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ORIGINAL PAPER

Data stories from urban loading bays

Giacomo Dalla Chiara [1] · **Lynette Cheah** [1]

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Abstract

Purpose Freight vehicle parking facilities at large urban freight traffic generators, such as urban retail malls, are often characterized by a high volume of vehicle arrivals and a poor parking supply infrastructure. Recurrent congestion of freight parking facilities generates environmental (e.g. pollution), economic (e.g. delays in deliveries) and social (e.g. traffic) negative externalities. Solutions aimed at either improving or better managing the existing parking infrastructure rely heavily on data and data-driven models to predict their impact and guide their implementation. In the current work, we provide a quantitative study of the parking supply and freight vehicle drivers' parking behaviour at urban retail malls.

Methods We use as case studies two typical urban retail malls located in Singapore, and collect detailed data on freight vehicles delivering or picking up goods at these malls. Insights from this data collection effort are relayed as data stories. We first describe the parking facility at a mall as a queueing system, where freight vehicles are the agents and their decisions are the parking location choice and the parking duration.

Results Using the data collected, we analyse (i) the arrival rates of vehicles at the observed malls, (ii) the empirical distribution of parking durations at the loading bays, (iii) the factors that influence the parking duration, (iv) the empirical distribution of waiting times spent by freight vehicle queueing to access the loading bay, and (v) the driver parking location choices and how this choice is influenced by system congestion.

Conclusions This characterisation of freight driver behaviour and parking facility system performance enables one to understand current challenges, and begin to explore the feasibility of freight parking and loading bay management solutions.

Keywords Urban freight deliveries · parking · driver behaviour · large traffic generators

This article is part of Topical Collection on Accommodating urban freight in city planning

✉ Lynette Cheah
lynette@sutd.edu.sg

Giacomo Dalla Chiara
giacomo_dc@sutd.edu.sg

1 Singapore University of Technology and Design, Engineering Systems and Design, 8 Somapah Road, Singapore 487372, Singapore

1 Introduction

1.1 Background

Large buildings in urban areas such as retail malls, hotels, hospitals and office buildings, are of interest to urban and transportation planners because they contribute a large share of the freight vehicles traffic. *Large urban Freight traffic Generators* (LFGs) are defined by Jaller et al. (2015) as "specific facilities housing businesses that individually or collectively produce and attract a large number of daily truck trips" [1].

The generation of large amounts of freight vehicle trips translates into a high demand for freight parking. At the same time, because of limited land availability, high land value and high opportunity cost of land usage in urban centres, LFGs often lack of adequate parking and logistics facilities [2]. The combination of high demand and scarce supply of infrastructure makes these hubs vulnerable nodes of the urban logistics network, creating bottlenecks that can trigger parking congestion and queueing, delays in the delivering operations and illegal parking. Failure to limit these problems cause environmental (e.g. air pollution), economic (e.g. loss of delivery reliability and higher delivery costs) and social (e.g. noise

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pollution and road traffic congestion) negative externalities that can propagate over the entire network.

There are two main approaches to tackle freight parking congestion: one is improving the parking supply through infrastructure investments; the second one is to influence freight parking demand through policies and regulations such that the existing infrastructure is better utilised and congestion is lessened. To support the first approach, cities' authorities often provide guidelines and regulations for the construction of adequate freight parking infrastructure. For instance, at least one loading/unloading bay for every 4000 m^2 of retail area is required in Singapore [3]; in the UK the requirement is set at a minimum of one lorry space per 750 m^2 of retail space [4]. The second approach consists of implementing *urban logistics initiatives*, i.e. policies and regulations enacted by the public sector to foster sustainable logistics practices [5]. Examples of suitable initiatives for LFGs are: centralized receiving [1, 6], off-hours delivery programmes [7, 8], off-site consolidation programmes [9–11], parking pricing [12] and loading bay reservation systems [13].

The design of freight infrastructure and urban logistics initiatives relies on the availability of data and data-driven models that can estimate their potential impacts and guide decision-making.

The first step is to quantify the demand for parking at these facilities. An important branch of the literature on parking demand modelling focuses on Freight Generation (FG) and Freight Trips Generation (FTG). These works are in search for efficient models that can estimate the number of freight vehicle trips attracted and produced by urban establishments. The mathematical framework used are often econometrics models which takes as inputs covariates such as industry category, establishment area and employment and outputs estimates for the number of freight vehicles arriving to an establishments, usually with a time scale of a single day to a week [14–16]. FTG methods provide useful insights on the magnitude of the freight parking problem of an urban area. Some studies went further in using FTG methods to assess urban logistics initiatives. For instance, Jaller. et al. (2013) and Zou et al. (2016) [17, 18] used FTG estimates together with average values of arrival rates and parking durations to assess the needed parking supply to satisfy demand and to evaluate urban logistics scenarios such as the use of smaller vehicles and the reduction of parking durations. However, to assess the impact of policies at the level of a single establishment, one should also consider the difference in vehicle arrival rates over time and vehicle drivers' parking behaviour (e.g. willingness to queue or to park illegally).

Some authors collected data at the level of individual establishments to quantify the freight parking congestion generated. For instance the works by Morris (2004) and literature therein [19, 20] performed "time-and-motion" studies at the loading bays of several commercial office buildings, reporting arrival rates and average dwell time. Also, Cherrett et al. (2012) and Allen et al. (2008) [21, 22] summarise empirical results from multiple establishment surveys performed in the U.K. However, this data was not used to assess the impact of urban logistics initiative, nor was statistical modelling used to describe freight driver behaviours.

Recent studies formulated data-driven models to capture freight drivers' parking behaviours. For instance Zou et al. (2016) [18] used disaggregate data obtained from surveying freight vehicles' drivers that parked on-street in New York to derive a Cox proportional-hazard model of parking durations, using as explanatory variables the arrival time, commodity handled, type of vehicle and parking location. Nourinejad et al. (2014) [23] similarly surveyed on-street parked freight vehicles to derive a parking choice model, and used it within a parking simulation software to assess different parking management strategies.

While the collection of disaggregate data in the urban freight literature is still scarce, it has been widely used in the empirical study of call centres, hospitals and inventory systems [24–26]. In these works, the activities performed by each agent in a system (e.g. the different phases a call goes through in a call centre, or the different stages experienced by a patient recovering in a hospital) are recorded by a series of time-stamps. Such data is useful in computing the congestion of the system and analyse the effect of congestion on agents' behaviours.

Taking inspiration from these works, we collect detailed data on the different operations performed by freight vehicle drivers while delivering/picking-up goods at large urban retail establishments. We use this data to characterize the freight parking systems of these establishments and to study the effect of parking congestion on the behaviours of freight vehicle drivers. Specifically, we describe (i) the arrival process of freight vehicles to the facilities, (ii) the distribution of parking durations and derive a parking duration model, and (iii) observe the effect of parking congestion on the drivers' choices of parking facilities. These empirical analyses are addressed in the context of a specific type of establishments, namely *urban retail malls*.

1.2 Motivation and research focus

A first practical motivation of this work is the recent interest of the Singapore government in piloting some of the aforementioned urban logistics initiatives to improve freight traffic flow and reduce congestion at urban retail malls [27, 28]. A *retail mall* is a conglomerate of retail stores located within the same building, each store attracting and producing freight vehicle trips from multiple suppliers and to multiple destinations. Large malls often have a *Loading Bay* (LB) facility, defined as an area comprising one or multiple parking lots (individual vehicle parking space) reserved for freight vehicles that temporarily park while delivering/picking up goods at the in-mall stores. The authors have identified a total of 113 large urban retail malls in Singapore, hosting around 12,500 stores (the median number of stores per mall is 114). Based on the average number of truck trips per business observed during our data collection, we estimated 37,500 truck trips generated daily by these malls, an average of 330 truck trips per mall. This number is not too far from other estimates found in the literature; for instance Jaller et al. [1] found that the Grand Central Station of New York hosts 184 businesses and attracts 100 to 250 trucks per day. Eidhammer et al. (2016) [29] reports an average of 5.1 shipments per week generated by a retail located in a shopping mall, and compared it with an average of 4.7 shipments/week for a retail store located on-street. However, we observed that many malls, although still complying with the governmental regulations of minimum parking requirements, host LBs with only 2–3 parking lots. We therefore expect and observe substantial externalities generated at these facilities. In the current work, we aim to quantify these externalities, characterizing the freight vehicles congestion generated at the LBs. This work is part of a larger project which empirical results here described are then used to inform data-driven models to evaluate the impact of different urban logistics initiatives at retail malls.

A second practical motivation is to contribute to the lack of empirical understanding of urban freight vehicle movements and of freight vehicles drivers' behaviours. Urban freight data is notoriously hard to collect; mainly because the urban logistics system is made of independent private enterprises, which may or may not collect data at different level of details and with most of the data being proprietary. Whenever urban freight data is available to the researchers, it often presents several difficulties to work with. First, it may not be detailed enough, containing aggregated data, e.g. traffic count data. The collection of more detailed data on individual truck trips often come at the expense of losing completeness, namely only a small sample of the whole population of vehicle-trips is captured by the researcher. Moreover, data collections are often not comprehensive, observing only a subset of the system agents. The current work is based on a dataset obtained at two typical urban retail malls in Singapore, between June 2015 and January 2016. Using simultaneously automated (video recordings and parking gates online data) and manual (driver and vehicle surveys) data collection methods we obtained data that is detailed, i.e. at the level of a single truck trip, and complete, i.e. we observed all freight vehicle trips that took place during the observation period. The resulting dataset offers a comprehensive empirical view of an urban freight parking system.

1.3 Structure of the article

The next Section introduces two perspectives to analyse a freight parking system of an urban retail mall. First, we describe the process flow of a single agent (driver) through the system; then, we represent the mall's freight parking as a queueing system and identify the main *system parameters* which include statistics for (i) the arrivals, (ii) the parking durations and (iii) the queueing time spent to access the LB and the agents' parking behaviour. The same components are empirically described respectively in Sections 4.1 to 4.3. The data sources and the site from which they have been collected are described in Section 3. We conclude with final remarks in Section 5.

2 Theoretical framework

The system under study is comprised of three main physical components: a commercial area hosting the mall's stores, the mall's parking infrastructure, which usually include a *Loading Bay* (LB) and a carpark, and a service road connecting the road network to the mall's parking facilities. The system agents are freight vehicle drivers that compete for the use of the mall's parking facilities, while delivering/picking up goods at the in-malls stores. Section 2.1 describes the baseline process flow of a single agent in the system. Then, in Section 2.2 we represent the mall's freight parking as a queueing system and define the system primitives: the parking demand, i.e. the number of arriving agents to the mall; the parking supply, i.e. the number of parking lots available for freight vehicles; and agents' parking behaviour in the presence of congestion of the parking facilities. Finally, Section 2.3 identifies metrics for quantifying the system performance and compare different malls parking facilities. The main definitions introduced here will be later used in the empirical analysis in Section 4.

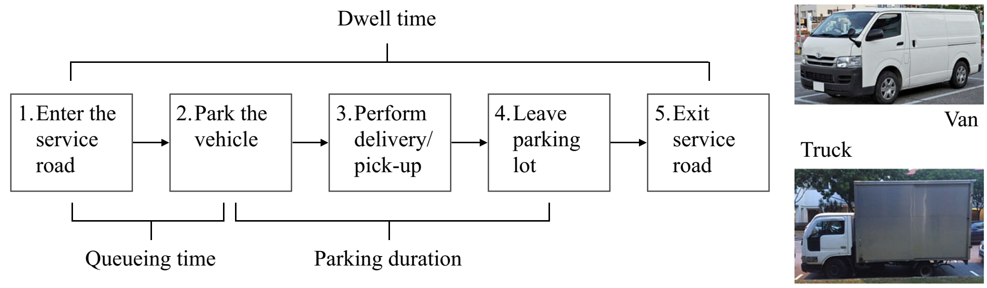
2.1 Overview of a freight vehicle operations

Figure 1 describes the typical flow of activities performed by a freight vehicle driver delivering/picking up goods at a retail mall. A driver *(1)* enters the service road, *(2)* parks the vehicle, *(3)* unloads and carries the goods to the in-mall stores and performs any delivery or pick up, *(4)* returns to the vehicle, loads any goods picked up and leaves the parking lot and *(5)* exits the service road.

We define *queueing time* as the time a driver waits before being able to park the vehicle; it is estimated as the difference between the time the vehicle enters the service road (activity 1) and when the vehicle become stationary (activity 2); *parking duration* is the time a vehicle remains parked while performing the delivery/pick up (estimated by the time interval between activities 2 and 4); *dwell time* is the total time between the entrance and exit of the service road (activities 1 to 5).

A freight vehicle driver faces three main choices: at what time to arrive to the system, how long to stay in the system and where to park the vehicle. While the first two choices are to some degree exogenous, i.e. chosen by the carrier company,

Fig. 1 Baseline process flow of a goods vehicle delivering or picking up goods. Right of figure: example of van (height < 2.5 m) and truck (height > 2.5 m)



the store manager or the supplier, we assume that the parking location choice is fully determined by the driver himself. According to the type of vehicle used, a driver faces a different set of parking location choices. We classify freight vehicles into *trucks* and *vans*: a freight vehicle with height above 2.5 m is defined as a truck, while below 2.5 m is defined as a van (right of Fig. 1). We introduce this definition to distinguish between those vehicles that are able to enter a passenger' carpark from those that are not able to. Off-site passengers' carparks in Singapore often have an overhead height clearance bar at 2.5 m. From this definition, a truck driver can only park in the LB or on-street; a van driver can additionally park inside the passengers' carpark.

The LB is usually the preferred choice because it is reserved for freight vehicles and offers extra services such as elevated loading/unloading platforms, freight elevators and security personnel. However, since it is often limited in the number of parking lots available, and these lots are shared among all the in-mall stores' suppliers, at any point in time there is a positive probability that all the lots are occupied and therefore a queue forms. Therefore, a driver might have to wait to access the LB. Since the LB is a scarce resource, its users are often required to pay a parking fee to make use of it. Moreover, the parking fee is usually tied to the length of the parking stay, and might be used to limit extremely large parking durations. Whenever the fee is not requested, other means of limiting parking durations are usually observed, e.g. the presence of parking guards. On the contrary, on-street parking is free of charge and does not involve any time spent waiting. However, parking and loading/unloading on-street involves other costs: the risk of being fined by the traffic police (in Singapore unloading on-street is often considered an illegal practice), longer walking distance to reach the in-mall stores, safety concerns due to driver exposure to road traffic, higher chance of incurring a theft. Finally, vans' drivers additionally park inside the carpark. Although freight vehicles should not load/unload inside the carpark, it is often a tolerated practice. In suburban malls, carparks are usually free of charge, since they are dedicated to the mall's customers to park their vehicles while shopping [30]. However, urban malls tend to impose a parking fee in order to limit its usage by non-customer vehicles [31]. Often, its parking fee is higher than the LB (in Table 1 we can see that this is the case for one of the two malls observed). Moreover, compared to the LB, the driver might have to walk a longer distance to reach the in-mall stores, no security service is provided and the driver often must cruise to look for an available parking lot. On the other hand, since the carpark is often larger than the LB, it rarely experiences congestion and therefore it does not involve any waiting time and it does not entail any risk of getting fined.

2.2 Freight parking as a queueing system

In the previous section, we described the typical operations of a freight vehicle driver delivering/picking up goods at a retail mall. While each agent acts independently, his/her decisions and performance are affected by the physical characteristics of the system (e.g. number of available parking lots), by how the system is managed (e.g. parking fees, information regarding the queue length) and by the other agents' decisions, whose parking location choices and parking durations determines the overall congestion of the system. We now describe the mall's freight parking as a queueing system in which agents are not analysed individually as in the previous section, but instead are represented as flows in the system.

Figure 2 schematizes a mall's freight parking system. The number of freight vehicles arriving to the system per unit of time, also referred to as *arrival process*, represents the *potential demand* for freight parking. The LB represents the main parking facility for freight vehicles, hosting multiple parking lots where freight vehicle park while delivering/picking up goods at the in-mall stores. When all the LB parking lots are occupied, vehicles are blocked from entering and must join a *queue*. The queue is described by its length, measured in the number of vehicles waiting for a parking lot to become available. The number of freight vehicles joining the queue per unit of time, called the *joining process*, represents the effective parking demand. The arrival process differs from the joining process (the potential parking demand is larger than the effective demand) when drivers park and unload their vehicles outside the LB: on-street or inside the carpark. We refer to the number of freight vehicles parking outside the LB per unit of time as the *balking process*. Other than joining the queue or balking, drivers have a third option: to leave and to return to the system later. We call these agents *retrials*.

Table 1 Description of observed retail malls and their parking facilities

	Mall A	Mall B
Number of stores	170 stores	162 stores
Total retail floor area	21,800 m^2 (234,653 ft^2)	29,200 m^2 (314,306 ft^2)
Number of floors	7	6
Retail mix	Dining (26%), Electronics (19%), Fashion (30%), Others (25%).	Dining (32%), Electronics (6%), Fashion (31%), Others (31%).
Anchor tenants[a]	3	5
Opening hours	10 am – 10 pm	10 am – 10 pm
Loading bay size	6 parking lots	16 parking lots
Loading bay cost[b]	Free	S$1 per 30 min
Carpark cost[b]	S$1.2 (first hour), S$0.8 per every subsequent 30 min	S$1.07 (first hour), S$0.32 per every subsequent 15 min

[a] Anchor tenants are those stores that are larger in size and tends to produce a larger amount of freight trips, compared to other stores (e.g. supermarkets, food courts and department stores)

[b] 1.0 Singapore dollar (S$) = 0.7 US dollar

2.3 Performance evaluation

Different metrics can be used to quantify and evaluate the system efficiency. The total time spent by freight vehicles waiting in queue or the average queue length evaluate the efficiency of the LB. Long queue and queueing times have negative economic and environmental impacts. The time spent waiting in queue could have been utilized to perform more deliveries. Receivers at the retail mall stores also see increased variability of delivery time with higher costs of personnel and probability of stock out. From an environmental standpoint, queueing freight vehicles often keep the engine on or idling, generating air and noise pollution, with negative impacts to the surrounding environment and to the shoppers.

There is a trade-off between the balking and joining processes: long queues incentivise drivers to balk and park on-street and inside the carpark. Measuring the total number of vehicles balking is important as high balking process is undesirable, as previously discussed in section 2.1.

Finally, retrials are also a source of inefficiency as they disrupt the delivery schedule of the driver, increasing the delivery time variability and increase the vehicle kilometres travelled by the vehicles.

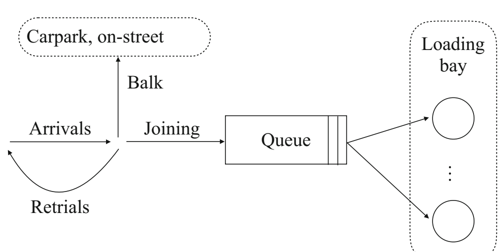


Fig. 2 Queueing system representation of a freight parking system of a retail mall

3 Data description

3.1 Data sources

Disaggregate data on freight vehicles parking and delivery patterns was collected at two large urban retail malls in Singapore. Section 3.2 describes the key features of the observed malls and the summary statistics of the data collection. In this section, we describe the data sources and the main variables recorded.

We combine three main data sources: (1) *road-side video recordings*, (2) *driver surveys and vehicle observations* and (3) *parking gates data*. All three data sources have the same observational unit: freight vehicle-trips at urban retail malls. Vehicle license plates are recorded in all data sources to uniquely identify each vehicle and to be able to merge the information across the different sources. Other than the vehicle license plate, the data sources differ in the type of variables collected and in the time span of data collection. Road-side video recordings and manual driver surveys and vehicle observations are collected simultaneously, over few days for each mall observed, approximately for 12 hours a day, from 6 am to 6 pm. Conversely, parking gates data records information on all vehicle-trips that took place over 6 months, 24 hours a day.

Together, these three data sources provide a detailed and complete view of the operational history of each vehicle trips at urban retail malls. Data is detailed in the sense that is disaggregate at the level of individual vehicle-trips; is complete because some basic variables such as license plate, arrival time and dwell time are collected for the totality of the freight vehicles passing through the system, during the time span of the data collection.

In the following paragraphs, the data collection method used for each data source is described together with the main variables obtained.

3.1.1 Road-side video recordings

Several video cameras have been placed roadside at different locations: at the entrance and exit of the service road and at the entrances and exits of the parking facilities. The recordings were then processed with a license plate recognition algorithm to retrieve the *(1)* plate of the vehicles passing by the different road sections and *(2)* the time at which the plate is first recognized. Merging the data obtained from the different cameras, we obtained for each single freight vehicle arriving at the mall, a sequence of time-stamps corresponding to the activities described in Fig. 1. The variables obtained are:

- *vehicle_ID*: unique vehicle identifier;
- *arrival_time*: time of arrival at the service road;
- *park_time*: time at which the vehicle parked;
- *park_location*: location where the vehicle parked, among LB, carpark and on-street;
- *exit_time*: time at which the vehicle exits the service road;
- *park_duration*: parking duration, computed as the difference between *exit_time* and *park_time*;
- *qtime*: queueing time, computed as the difference between *park_time* and *arrival_time*;
- *dtime*: dwell time, computed as the difference between *exit_time* and *arrival_time*.

3.1.2 Driver surveys and vehicle observations

Driver surveys and vehicle observations have been manually collected: surveyors were staged at the different freight parking locations of the malls (including on-street illegal parking locations and inside the passenger carparks) and observed the parked freight vehicles and interviewed the drivers. Drivers were randomly selected for interview among those parked, and the interviews were carried out at the end of the delivery/pick-up to not interrupt the drivers' work. To maintain a constant rate of drivers interviewed over different times of the day, the number of surveyors were increased during peak hours (between 10 am and 2 pm). Surveyors have been trained to be able to approximately recognize volumes in order to quantify the total size (in m^3) of goods transported by the drivers.

For each interview, the following variables are recorded:

- *vehicle_ID*: unique vehicle identifier;
- *vehicle_type*: type of freight vehicle, classified as small and large vans, small and large trucks and others;
- *vehicle_loading*: percentage of vehicle capacity filled with goods as observed by a surveyor before any delivery/pick-up is performed;
- *commodity_type*: types of commodities handled;
- *pickup*: binary variable recording whether any goods have been picked-up and loaded in the vehicle;
- *size*: total volume (m^3) of goods delivered and/or picked-up;
- *workers*: number of personnel from the vehicle performing the delivery/pick-up of goods, including the driver.

3.1.3 Parking gates data

At one of the sites observed, vehicles entering the mall's parking facilities must pass through a *gate*, i.e. a barrier, equipped with a vehicle recognition system, which lifts once the vehicle has been correctly recognised and whenever there are available parking lots inside the parking facility. The system is used to automatically charge the vehicle owner for the parking time at the mall. We were granted access to 6 months of the electronic recording of the parking gates for both the LB and the carpark of mall B. The following main variables have been obtained:

- *vehicle_ID*: unique vehicle identifier;
- *park_location*: type of parking facility the vehicle accessed (LB or carpark);
- *park_time*: time at which the vehicle has entered the gate;
- *park_duration*: length of time interval a vehicle stayed inside the parking facility.
- *paid_amount*: total amount paid in Singapore dollars.

3.2 Data collection

The data sources previously described have been collected at two large urban retail malls in Singapore, which we refer to as *mall A* and *mall B*. The malls were selected given the availabilities of the respective landlords in participating in the study. Table 1 describes each mall's key features: size, retail mix and the parking facilities.

Both malls have similar retail floor area, number of stores and retail mix, with the only difference of mall B having a larger share of stores selling digital products and having two more department stores which are not present in mall A. Moreover, the retail mix of the malls is relatively balanced, and the malls' sizes is comparable to an average mall in Singapore (on average a mall hosts 133 stores).

The malls' parking infrastructure are different. Compared to mall B, mall A has a much smaller LB, and illegal on-street parking is a well-known problem for the management, while mall B's service road presents roadside barriers which limits on-street parking.

At the time of the data collection, both malls did not support the carriers and receivers in performing the deliveries, e.g. no centralized receiving policy was implemented. From observations, drivers perform the delivery by hand, carrying the goods directly to the receiver location inside the mall. Only for one large receiver (a supermarket), store employees were observed helping the driver in unloading the truck.

Roadside video recordings and vehicle observations and driver surveys were collected for one day at mall A (Friday 26th July 2015) and for two days at mall B (Thursday 21st and Friday 22nd January 2016), from 6 am to 6 pm. Table 2 summarizes the number of vehicle trips recorded by each data source, per day of data collection. From the road-side video recordings we observed the total number of vehicle-trips generated by the malls. These values include not only those vehicles that park in the parking facilities or illegally on-street, but also those vehicles that pass-by the site without stopping. We assume that those with a dwell time larger than 4 min are vehicles that stop at the mall, while those with a dwell time below 4 min are passing through. We note that there are more vehicles passing through site B than site A. This is expected as the mall B service road is shared with another mall.

On average, 40% of the vehicles that stopped were recorded manually (surveyors performed the vehicle observations). Of the observed vehicles, around 90% of the drivers accepted to answer at least one question of the interview.

4 Empirical analysis

4.1 Arrival process

In section 2.2 we distinguished between the *arrival process* and the *joining process*. The arrival process represents the potential parking demand; the joining process represents the effective parking demand, and is quantified by the number of freight vehicles that join the queue and park inside the LB. Any difference between then arrival and the joining processes is explained by a third process, called the *balking process*, quantified by the number of freight vehicle that parks on-street or in the carpark. We focus here on the arrival process. The balking process is discussed in Section 4.3.

Figure 3 displays the observed hourly number of freight vehicles arriving and parking at the malls between 6 am and 6 pm. A total of 456 freight vehicles were recorded at mall A; 546 vehicles during the first day and 500 vehicles during the second day at mall B. Mall A has a mean arrival rate of 41 vehicles per hour, with a standard deviation of 15 vehicles (37% of the mean). Mall B shows higher mean arrival rates, 50 vehicles per hour the first day, 46 the second day, with standard deviations respectively of 22 and 21 vehicles (about 44% of the means). All arrival processes show a bimodal pattern with two main peaks: the morning peak is around 10 am while the afternoon peak is between 1 and 2 pm. It seems that the arrivals are highly influenced by the stores opening time (most of them open at 10 am). Moreover, the morning peak for freight is postponed in respect to the passenger peak, as shown in other studies [12].

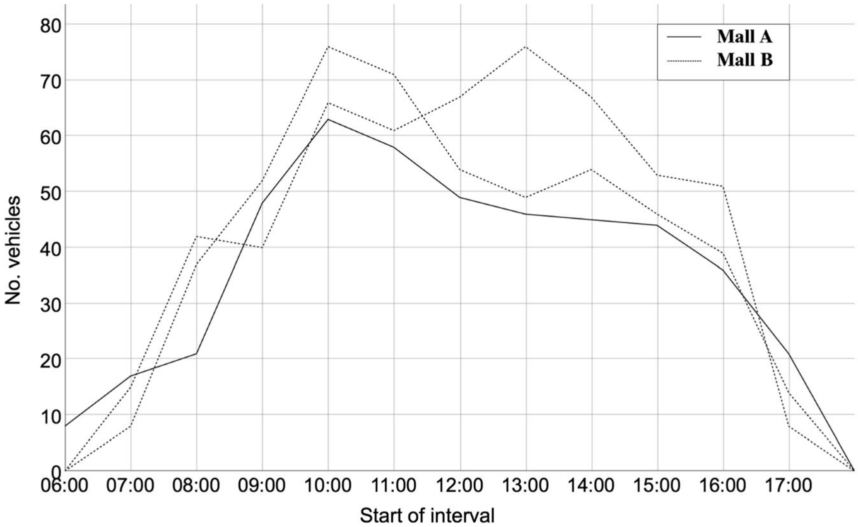
We further note that the afternoon peak of the first day at mall B is higher than the morning peak; while the morning peak is higher for the other two days. No explanation could be offered for this phenomenon. Perhaps, since the other two days are both Fridays while the one with a different behaviour is a Thursday, Fridays seem to experience a reduction of arrivals in the afternoon.

Table 2 Number of vehicle-trips recorded

	Mall A	Mall B	
	Friday, 26th July 2015	Thursday, 21st January 2016	Friday, 22nd January 2016
Roadside video recordings	598 trips, of which 456 stopped[a]	927 trips, of which 546 stopped[a]	876 trips, of which 500 stopped[a]
Vehicle obs. and driver surveys	189 trips	168 trips	246 trips
Parking gates data	No data available	3502 trips, of which: • 391 in the LB • 3111 in the carpark[b]	3806 trips, of which: • 420 in the LB • 3386 in the carpark[b]

[a] While the total number of trips recorded by the roadside video cameras include vehicle passing by, we defined those vehicles trips with a dwell time > 4 min as vehicles that stopped at the mall

[b] Vehicle-trips to the carpark include the passenger vehicles



	Total arrivals	Arrivals per hour	
		Mean	St. dev.
Mall A	456	41	15
Mall B (day 1)	546	50	22
Mall B (day 2)	500	46	21

Fig. 3 Number of freight vehicle arrivals per hour, observed for one day at mall A and two days at mall B

We define *retrials* as those vehicles that visited the mall earlier during the day but then rescheduled the delivery/pick up to a later time, perhaps because of congestion. This behaviour is similar to the phenomenon of *cruising*, described for the passenger vehicle drivers' parking behaviour by Shoup (2006) [32] as a "mobile queue of cars that are waiting for curb vacancies"; with the difference that in the current setting, freight vehicles might reschedule the delivery to a later time and perform other tasks in the meantime. Using the data obtained from the video recordings we quantify the retrials during one day at mall A at only 2% of the arriving vehicles; while during the two days at mall B, retrials are respectively the 4% and 5%. We conclude that, in the observed malls, retrials do not represent a significant share of the arrivals and that freight vehicle, once they entered the system, either park in the LB or balk. Similar behaviour was found in Nourinejad et al. [23], noting that compared to passenger vehicles, commercial vehicles spend less time cruising and are more willing to park illegally.

We conclude noting that seasonal variations of consumption at the malls could explain the differences of arrival rates between mall A and B, as mall A was observed in July and mall B was observed in January. Mall B's arrival rates might be higher than mall A's because it was observed in the weeks preceding Lunar New Year, a major holiday period in Singapore which took place on the 8th and 9th of February 2016.

4.2 Parking duration

The main variable of interest in this section is the *parking duration* (PD), defined as the time span a vehicle remains parked while performing a delivery/pick-up. This time interval includes the time to unload/load goods, walk to the receiver's location, perform any delivery/pick-up, return to the vehicle and perform any other non-goods related tasks (such as taking a break).

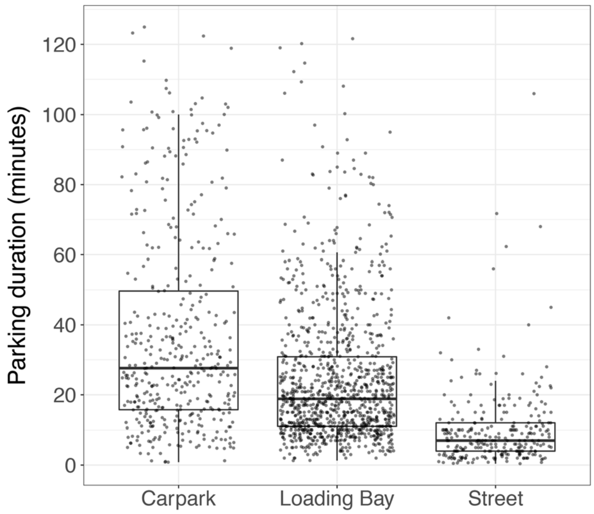
PD is a central variable in our analysis as it determines the utilisation of the parking infrastructure. Long PDs, together with high arrival rates, are the main causes of congestion of the LB, which in turn is correlated with higher levels of balking, as shown later in Section 4.3. Therefore, a better understanding of the nature of PD is needed to better manage the scarce parking resources.

In section 4.2.1 we compare the distribution of PDs across freight vehicles that parked in different locations: we observe that durations of freight vehicles parked at the LB are significantly different from those parked on-street and inside the carpark. We then focus the rest of the analysis only on the PDs for the vehicles that parked in the LB and plot its distribution in section 4.2.2 and identify the lognormal distribution as the best fit to the data. Section 4.2.3 analyses the time series of PDs of individual freight vehicles and introduce the concept of *weak stationarity.* Finally, in Section 4.2.4 we perform a regression analysis on the log(PD) over multiple observed variables (size of delivery, number of helpers etc.) to shed light on which factors explain longer durations.

Beyond the empirical results reported in this section, little is known of the nature of activities performed by the driver inside the mall, as that would involve following the drivers outside the LB, which encompass significant difficulty in the data collection and privacy concerns.

4.2.1 Parking duration and parking location choice

The empirical distribution of PDs significantly differs between the vehicles that parked at the LB, on-street and inside the carpark. In Fig. 4, each "box" displays the main statistics describing the empirical distribution of the PD: from bottom up the horizontal lines represent respectively the first quartile,



	Carpark	Loading Bay	Street
1st quartile	15.7	11.0	4.0
Mean	36.9	24.5	10.3
Median	27.6	18.9	7.0
3rd quartile	49.7	30.9	12.0

Values are in minutes

Fig. 4 Boxplot and descriptive statistics of parking duration distributions by parking location

the median and the third quartile of the empirical distribution. We can observe that PDs of on-street parked vehicles have significantly lower quartiles compared the LB and carpark parked vehicles, while those inside the carpark show the largest quartiles as well as the largest deviation.

One explanation could be that the driver knows in advance the expected PD needed to perform his task and the time it should leave the site in order to visit other receivers and then selects the parking location accordingly: the driver will select illegal on-street parking if a short PD is expected and the probability of getting a parking ticket is low; however, if the driver expects a long PD, he prefers the LB or the carpark. Further analysis of the effect of LB congestion on parking facility choice is carried out in Section 4.3.3.

4.2.2 Parking duration distribution

In the following analysis, we use a sample of about 63,700 freight vehicle-trips to the loading bay (LB) of mall B, obtained from the parking gates dataset. From this initial sample, we eliminate the top 0.5% of the PDs from each tail, such that the remaining PDs (about 63,000 data points) are between 1.5 min and 3 h, treating the observations outside this range as outliers. The sample mean, median and standard deviation are respectively 30, 20 and 28 min.

Figure 5a plots the histogram of the of PDs, which shows a right-skewed (the mean is significantly larger than the median), heavy tailed distribution of positive values. For this type of histograms, the lognormal distribution is a good candidate model. We estimate the distribution parameters using the Maximum Likelihood Estimator (MLE), which in this case is the sample mean and standard deviation of the logarithm transformation of the PDs, which are respectively $\mu = 3.02$ and $\sigma = 0.89$. We overlay the best fitting lognormal distribution in Fig. 5a, showing a remarkable fit. We then plot in Fig. 5b the Q-Q plot of the log(PD). The points almost perfectly follow the straight line, revealing a very good fit. However, exact lognormality of PD cannot be stated. Using a Kolmogorov-Smirnov test we reject the null hypothesis of lognormality (the KS-statistic found is 0.016, the respective p-value is approximately 0). Since the KS test here is applied to a very large dataset, any small deviation from the hypothesised distribution result in a rejection of the null hypothesis [33]. From the Q-Q plot we can identify the source of this deviation: the data show lighter tails than a lognormal distribution with fewer large PDs and more PDs being concentrated around the median.

A similar analysis of PD data collected at mall A shows similar results: also in this case, a lognormal distribution ($\mu = 2.83$, $\sigma = 0.78$) provides a good fit for the data, although in this case we have fewer data points as the parking gates data is not available for mall A.

4.2.3 Vehicle-by-vehicle analysis

We now analyse the PDs of individual freight vehicles. We selected the top 100 freight vehicles that have the largest number of data points (frequently returning vehicles) that span the whole study period (January to July 2016).

We introduce here the concept of *weak stationarity* in the context of parking durations. Loosely speaking, a sequence of observation that varies in time is weakly stationary if it shows the same behaviour over different time windows [34]. In the specific case of a single freight vehicle often returning to the LB of a mall, having a weakly stationary sequence of parking durations means that its recorded PDs at the observed mall vary randomly around the mean with a constant standard deviation, and the mean PD does not change over time.

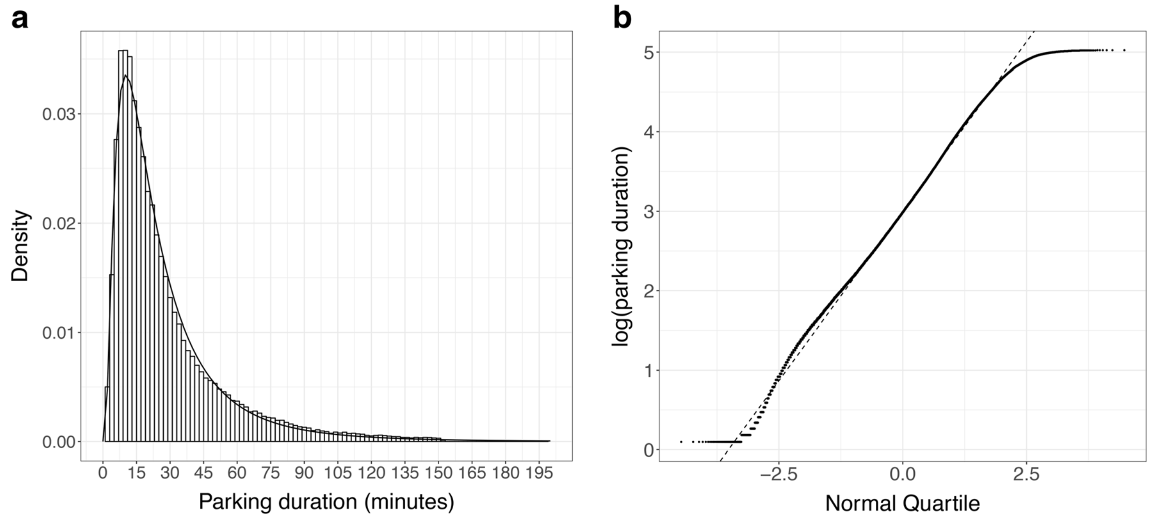


Fig. 5 **a** Histogram of parking duration with a lognormal ($\mu = 3.02$, $\sigma = 0.89$) superimposed. **b** Normal Q-Q plot of the logarithm of parking duration

A weakly stationary time series does not show seasonal variations nor trends in the mean; in other words, time does not influence the processes which determine the PD, at least for the timeframe considered. This suggest that the same factors that determine the PD during the observed period of data collection (during the few days in which the driver and vehicle surveys have been collected) might have not changed over time. Hence, it would be reasonable to study PD and its determining factors, using data collected over only few days of the year.

We can formally test whether there is any significant trend in the mean PD for individual returning freight vehicles using regression analysis of log(*parking_duration*) over time. This methodology has been used to identify the effects of *learning* and *forgetting* in agents performing the same type of task over time [24]. Using data from each of the 100 freight vehicles identified, we fit the following curve:

$$\log(PD_{ki}) = \alpha_i + \beta_i \log(k) + \epsilon_i, \quad \forall i = 1, \ldots 100 \;;$$

where PD_{ki} is the k$^{\text{th}}$ parking duration for vehicle i; $k \in \{1, 2, \ldots\}$ is a chronological index; α_i and β_i are the unknown parameters to be estimated using data from each freight vehicle i and ϵ_i is a zero-mean normally distributed error term. For each freight vehicle i we use Ordinary Least Squares (OLS) to estimate the unknown parameters ($\hat{\alpha}_i, \hat{\beta}_i$) and their respective *p*-values. A negative value for $\hat{\beta}_i$ shows that the mean PD for the i^{th} vehicle decreases over time; a positive value indicates that the mean PD increases over time; a close to zero value indicates that there is no change in the mean over time. We are particularly interested in the *p*-values as, whenever this value is large enough (we use standard threshold of 0.05), we conclude that the estimated coefficient $\hat{\beta}_i$ is not statistically significantly different from zero. Table 3 reports the estimates and their respective *p*-values for the first 45 freight vehicles; coefficients with p-values larger than 0.05 are reported with a shaded background. Most of the estimated coefficients are non-significant, with the few significant ones being relatively small and negative.

4.2.4 Explaining parking duration

In the previous paragraphs, we gained two main insights about the PDs: (1) they are lognormally distributed and (2) weak stationarity might be assumed, but the mean and standard deviation vary across vehicles. Lognormality is a welcomed property to use standard regression techniques to study the mean of log(PD) over different covariates. Moreover, stationarity ensures that the factors affecting PD and identified with data collected over a short time span, are still determining the PD if data was collected at a different time. In the rest of the section we analyse which covariates affect the PD. We regress the log(PD) on the following covariates:

- *vehicle_loading*: percentage of the vehicle that was filled with goods before the delivery is performed;
- *pickup*: binary variable that indicates whether any pick-up was performed;
- *size_worker*: total size in cubic meters of goods delivered and/or picked-up divided by the total number of people in the vehicle including the driver;
- *qtime*: total time (in minutes) spent in queue outside the LB;
- *van*: binary variable indicating whether the vehicle is a van.

Table 3 Estimated coefficients and p-values for the first 45 freight vehicles. *P*-value > 0.05 are underlined with shaded background

vehicle_ID	$\widehat{\beta}_i$	p-value		vehicle_ID	$\widehat{\beta}_i$	p-value		vehicle_ID	$\widehat{\beta}_i$	p-value
104201	0.002	0.927		201037	-0.634	0.019		104261	0.023	0.402
104263	0.009	0.547		104263	-0.006	0.856		151076	-0.067	0.030
201025	-0.021	0.345		104265	-0.013	0.582		151077	0.026	0.001
104190	-0.009	0.739		104207	-0.055	0.113		151057	0.056	0.062
104251	-0.068	0.000		151066	-0.015	0.562		104197	-0.014	0.274
151079	-0.017	0.089		151088	0.031	0.081		104198	0.000	0.999
151078	-0.009	0.614		104178	-0.007	0.746		151085	-0.002	0.961
151063	0.000	0.987		152011	-0.139	0.006		104185	-0.012	0.531
151053	0.023	0.374		104258	-0.069	0.012		151060	-0.104	0.000
104270	-0.144	0.000		104199	0.062	0.060		104267	0.037	0.283
151087	-0.029	0.419		104208	-0.085	0.000		151075	0.029	0.332
151053	0.078	0.025		104230	-0.030	0.182		104073	0.011	0.381
151065	0.000	0.973		151080	-0.024	0.145		104260	-0.115	0.000
151078	0.012	0.603		104265	-0.022	0.221		104205	0.009	0.862
151058	0.093	0.001		104260	-0.0148	0.499		104260	-0.025	0.229

Table 4 contains the results from the regression of log(PD) on the above listed covariates, using data collected from both malls together and for each individual mall separately. We focus our analysis on the sign of the estimated coefficients and their statistical significance (*p*-values); rows of Table 4 containing coefficients with p-values lower than 0.05 are shown with a darker background.

The signs are consistent using different subsets of the data, with the regression using data from mall A showing the highest goodness of fit (the adjusted R squared is 0.295). The estimated coefficient of *size_worker* is significant and positive, showing that larger is the quantity of goods handled per worker, longer the PD. A larger number of workers will instead reduce the parking duration, given a constant volume of goods transported. Also, the estimated coefficient for *vehicle_loading* is significant and positive. This variable can take only four possible integer values ranging from 1 (0 to 25% of the vehicle is filled with goods) to 4 (75 to 100% of the vehicle is full). Perhaps, when the vehicle is filled more, the loading/unloading of the specific goods takes longer time, as goods inside the vehicle must be sorted. Another possibility is that if the vehicle is fuller might indicate that the driver is at the beginning of its tour and therefore is less in hurry. The estimated coefficient for *pickup* is also significant and positive: whenever the task performed include returning with some goods picked-up to be loaded in the vehicle, the PD is longer. The coefficient for *qtime* is negative for two of the three subsets, possibly indicating that longer waiting times in queue are related with lower PD. However, we cannot trust this result as the *p*-values are very large, hence the estimates are not statistically significant. Lastly, the estimated coefficient for the binary variable *van* is negative, indicating that the PD for vans are shorter than for trucks. However, only combining data from both malls we obtained a slightly significant estimate, while using data from mall A and B individually the estimates are not statistically significant.

4.3 Queueing time and parking behaviour

In the previous two sections, we analysed the arrival rates and the parking durations of freight vehicles delivering/picking up goods at retail malls. In this section, we analyse the congestion of the Loading Bay (LB) and its effect on drivers' parking facility choice.

Table 4 Regression results for the log(parking duration). *P*-value > 0.1 are underlined with shaded background

	Both malls		Mall A		Mall B	
	estimate	p-value	estimate	p-value	estimate	p-value
(Intercept)	2.624	0.000	2.452	0.000	2.846	0.000
size_worker	0.131	0.000	0.195	0.000	0.082	0.000
vehicle_loading	0.117	0.000	0.104	0.012	0.095	0.029
pickup	0.400	0.000	0.478	0.000	0.289	0.016
qtime	-0.005	0.278	-0.004	0.481	-0.0002	0.980
van	-0.118	0.075	-0.149	0.114	-0.105	0.240
Adj. R-squared	0.211		0.295		0.116	

4.3.1 When is the loading bay congested?

Using the data from the parking gates of mall B, we compute the total number of vehicles parked in the LB at any point in time, between January to July 2016. We define a *congestion event* as the moment in which the number of vehicles in the LB reaches capacity (16 parking lots). For each event, we record (1) the length of time interval until one parking lot is freed and (2) the time at which the event happened. Figure 6a shows the distribution of the total number of hours per day the LB is congested. We observe the peak at 0 hour: these are mostly Sundays, when the LB never experience congestion. For the rest of the days the average time per day in which the LB is full is 4 hours, with the most congested day being Wednesday. Figure 6b shows that most of the congestion events take place between 9 am and 3 pm, with the first peak hour between 10 and 11 am and the second peak between 1 and 2 pm.

4.3.2 Waiting time distribution

When a freight vehicle arrives to the mall it joins a queue to access the LB, and therefore it experiences a *queueing time* greater or equal to zero, according to whether the LB is full or not.

We compute the queueing times for each vehicle that parked in the LB as the difference between the arrival time to the service road (*arrival_time*) and the entry time in the LB (*entrance_time*). This definition of queueing results in values that are always greater than 0, as they contain not only the time a vehicle waits in queue but also the time it takes a vehicle to travel the service road. We then subtract the smallest travel time recorded (around 1 min) from all queueing times. Clearly, only when the system is congested the queueing time is larger than 0. Following Brown et al. [25] we distinguish *queueing time* from *waiting time* (WT), the latter being always larger than 0. In the rest of the section we analyse the distribution of WT.

Summing all the waiting times for all the vehicles that parked in the LB in a single day, we obtain an average of 20 h of cumulative waiting time.

Figure 7a plots the histogram of the WT. The mode of WTs is close to 0. The sample mean ($\mu = 7.7$ minutes) is close to the sample standard deviation ($\sigma = 7.1$ minutes), which is a property of the family of exponential distributions. We then plot the best fitting exponential distribution with parameter λ estimated using the Maximum Likelihood Estimator, computed as the inverse of the sample mean ($\lambda = 1/\mu = 0.13$). Figure 7b shows a Q-Q plot of the WT against the quartiles of the best fitting exponential distribution, revealing an acceptable fit to our data.

We then estimate the WT from the queue length (*n_queue*) as follows:

$$WT = \alpha e^{\beta\ n\_queue}$$

where α and β are parameters that we will estimate using data collected at the observed malls. Using data from mall A we obtain estimates: $\hat{\alpha}_A = 0.9$, $\hat{\beta}_A = 0.2$. Using data from mall B we obtain estimates: $\hat{\alpha}_B = 0.1$, $\hat{\beta}_B = 0.2$. Interestingly, we obtain the same estimates for $\beta = \beta_A = \beta_B$, but different estimates for α. We then compare the WT at mall A (WT_A) with the WT at mall B (WT_B):

$$WT_B = \frac{\alpha_B}{\alpha_A} WT_A.$$

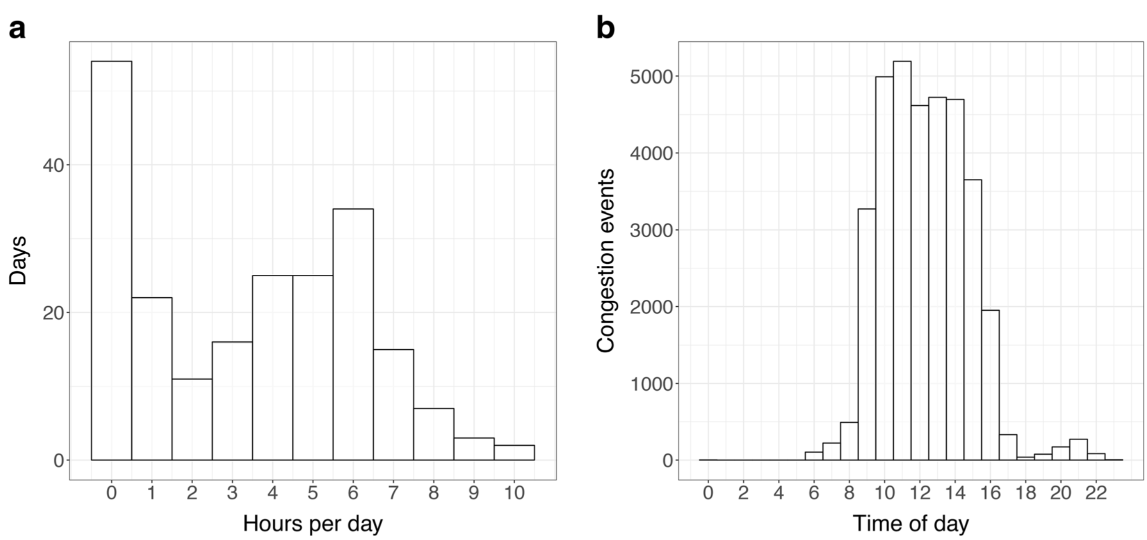


Fig. 6 **a** Number of hours per day in which the LB is full. **b** Time of the day when congestion events are observed. Both figures are derived using the gantry data, obtained for the period January to July 2016

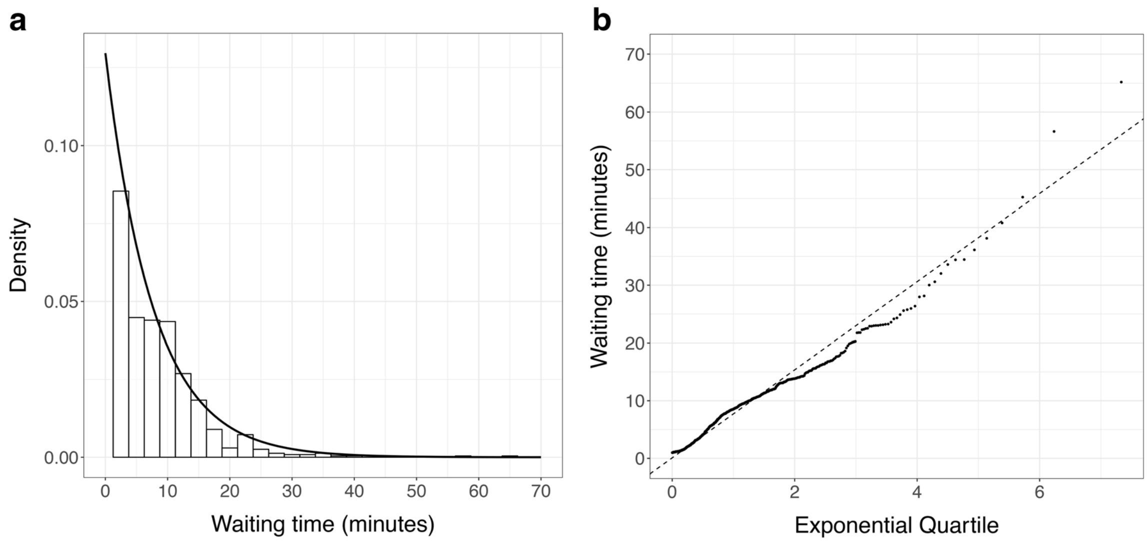


Fig. 7 **a** Histogram of waiting times with an exponential ($\lambda = 0.13$) superimposed. **b** Exponential Q-Q plot of the waiting times

Substituting the estimated parameters ($\hat{\alpha}_A$, $\hat{\alpha}_B$) in the equation above we obtain $\hat{\alpha}_B / \hat{\alpha}_A = 0.1$. For the same number of vehicles waiting in queue, a vehicle arriving at the LB of mall B waits on average the 10% of what it would have to wait to access the LB at mall A. This is most likely due to the different LB capacities at the two malls: the LB at mall a has 6 parking lots while the LB at mall B has 16. However, this result is based on the data collected at the two sites and might not be true for other sites.

4.3.3 Parking facility choice and congestion

Not all drivers are willing to wait in queue to park at the LB and might choose to park the vehicle elsewhere. Following the terminology used in [35], we refer to the decision of refusing to join the queue as *balking*. According to the type of freight vehicle used, alternative parking options are on-street parking and the passengers' carpark (only for the smaller vans can enter the carpark). Quantifying the phenomenon of balking and understanding why drivers decide to balk is a fundamental quest to improve the management of the LB and implement effective freight parking policies. On the contrary, not accounting for balking vehicles leads to the implementation of inefficient policies. For instance, a higher LB parking price might have a positive effect on waiting times, but a detrimental one for balking as more vehicles will choose to park on-street or in the carpark, increasing the congestion on the surrounding roads and in the parking areas reserved for the mall's customers.

In the current setting, we identified balking vehicles as those parking inside the carpark or on-street. Table 5 reports the shares of parking choices for each day of data collection. We found that LB is the least common parking location choice at mall A. While LB is the preferred choice at mall B, almost half of the drivers choose to park elsewhere. In general, we can conclude that balking is a relevant phenomenon that must be considered when studying such systems.

What causes the drivers' balking behaviour? Clearly, the fact that there is a positive probability at any point in time that the LB is full, and therefore that the drivers must wait in queue before parking, should discourage the drivers in choosing to park in the LB. However, waiting time is not known a priori. In the previous section, we assumed that the best estimate of expected waiting times comes from *n_queue*, the length of the queue of vehicles waiting for parking in the LB. In Fig. 8 we visually check this hypothesis by plotting the fraction of vehicles that choose to park at the LB, given that at the time of arrival, *n_queue* vehicles were waiting to access the LB. Overall, for all days the fraction of vehicles choosing the LB tends to decrease as the queue length increases. However, while the curve obtained using data from mall A is almost monotonically decreasing and show a steep downward slope, the curves obtained using mall B data show a larger variation and a less steep downward slope. It seems that drivers arriving at mall A are more discouraged by congestion than those arriving at mall B, given the same queue length, and that drivers at mall B are willing to join much longer queues

Table 5 Percentages of vehicles parking inside the loading bay, the carpark and on-street

	Mall A	Mall B	
	Friday, 26th July 2015	Thursday, 21st January 2016	Friday, 22nd January 2016
Loading bay	31%	49%	57%
Carpark	35%	25%	23%
On-street	36%	26%	20%

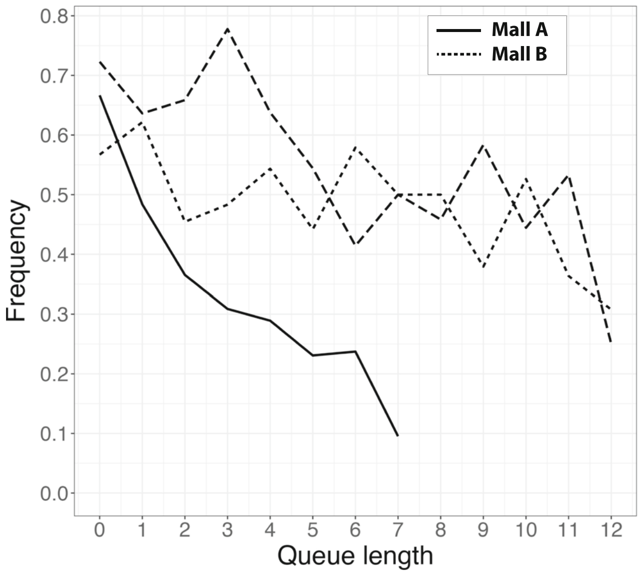


Fig. 8 Fraction of freight vehicles choosing to join the queue vs. the length of the queue. We observe one day at mall A and two days at mall B

compared to drivers at mall A. This is probably because mall B has a much larger LB, in number of parking lots. Therefore, given the same queue length, it is reasonable to expect a shorter the queueing time at mall B compared to mall A. In fact, we reached the same conclusion in the previous section. Freight vehicle drivers seem to take into consideration not only the queue length but also the speed of the server (considering the LB as a single server with service rate equal to the vehicles' parking durations).

5 Conclusion

5.1 Summary of empirical results

In this study, we empirically characterise the parking behaviour of freight vehicle drivers at large urban retail establishments. Combining traditional data collection methods (driver surveys and vehicle observations) with new sources of data, such as road-side video recordings and the electronic records of the parking facilities gates, we reconstruct the entire operational history of freight vehicles parking and loading/ unloading at urban establishments. Using data collected at two large urban retail malls in Singapore, we perform an empirical analysis of the key variables that can be used to characterise the freight vehicle parking system of these establishment, quantify the congestion levels of the parking facilities and assess its traffic impact. We therefore discussed the effect of arrival rates, parking congestion and parking durations on the behaviours of freight vehicle drivers at the observed urban retail malls. We summarize here some of the empirical results obtained.

The malls observed, which we refer to as mall A and B, attract between 400 to 500 vehicles trips a day (from 6 am to 6 pm). Most of the arrivals are between 10 am and 2 pm, showing a bimodal pattern with peaks in late morning (around 10 am) and early afternoon (1–2 pm). During these peak periods arrival rates are between 50 to 80 arrivals per hour. Peak arrivals correspond also to the times when the Loading Bay (LB), the parking area reserved for freight vehicles, is more likely to be congested. We observed little cruising of the freight vehicles: we identified the vehicles that pass through the system without stopping at least once before parking and performing the loading/unloading during the same day. These vehicles are a small share of all the vehicles parking at the malls, indicating that drivers of freight vehicles are less willing to cruise or reschedule their trip - once they arrive at the mall they perform the delivery, even if the parking facilities are congested.

Parking congestion at the LB affects the drivers' choice of parking facility, with higher level of congestion being associated with a higher rate of vehicles parking and loading/ unloading inside the carpark, which is usually reserved for passenger vehicles, and on-street, which is an illegal practice in Singapore. Interestingly, mall B experiences longer queues than mall A, even though they are similarly sized and mall B has a larger LB (16 parking lots compare to 6 at mall A). This might reflect a higher willingness to queue at mall B, as drivers expect the queue forming outside the larger LB to deplete faster than the one forming at a smaller facility. The empirical distribution of queueing times experienced by the vehicles at the two malls fits an exponential distribution, with a sample mean and standard deviation of around 7.5 min.

We analysed the parking durations of the freight vehicles. Vehicles parked in different locations show different distribution of parking durations, with vehicles parked on-street having the shorter parking durations and vehicles that park in the carpark showing longer durations. We then considered only the parking durations of vehicles inside the LB, showing a remarkable fit with the lognormal distribution and a sample mean of about 30 min. Analysing the time series of parking durations of individual vehicles that parked in the LB between January and July 2016, we see that there is no clear trend in the mean. It seems that parking durations are not affected by seasonal variation, nor the drivers seem to improve its performance overtime. Finally, longer parking durations are associated with a larger volume of goods handled per worker, for vehicles with higher loadings and whenever a pick-up is performed; while lower durations are associated with the vehicle type being a van, with a higher number of workers helping the driver in performing the delivery/pick-up and with longer experienced queueing times.

5.2 Managerial insights

In the empirical analysis above, we established a link between the drivers' parking choices, the parking congestion, the arrival times and the parking durations. For two urban retail malls, the parking congestion has been quantified, showing that the observed parking system suffer of long queueing times and large share of vehicles parking illegally or occupying parking areas reserved for the malls' customers. Such behaviours negatively impact the whole urban supply chain and on society, causing delivery delays, air and noise pollution and affects road safety when the drivers load and unload goods on-street.

Since most vehicles arrive during the stores opening time, off-peak delivery programs might have a positive effect on reducing peak hour congestion at the loading bays. However, these initiatives could impose extra cost on the retailers who must employ shop keepers at earlier or later times. More research effort should be directed in evaluating off-peak deliveries for large establishments [8].

An alternative solution is to establish centralized receiving stations, deploying a third-party logistics partner receiving the goods at the loading bays and carrying them to the stores whenever the retailer prefers. Although this initiative is relatively unexplored, it could reduce parking congestion since (1) it reduces the parking durations, and therefore increase the parking turnover at the loading bay and (2) it gives vehicles' drivers more freedom in choosing the arrival time and in scheduling their deliveries. However, to be effective, we recommend that such centralized receiving stations should (1) operate off-peak and outside the store opening times and (2) should be able to handle pick-ups, namely retrieving the goods from the stores and staging them at the loading bay until the drivers arrive at the mall.

5.3 Concluding remarks

One limitation of the study is that the observed parking behaviours might be different at other establishments, depending on the characteristics of the parking infrastructure and type of receivers hosted by the establishment. Whenever possible, we underlined the similarities and differences between the two locations observed, linking the physical characteristics of the parking systems with the observed behaviours. Moreover, the consider the observed malls to be representative of an average urban retail mall in Singapore, in terms of retail mix and number of stores hosted. The same data collection approach can be performed at other facilities to improve the generalisability of the empirical results.

The study focused on the behaviours of only one of the main agents of the urban freight system, namely the freight vehicle drivers, neglecting the influence of other agents: the shippers and the receivers. However, we have acknowledged such limitation focusing on two main decisions which we consider determined in most part by the drivers' alone, and which still have an important impact on the parking congestion and road traffic: the parking facility choice and parking duration. However, the describe data collection should be complemented with a retail and carrier surveys.

Finally, while the data collected is disaggregate at the level of each vehicle-trip, most of the analysis carried out used aggregated data (see sections 4.2.3 and 4.2.4). This paper presented the data collection and described a data analysis, which are the initial necessary step to characterize the systems being studied, before considering the impact of potential solutions. The future direction of the research is to use the disaggregate data to train mathematical models of drivers' parking behaviour, examining parking facility choice and parking duration. A preliminary result of this direction is presented in [6], where a parking choice model was developed and used in a queue simulation framework to analyse the impact of a centralized receiving initiative.

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