	Free carpark parking
	PRC-2	Expensive carpark parking (1.5 SG\$/15 minutes)
Parking fine	PF-1	Decrease parking fine by 25%
	PF-2	Increase parking fine by 25%
Parking enforcement	PE-1	Low enforcement level (1 visit per day)
	PE-2	High enforcement level (5 visits per day)
Centralized receiving	CR-1	Efficient centralized receiving (15 minutes upper bound)
	CR-2	Inefficient centralized receiving (30 minutes upper bound)

travel speed by using the formulas derived by Amer and Chow (2017).

According to the changes in financial and environmental impacts with respect to the baseline scenario, we categorized the policy scenarios into four categories, represented on a two-dimensional plot in Figure 8: (I) *cost-saving scenarios* are those that decrease costs but increase emissions; (II) *inefficient scenarios* are those that increase costs and emissions; (III) *optimal scenarios* are those that decrease both costs and emissions; (IV) *green scenarios* are those that only decrease emissions but increase costs.

7.4. Simulation Results

The DES model described was implemented by using the Simmer package for the R software (Ucar, Smeets, and Azcorra 2019). For a given scenario, each day of recorded vehicle arrivals was simulated 1,000 times. For each day, vehicles' arrival times, vehicle- and activity-specific characteristics, and their parking durations did not change across simulations. The only sources of randomness were the parking choices (for which the probability distribution was estimated for each vehicle arrival by the random utility model derived in the previous sections), the resulting parking congestion (hence the queueing times), and the road travel times.

For each simulated day, the operational, financial, and environmental impact metrics were derived, and the percentage changes with respect to the baseline scenario values were computed (see Appendix E in the online supplemental material). The mean percentage changes in

financial and environmental impacts (the averages were taken over all days for which input arrivals were recorded in the same mall) for all the 12 policy scenarios are reported in Table 11, separately for mall A and mall B. The scenario operational impact metrics are reported in Appendix F in the online supplemental material. According to the resulting impact changes, scenarios are classified into optimal, green, cost-efficient, and inefficient (Figures 8 and 9).

Three scenarios were classified as "optimal" in both malls: increase parking capacity (PC-1), free-of-charge carpark (PRC-1), and efficient CR policy (CR-1).

By enlarging the LB capacity, more vehicles could park inside the LB and the queue would be perceived as faster. Consequently, we would expect demand for the LB to increase, whereas demand for both STR and CRP to decrease. An increase in LB demand would not cause an increase in queueing because of the increase in parking capacity. This would result in an overall decrease in mean delivery cost, due to a decrease in queueing times, and a decrease in emissions, as fewer vehicles would be parked on-street and road congestion would be lessened.

By making the CRP the cheapest alternative, its demand would be expected to increase for LGVs (HGVs are not able to park inside the CRP). In particular, those LGVs with longer parking durations (hence with the highest parking costs) would benefit the most from a free-of-charge CRP. Therefore, the LB would be freed from LGVs with long parking durations (often service vehicles), and more parking capacity would be available for HGVs, which otherwise would be forced to park illegally on-street. This would result in a more efficient distribution of vehicles across the parking facilities, a reduction in costs, and reductions in CO₂.

The CR-1 scenario would bring about the largest reduction in mean cost and CO₂ emissions. The significant reduction in parking durations for LB parked vehicles would increase the demand for LB and reduce illegal and carpark parking. Interestingly, even if the CR regime added an additional service fee to the total delivery cost, the cost increase would be offset by the reduction in parking durations (hence savings in labor cost). Further, by reducing queueing and illegal parking, CO₂ emissions would decrease. However, such improvements would be reached under the condition that the CR regime was efficient, that is, had the ability to effectively reduce the parking durations to under 15 minutes. The inefficient CR scenario (CR2) showed mixed results.

Scenario PRL-2 was classified as "green" for both sites. As the LB becomes more expensive, we would expect demand for it to decrease, as more vehicles would choose to park elsewhere. This, in turn, would reduce queueing. Interestingly, the reduction

Figure 8. Classification System for Parking Policy Scenarios Impacts

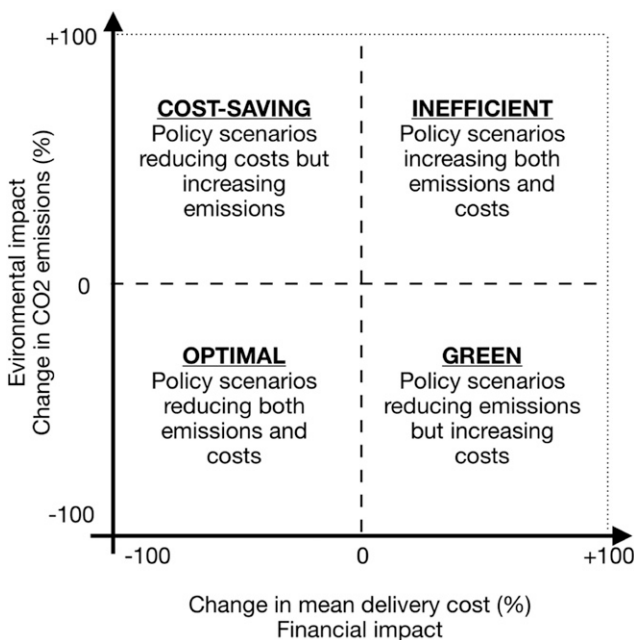
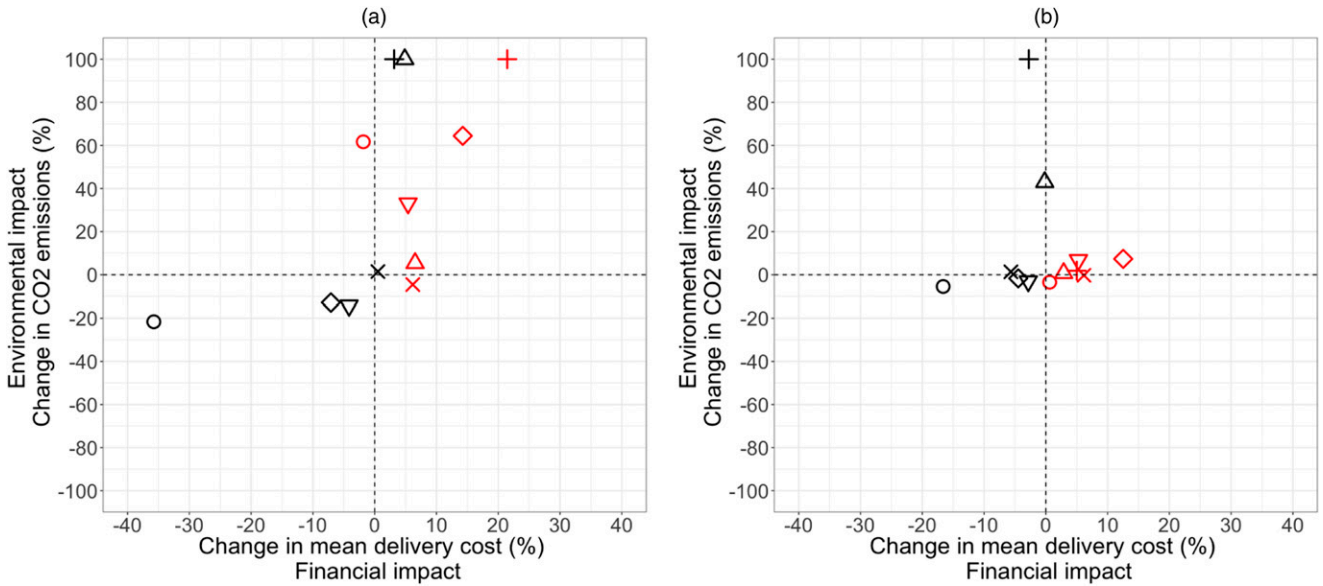


Figure 9. (Color online) Comparison of Policy Scenarios Impacts (see Legend in Table 11)



in vehicles idling on-street while waiting to park would not be offset by an increase in illegal parking, and the total environmental impact would improve. However, the mean cost would increase, because of the higher parking price.

Three scenarios, namely PRL-1, PF-1, and PE-1, showed mixed results, being classified as inefficient for mall A and “cost savings” for mall B. A common trait of all these scenarios was that they would result in an increase in vehicles idling on-street. PRL-1, by making the LB free of charge, would increase LB demand and consequently increase queueing times. PF-1 and PE-1 would decrease the expected fine, and therefore increase STR demand, with consequently more vehicles parking illegally on-street. The vehicles idling on-street would create road blockages, slowing

traffic and increasing emissions. The reduction in parking fee or parking fine would generate savings at mall B. However, although mall B had an LB with a large capacity, mall A had a smaller LB. Consequently, the cost savings were offset at mall A because of an increase in queueing time, hence an increase in labor cost.

Scenarios PRC-2, PF-2, and PE-2 made the system worse-off. These scenarios either increased the cost of CRP or the expected cost of STR. By making these alternatives more expensive, the demand for LB would increase, and consequently queueing times would increase. Moreover, reducing LB parking capacity, even if by a small amount, would have a negative impact on the system, generating longer queues and shifting demand on-street, with the consequence of increasing both costs and emissions.

Table 11. (Color online) Financial and Environmental Impacts Results

Scenario (symbol)	Mall A			Mall B		
	Financial impact (%) ^a	Environmental impact (%) ^a	Category	Financial impact (%) ^a	Environmental impact (%) ^a	Category
PC-1 (∇)	-4.15	-14.22	Optimal	-2.84	-3.03	Optimal
PC-2 (▽)	5.4	33.12	Inefficient	5.28	6.83	Inefficient
PRL-1 (×)	0.52	1.48	Inefficient	-5.66	1.36	Cost-saving
PRL-2 (×)	6.15	-4.55	Green	6.17	-0.24	Green
PRC-1 (◊)	-7.09	-12.8	Optimal	-4.46	-1.68	Optimal
PRC-2 (◊)	14.26	64.46	Inefficient	12.52	7.37	Inefficient
PF-1 (△)	4.87	362.1	Inefficient	-0.18	42.98	Cost-saving
PF-2 (△)	6.54	5.38	Inefficient	2.89	0.77	Inefficient
PE-1 (+)	3.16	460.41	Inefficient	-2.75	114.43	Cost-sav.
PE-2 (+)	21.45	158.09	Inefficient	5.01	1.85	Inefficient
CR-1 (○)	-35.75	-21.6	Optimal	-16.62	-5.45	Optimal
CR-2 (○)	-1.85	61.7	Cost-saving	0.62	-3.47	Green

^aPercentage change with respect to baseline scenario.

8. Conclusion and Policy Implications

In this paper, we study commercial vehicle driver parking choice behaviors in urban areas. In particular, we study how a driver's choice between legal parking (in a loading/unloading area or in a carpark) and illegal parking (in the travel lane) is affected by parking cost, parking fine, and parking congestion. We then explore the implication of drivers' parking behavior on the environmental and economic impacts of different parking management strategies, using urban retail malls in Singapore as case studies.

In the first part of the paper, we formulated a random utility model of parking choice model for commercial vehicle drivers. To our knowledge, this is the first study formulating a policy-sensitive parking choice model for commercial vehicle drivers. Most of the scientific literature has focused on studying parking choice of passenger vehicles. We found that, as expected, higher parking costs disincentivize vehicle drivers parking in off-street parking facilities. However, not all vehicles have the same willingness to pay. We found that service vehicles are more willing to pay for parking in carparks (reserved for passenger vehicles) than loading/unloading bay areas, compared with vehicles delivering/picking up goods. Regarding the parking fine, we found that commercial vehicles are generally rule-abiding, with one dollar paid for parking in an off-street parking facility carrying less disutility than one dollar paid in parking fine. However, we found that drivers of heavy goods vehicles are more prone to park illegally in the travel lane than light goods vehicles. Finally, we found that commercial vehicle drivers behave as informed drivers: they are more willing to join longer queues for loading/unloading areas that have larger parking capacities.

In the second part of the paper, we used the estimated parking choice models within a simulation framework to test the impacts of different parking management strategies, taking into consideration drivers' parking behaviors. Large urban freight traffic generators (e.g., retail malls) provide loading/unloading bay areas to accommodate the parking demand of commercial vehicles delivering/picking up goods or performing services. However, we found that excessive freight parking demand generates parking congestion, forming queues of vehicles waiting to park, spilling over neighboring streets, blocking traffic, increasing air pollution, and generating unsafe situations. Moreover, long queueing times, besides increasing delivery costs, also reduce the attractiveness of the loading/unloading bay areas, and incentivize drivers to park illegally in the travel lane, causing further road blockages. In the observed study areas, we

found that between 15% and 35% of the commercial vehicles parked illegally in the travel lane. Moreover, drivers waited on average approximately 5.7 minutes to park in the loading/unloading bay area. The only way to improve the parking system at large urban freight traffic generators is to reduce both queues and queueing times for vehicles waiting to park at loading/unloading bay areas and illegal parking in the travel lane. Although parking pricing and parking enforcement are commonly used parking policies to manage parking demand, such policies resulted in a worse-off system when applied to commercial vehicles. Excessive pricing of the loading/unloading bay area increases illegal parking, whereas excessive parking enforcement increases demand for loading/unloading bay area parking and therefore queueing. Through our simulations, we found that, to both reduce queueing and illegal parking, two strategies are most effective: reduce parking durations and provide incentives for lights goods vehicles and service vehicles to park in larger carparks usually reserved for passenger vehicles.

New data collection opportunities arise when traditional manual data collection techniques (in this case face-to-face surveys) are enhanced with new automatic data collection methods such as image recognition technology and automatic video processing. The empirical framework here proposed collecting "time-stamps data" on commercial vehicle parking and delivery operations. This is a new approach to the subject, providing a better understanding of commercial vehicle movements in urban areas. This type of data are commonly collected for other fields of service engineering, such as emergency services, hospitals, and call centers but less common in urban logistics.

Future research will work to address some of the study limitations. In the presented parking choice model, parking duration is a key explanatory variable. Although it was assumed as exogenous, no difference was made between observed (realized) parking duration and expected duration (before the parking choice is made). In such a case, parking duration could be more correctly treated as a latent variable.

Furthermore, although in this paper we describe simulating a single node of a logistics network, the model could be implemented in a larger network by using an agent-based transport simulator to estimate the impacts of freight parking policies on a wider urban area. The extension from a single node to a whole network of commercial activities would raise several interesting questions, such as, How should parking pricing be coordinated across different facilities? What is the impact of commercial vehicle parking policies on passenger vehicles and vice-versa?

Which other area-wide policies can reduce road and parking congestion in central urban areas?

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