Transport Policy 97 (2020) 26–36

Contents lists available at ScienceDirect

Transport Policy

journal homepage: http://www.elsevier.com/locate/tranpol

Do commercial vehicles cruise for parking? Empirical evidence from Seattle

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ARTICLE INFO

Keywords:
Cruising for parking
Urban logistics
Freight parking
Google maps route data
Commercial vehicles

ABSTRACT

Parking cruising is a well-known phenomenon in passenger transportation, and a significant source of congestion and pollution in urban areas. While urban commercial vehicles are known to travel longer distances and to stop more frequently than passenger vehicles, little is known about their parking cruising behavior, nor how parking infrastructure affect such behavior.

In this study we propose a simple method to quantitively explore the parking cruising behavior of commercial vehicle drivers in urban areas using widely available GPS data, and how urban transport infrastructure impacts parking cruising times.

We apply the method to a sample of 2900 trips performed by a fleet of commercial vehicles, delivering and picking up parcels in Seattle downtown. We obtain an average estimated parking cruising time of 2.3 min per trip, contributing on average for 28 percent of total trip time. We also found that cruising for parking decreased as more curb-space was allocated to commercial vehicles load zones and paid parking and as more off-street parking areas were available at trip destinations, whereas it increased as more curb space was allocated to bus zone.

1. Introduction

Urban curb-space is a scarce resource that must satisfy the concurrent needs of an increasing number of users, including passenger, commercial, ride-hailing and public transit vehicles. In particular, there is an increasing demand for curb-space for commercial vehicles to park, load/unload, and deliver goods as more people live in urban areas, order more things online, and expect faster deliveries (Crainic et al., 2009). The increase in curb-space demand for commercial vehicles has often not been met with an increase in curb-space supply. One reason is that commercial vehicles are usually seen as a nuisance: they are larger and occupy more space, they generate more air and noise pollution than cars, and they often adopt parking behaviors that negatively affect other curb-space users. Consequently, public intervention has often limited freight traffic to certain areas and time windows, while repurposing space to activities considered more environmentally friendly, e.g., by pedestrianizing urban areas and creating bike lanes, thereby further reducing available curb-space (Conway et al., 2017). Consequently, commercial vehicle drivers are experiencing greater challenges in finding available parking. The cost and externalities of these challenges are not yet known.

1.1. Cruising for parking

A well-known consequence of lack of available parking is cruising for parking. In the absence of available curb-space, passenger vehicle drivers circle around their destinations searching for parking. The cost of cruising for parking is two-fold. First, the time spent searching for parking could be used for other, more useful purposes, and therefore it represents a direct cost to cruising drivers and passengers. Second, cruising vehicles contribute to traffic, thus increasing congestion and pollution and generating negative externalities to other vehicles and city dwellers.

The cruising costs of parking are difficult to measure. By simply looking at traffic, it is impossible to distinguish in-transit vehicles from cruising vehicles. In the past decades, researchers developed methods to study cruising from the perspective of passenger vehicles (we review some of these efforts in the next section). These studies shed light on the problem of cruising by quantifying its costs and externalities and fostered policy efforts in many cities around the world aimed at reducing cruising and improving urban traffic.

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https://doi.org/10.1016/j.tranpol.2020.06.013
Received 17 March 2020; Received in revised form 19 June 2020; Accepted 24 June 2020
Available online 9 July 2020

1.2. Commercial vehicles parking

While cruising studies and parking policies have focused on passenger vehicles, little is known about whether commercial vehicles experience a similar phenomenon.

Although commercial vehicles represent a small share of the urban vehicle population, their numbers have been growing in recent years. The registration of single-truck units in the U.S. increased on average 2 percent a year between 1970 and 2017 (Davis and Boundy, 2020) and their number is predicted to further increase by 36 percent in urban areas in the next 10 years (World Economic Forum, 2020). Moreover, commercial vehicles travel longer distances than passenger vehicles. Trucks in the U.S. have seen a 3.1 percent annual increase in vehicle miles travelled (Davis and Boundy, 2020). As a consequence, their contribution to total vehicle miles travelled is significantly growing. Although data from urban commercial vehicle travel is limited, they are expected to contribute between 20 and 30 percent of total vehicle miles travelled in cities (Dablanc, 2007). Commercial vehicles also stop more frequently than passenger vehicles. While passenger vehicles tours usually encompass few trips related to daily activities such as commuting or shopping, commercial tours in urban areas are characterized by a larger number of stops (Khan and Machemehl, 2017). Considering also the fact that only a limited amount of curb-space is allocated to commercial vehicle loading/unloading, we would also expect these vehicles to cruise for parking.

While the literature on commercial vehicle parking behaviors is limited, previous studies have assumed that commercial vehicle drivers do not cruise for parking but instead either park in commercial vehicle loading zones or park in the travel lane as close as possible to their delivery destinations. However, as shown in section 2, these studies have had little empirical ground truth, and more research should be spent on analyzing the cruising phenomenon from the perspective of commercial vehicles.

1.3. Research objectives

In this study we proposed a novel, and simple method to explore evidence of cruising for parking for commercial vehicle drivers in urban areas. We use widely available GPS data from a set of observed trips performed by a parcel carrier fleet of vehicles delivering and picking up goods in downtown Seattle. The obtained cruising time estimates were then analyzed to answer the following research questions:

1. Is there any empirical evidence of commercial vehicles cruising for parking?
2. How curb-space allocation influences commercial vehicles cruising behavior?

Understanding and quantifying the problem of commercial vehicles cruising for parking is a first step toward the design of data-driven policies that take into consideration the growing demand for curb-space for commercial vehicles, as well as improved models to estimate commercial vehicles demand in urban areas. The analysis is not intended to be a robust and final evaluation of commercial vehicles cruising for parking, but to evaluate whether the proposed approach and data can be used to identify and quantify this behavior. GPS data can be collected for a very large number of vehicles daily, and if the proposed method can be used to obtain robust estimates of cruising time, it would prove to be a cost-effective approach for developing much needed insight into urban commercial vehicle parking behaviors. We test the proposed method on a data sample from a commercial carrier and explore the effect of curb-space allocation policies on cruising time estimates.

In the next section we review empirical studies of cruising and describe our contributions to the literature. Sections 3 gives an overview of the methodology, and section 4 describes the data at hand. Results on the cruising parking estimation and the regression analysis are reported in section 5. We conclude with a discussion on the main findings in section 6.

2. Relevant literature and research contributions

2.1. Cruising in passenger vehicles

Despite cruising for parking being one of the most studied topics in the parking literature (Inci, 2015), measuring cruising is inherently difficult. As Donald Shoup wrote, “cruising is invisible” (Shoup, 2006), as cruising vehicles are mixed with other vehicles that are headed elsewhere and not searching for parking.

Most of the empirical studies on cruising have focused on passenger vehicles and have attempted to estimate three measures of cruising cost: (1) the cruising time/distance, i.e., the additional travel time/distance drivers need to find available parking, (2) the share of traffic volume that is cruising, and (3) the time cost that an additional parked vehicle imposes on other drivers. The first metric provides an estimate of the “internal” costs of cruising, whereas the latter two quantify the “external” costs, as cruising and parked vehicles affect other road and curb users.

Shoup (2006) reviewed several empirical studies and found cruising time estimates of between 3.5 and 13.9 min and shares of traffic cruising of between 8 and 74 percent. In Table 1 we extend this review by adding recent empirical studies on cruising.

One common method to estimate cruising time is to survey drivers. Van Ommeren et al. (2012) used data from the Dutch National Travel Survey and estimated an average cruising time of 36 s. The authors explained the remarkably lower estimate by the fact that the drivers were sampled across the whole country, not only at busy urban areas, and that The Netherlands have an efficient on-street parking pricing policy. The authors also found that cruising has a distinctive spatial and time component. Lee et al. (2017) performed an intercept survey in a busy commercial district in Brisbane (Australia) and estimated average cruising times of between 13 and 16 min. They also found that drivers that had familiarity with the local traffic and parking conditions spent less time cruising.

Shoup (2006) and Alemi et al. (2018) used field experiments to estimate cruising times: researchers measured how long it took drivers to find available parking by driving through traffic along pre-determined routes. They estimated cruising between half a minute to 3 min.

Table 1
Recent empirical studies on cruising for parking.

Study	Metrics of interest			Method
	Time/ distance	Traffic share	Cruising factors	
Shoup (2006)	✓			Field experiments
Martens et al. (2010)	✓			Simulation
Van Ommeren et al. (2012)	✓		✓	Survey
Millard-Ball et al. (2014)	✓			Simulation
(Holguín-Veras et al., 2016) [a]	✓			Survey
Lee et al. (2017)	✓		✓	Survey
Inci et al. (2017)	✓			Traffic observations
Alemi et al. (2018)	✓			Field experiments
Hampshire & Shoup (2018)		✓		Traffic observations
Millard-Ball et al. (2019)	✓			GPS data
Cao et al. (2019)	✓	✓		Simulation

[a] Commercial vehicle drivers were surveyed.

By monitoring traffic and parking events, Hampshire and Shoup (2018) found an average of 15 percent of traffic was cruising. Inci et al. (2017) also monitored traffic to estimate that a car parked for 1 h induced 3.6 other cars to cruise, with an average cruising time of 4.2 min.

Cao et al. (2019), Martens et al. (2010), and Millard-Ball et al. (2014) estimated cruising time by developing simulation models of cruising, partially informed by real data.

Millard-Ball et al. (2019) developed a novel method to estimate cruising distance from GPS data. They considered the last portion of recorded trips and computed the difference between the actual distance travelled and the respective shortest path distance. The estimates were then filtered to identify cruising, e.g., by retaining only trips where the driver passed at least twice through any road segment. They obtained a mean cruising distance of 32.1 m.

2.2. Cruising in commercial vehicles

While the cruising for parking literature focused on passenger vehicles, little is known about commercial vehicles' cruising behavior. Commercial vehicles are different than passenger vehicles: (1) they are larger and require wider parking spaces to load/unload; (2) they need to park closer to destinations as walking with cargo is more cumbersome; (3) for security reasons their drivers prefer to stay close to the vehicle and (4) most of their drivers also work on strict time constraints. Considering also that less curb-space is allocated to commercial vehicles, we would expect longer cruising times than those of passenger vehicles.

However, many studies modelling commercial vehicles movements in urban areas have assumed that drivers do not cruise for parking but instead either park in commercial vehicles load zones or in travel lanes as close as possible to destination (e.g., Amer and Chow, 2017; Iwan et al., 2018).

Such assumption is often motivated by the fact that carriers are known to pay large sums of money for urban parking citations. While data from parking citations are often cited as empirical evidence that commercial vehicles do not cruise, it is important to note that such data have several limitations: (1) citations quantify only how many vehicles committed parking violations but do not show how many vehicles parked legally; (2) there are different types of citations and not all of them are parking in the travel lane.

Kawamura et al. (2014) and Wenneman et al. (2015) analyzed commercial vehicles citations in Chicago and found that only 2 percent were for parking in travel lanes, while the majority were for parking meter violations or unauthorized curb-side parking. Similarly, Rosenfield et al. (2016) reported that the most common reasons for parking citations in Toronto were time of day, permit, and meter violations. Therefore, the majority of infractions seems to be related to unauthorized curbside parking, rather than parking in the travel lane (see summary in Table 2).

To overcome the limitations of parking citation data, several studies collected field observations, recording all commercial vehicle parking events, both authorized and unauthorized, in a given urban area. Jaller et al. (2013) surveyed 374 commercial vehicles in New York and found that only 25 percent of them were unlawfully parked, and of these, 10 percent parked in the travel lane. The remaining 85 percent of commercial vehicles parked in authorized load/unload zones. Girón-Valderrama et al. (2019) collected data in Seattle and observed that 34.6 percent of commercial vehicles parked in on-street loading/unloading zones and only 2 percent parked in the travel lane. These studies show that a significant portion of commercial vehicle drivers choose to park in authorized zones on the curb, and only a small portion of them choose to park in the travel lane.

Table 2
Percentage of unauthorized parking events that took place in the travel lane.

Reference	Parked in the travel lane[a]	Data source	City
Kawamura et al. (2014)	2.8%	Parking citation data	Chicago
Wenneman et al. (2015)	2.4%	Parking citation data	Toronto
Jaller et al. (2013)	2.5%	Field observations	New York
Girón-Valderrama et al. (2019)	1.3%	Field observations	Seattle

[a] Percentage over unauthorized commercial vehicles parking events.

In summary, the empirical literature on commercial vehicle parking shows that: (1) a significant portion of parking events still take place in authorized load/unload zones and (2) the share of unauthorized parking that takes place in the travel lane is very small. If most commercial vehicles park legally or park in unauthorized spaces at the curbside, this means that they compete for curb-space as much as passenger vehicles, and therefore it is reasonable to assume some amount of cruising occur. As for the case of passenger vehicles, we also expect commercial vehicles cruising behavior to vary over time, according to the current state of traffic and parking congestion, across space, according to different curb-space allocation, and across different vehicles, drivers and type of activities the drivers need to perform.

However, empirical studies on commercial vehicle cruising are almost non-existent. In general, cruising is a difficult phenomenon to observe, to quantify, and to account for in models and simulations. Moreover, there is a lack of data on freight behaviors and commercial vehicle movements. Only Holguín-Veras et al. (2016) surveyed commercial vehicle drivers with an online questionnaire to estimate their cruising time; they reported cruising time estimates of between 3 and 60 min per trip (with a mode of 20 min per trip). Unfortunately, only 16 drivers were surveyed, each reporting only one observation. Most other studies have estimated commercial vehicle cruising times by using simulation, with little empirical evidence (Figliozzi and Tipagornwong, 2017; Lopez et al., 2019; Nourinejad et al., 2014). By recording parking choices in commercial areas in Singapore, Dalla Chiara and Cheah (2017) and Dalla Chiara et al. (2020) observed that commercial vehicles drivers waited on average 7.7 min in a queue to access load/unload areas; queueing behavior is a phenomenon similar to cruising, with the difference that queueing does not involve circling in search for parking but only waiting.

To summarize, while the literature on commercial vehicle cruising for parking is almost non-existent, previous parking observations and citation data have shown that commercial vehicle drivers do not only park in the travel lane but instead exhibit more complex and heterogeneous parking behaviors that might involve cruising for parking. In this work we introduce a simple method to estimate cruising for commercial vehicles using widely available GPS data from a commercial fleet of vehicles and analyze the factors affecting cruising for parking in urban areas.

2.3. Research contributions

The contributions of this paper are methodological, empirical, and theoretical. On the methodological side, we developed a novel method to estimate cruising times from GPS data. Our method is similar to the one developed by Millard-Ball et al. (2019), with the differences that (1) it is used to estimate cruising times and not distances, (2) it is applied to analyze commercial vehicle cruising behavior and (3) it takes into account historical traffic conditions. On the empirical side, by applying the cruising estimation method to data from a commercial carrier, we provide the first significant empirical evidence of cruising for commercial vehicles. While most of the empirical cruising literature has focused on passenger vehicles, only Holguín-Veras et al. (2016) estimated cruising times for commercial vehicles. However, such estimates were based on a very small sample of 16 surveyed drivers. On the theoretical side, we provide the first analysis of the factors that influence cruising for commercial vehicles, analyzing how parking infrastructure allocation and the built environment affect cruising.

3. Methodology

In this section we describe the method used to estimate cruising time for commercial vehicles. Consider a trip performed by a commercial vehicle between two delivery/pickup locations, as depicted in Fig. 1. This vehicle departs at time $t^{departure}$, drives toward destination, searches for parking, and parks at time $t^{arrival}$ in an available parking lot. We define as *trip time* (T) the time difference $T = t^{arrival} - t^{departure}$. Suppose that, in a hypothetical scenario, an identical vehicle departs at $t^{departure}$ from the same location but, this time, its driver knows in advance where the available parking lot is, assuming that there exists a parking lot near the desired destination. Therefore, he/she will directly drive towards the guaranteed parking lot without spending time cruising, taking the fastest route. We define *driving time* (T^d) as the time it takes the second vehicle to reach the available parking lot in this scenario with perfect parking occupancy information and considering current traffic conditions. Then, the trip time *deviation* (D) is the difference between the trip time and the respective driving time, $D = T - T^d$.

Suppose we observe real trip times T_i where i is an index for a single trip, and for each trip, we estimate its respective $\widehat{T}_i^d$, where the “hat” indicates that it is an estimate of the unobserved T_i^d. Therefore, we obtain an estimate of the trip time deviations $\widehat{D}_i = T_i - \widehat{T}_i^d$ and use such trip time deviations as estimates of the time spent cruising for parking.

A set of real trip times (T^d) was obtained from GPS data from commercial vehicles delivering/picking up goods in downtown Seattle. We estimated the respective driving times ($\widehat{T}^d$) by querying the Google Maps Distance Matrix API, using the same trip origin, destination, departure time, day of the week, and month as those of the respective observed trip time. We assumed that the times obtained via the API were good estimates of the unobserved driving times, as the API takes into account historical traffic conditions, given the input parameters of the query. Finally, we obtained the trip time deviations by subtracting the two obtained values for each observed trip and analyzed their empirical distribution. Finally, using regression analysis, we observed how trip time deviations were affected by parking infrastructure at the respective trip destinations, including curb-space allocation, off-street parking, and private loading bays.

4. Data description

4.1. Context

The data used in the current study were collected in downtown Seattle, the largest and densest city in Washington state, U.S. Around 85 km (52 miles) of curb space in the downtown are allocated to vehicle parking, of which 11 percent are commercial vehicle load zones (CVLZs), which are designated by a sign and yellow paint markings (City of Seattle Department of Transportation, 2019b). To access CVLZs, commercial carriers have to purchase a permit, which costs US$250, lasts for a year, and grants access for a maximum of 30 min per loading/unloading event (City of Seattle Department of Transportation, 2019a). Alternatively, commercial vehicles can also use paid parking areas (to which around 60 percent of curb-space is allocated), provided that they pay for parking using parking permit machines or parking mobile apps.

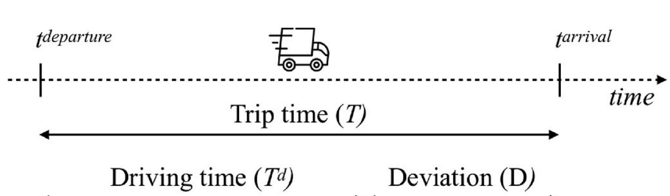

Fig. 1. Decomposition of the trip time (T) into driving time (T^d) and trip time deviation (D).

We were fortunate to collaborate in this study with a parcel delivery company, which provided GPS data from a sample of truck delivery routes. The carrier reported that, because of (1) a lack of available CVLZs, (2) the fact that several CVLZs are often too short to fit commercial vehicles, and (3) their busy delivery schedule, drivers often have to search for alternative parking locations, including unauthorized parking. They reported the following preferred parking criteria: (1) the parking space should be large enough to allow loading/unloading; (2) drivers do not need to back the vehicle to exit the space; (3) parking is close enough to the delivery destination(s); and (4) the chosen parking locations do not generate conflicts with other vehicles or unsafe situations.

In the next sections we describe three main types of data sources:

- trip data;
- estimated driving time data;
- parking infrastructure data.

4.2. Trip data

The data consisted of truck trips performed by drivers for a parcel delivery carrier in downtown Seattle. A truck trip was defined as an uninterrupted movement (i.e., without any intermediate stops) of a commercial vehicle between two delivery/pick-up locations. For each trip, the trip departure and arrival timestamps were recorded, from which trip times were obtained. Moreover, trip departure and arrival GPS coordinates are also obtained. These coordinates reflect the locations where the vehicles parked, and not the locations of the carrier’s customers, which were not reported.

A total of 2894 trips were obtained, performed by 11 drivers over 28 weekdays (Monday to Friday), between October and November 2018. Trips were organized in truck tours, that is, a consecutive sequence of trips performed by the same driver in a given day, starting and ending at the depot. In the observed data, each driver performed one tour per day. On average, around 30 trips were performed per tour.

From the initial data set, we excluded around 14 percent of the trips, including trips to and from the depot, trips with very short trip times (below 20 s), and trips whose destinations were outside downtown Seattle. The remaining number of trips was 2477.

Table 3 reports the main summary statistics of the variables used in the study. The mean trip time was 8.2 min. Most of the trips departed between 8:00 a.m. and 6:00 p.m. While we did not have the actual trip distances, the mean shortest trip distance (assuming the fastest route) was 0.7 km (0.4 mile).

4.3. Driving times estimation

In the current study, we used the Google Maps Distance Matrix API (Google Maps Platform, 2019) to estimate, for each recorded trip time, the associated driving time. Google Maps has proved to be a reliable source of driving time estimates in several previous studies (Gruber and Narayanan, 2019; Rothfeld et al., 2019; Wang and Xu, 2011).

The API provides the same functionality as the Google Maps user interface, returning driving time for a given trip origin, destination, departure time, day of the week, and travel mode, with the only difference that the API allows multiple simultaneous queries to be processed automatically.

The available travel modes are driving, walking, bicycling, and transit. When using the driving mode, the API estimates driving time by using two sources of data: historical road traffic data and current traffic information. If the trip departure time/day is near the time/day of the

Table 3
Sample description.

Variable	Stat.	Value	Variable	Stat.	Value
Trip Variables					
Trip time (minutes)	Min.	0.02	Driving time (minutes)[a]	Min.	0.02
	Mean	8.21		Mean	2.59
	Max.	65.45		Max.	24.60
Num. trips per tour	Min.	12.0	Trip distance (meters)[a]	Min.	11.0
	Mean	30.54		Mean	688.80
	Max.	52.0		Max.	8406.0
Share of trips by departure time (hour)	8–10	15%	Share of trips by day of week	Mon	20.5%
	10–12	20%		Tue	20.3%
	12–14	21%		Wed	21.4%
	14–16	22%		Thu	17.1%
	16–18	20%		Fri	20.7%
	18–20	2%			
Parking infrastructure and occupancy variables					
Commercial vehicle load zone (meters)	Min.	0.0	Bus zone (meters)	Min.	0.0
	Mean	43.05		Mean	62.79
	Max.	181.36		Max.	405.38
No parking (meters)	Min.	168.2	Paid parking (meters)	Min.	0.0
	Mean	454.2		Mean	253.2
	Max.	1385.3		Max.	463.3
Num. off-street parking areas	Min.	0.0	Num. of private loading bays	Min.	0.0
	Mean	1.71		Mean	2.25
	Max.	7.0		Max.	9.0
Mean paid parking occupancy (vehicles)	Min.	0.0	Num. bus routes	Min.	0.0
	Mean	39.36		Mean	15.89
	Max.	155.70		Max.	162.00
Tot. buildings volume (m^3)	Min.	0.0			
	Mean	9×10^4			
	Max.	2×10^3			

[a] Estimated from Google Maps' distance matrix API.

query, then current traffic information is predominantly used in the estimation. This means that exceptional traffic conditions due to unforeseen events that occurred at the time of the request, such as road accidents, are included in the estimate. Otherwise, if the trip departure time/day is different from the time/day of the request (which was our case), historical traffic data are used in the estimation. While traffic conditions are included in the driving time estimation, parking congestion, and therefore any additional time/distance travelled to search for available parking, are not included in the estimate.

Additionally, a "traffic model" parameter—with alternatives being "best guess," "optimistic," and "pessimistic"—is used to obtain driving time estimates that assume, respectively, average, lighter than average, or heavier than average traffic conditions, based on historical averages. This parameter controls the effect of congestion on the resulting driving time estimates. See the Google developers' guide (Google Maps Platform, 2019) for more information. We mostly used a "best guess" traffic model in our analyses.

For each recorded trip time, we obtained its respective driving time estimate by querying the API using the same trip origin, destination, departure time, day of week, and month. We highlight that such driving time is an estimate obtained from historical data, as the API was queried after the data was recorded, and not simultaneously to the trips performed.

4.4. Parking infrastructure and occupancy data

For each trip destination, we obtained several variables describing the parking infrastructure available in its surroundings. To compute these variables, we made use of several Geographic Information System (GIS) data layers describing the parking infrastructure of downtown Seattle (City of Seattle Department of Transportation, 2019c). For each trip destination we computed the total length in meters of curb allocated to different types of parking that were contained within a buffer centered at the trip destination with a radius of 100 m (328 ft), which corresponded approximately to the average length of a block face. Fig. 2 shows an example of a trip destination, the respective buffer, and the curb-space allocation GIS layer. The curb-space allocations measured were as follows:

- commercial vehicle loading zone (CVLZ);
- paid parking;
- bus zone;
- no parking zone.

In the observed buffers, on average 6 percent of curb-space was allocated to CVLZs, 7 percent to bus zones, 31 percent to paid parking, 54 percent to no parking, and the remaining to other uses. We also recorded the number of off-street parking areas and private loading/unloading bays located within the buffers.

In addition to parking infrastructure, cruising for parking depends on the parking occupancy observed upon arrival. As the exact occupancy cannot be known, we computed two proxy variables. The first was the paid parking occupancy observed at each trip end time and within the buffers obtained from parking meters data (City of Seattle Department of Transportation, 2018). On average, 31 vehicles paid for parking at arrival near a trip destination. The second proxy variable used was the total volume (measured in cubic meters) of buildings located within each buffer centered at a trip destination. We expected both variables to be positively correlated with parking demand and therefore occupancy.

Finally, for each trip we also recorded the number of bus stops and the total number of bus routes within the buffers.

5. Results

5.1. Empirical distributions of trip time deviations

Trip time deviations were estimated by subtracting from the observed trip times the respective driving times estimated by the Google Maps' API. We obtained 2477 trip time deviations.

Fig. 3-a shows their empirical distribution. We observe a right-skewed distribution with a peak around 0 min, indicating that driving times often corresponded to their respective trip times. Approximately 16 percent of trips were characterized by negative deviations, showing that the observed commercial vehicles were not necessarily slower than an average vehicle driving in downtown, and sometimes were even faster. However, the right-skew (84 percent were characterized by positive deviations) shows the presence of a positive trip time deviation.

Fig. 3-b shows the cumulative empirical distributions of the deviations obtained by using the "best guess," "pessimistic," and "optimistic" travel models. The curves of the respective cumulative distributions differed only for the negative values of the distribution but almost coincided for positive values. This shows that our conclusions were robust, even if we assumed that the observed commercial vehicles were generally on the slower end of the driving time distribution.

The mean deviation was 5.8 min, the median was 2.3 min, and the first and third quartiles were respectively 0.5 min and 8.4 min.

5.2. Geographical distribution of trip deviations

Fig. 4 shows the geographical distribution of the trip time deviations. We first clustered trips by their destination locations using a hierarchical clustering algorithm, such that the Euclidean distance between any two trip destinations belonging to the same cluster was not larger than 100 m. A total of 25 clusters were identified. Then, the mean cluster deviations were computed and color-coded on a map of downtown Seattle. Note an increase in mean cluster deviations going from 1st Avenue (southwest) to 4th Avenue (northeast). 1st and 2nd avenues are characterized by the presence of significant off-street parking locations, and 3rd and 4th avenues are characterized by the presence of a bike lane and busy transit stations. These geographical patterns in trip time deviations

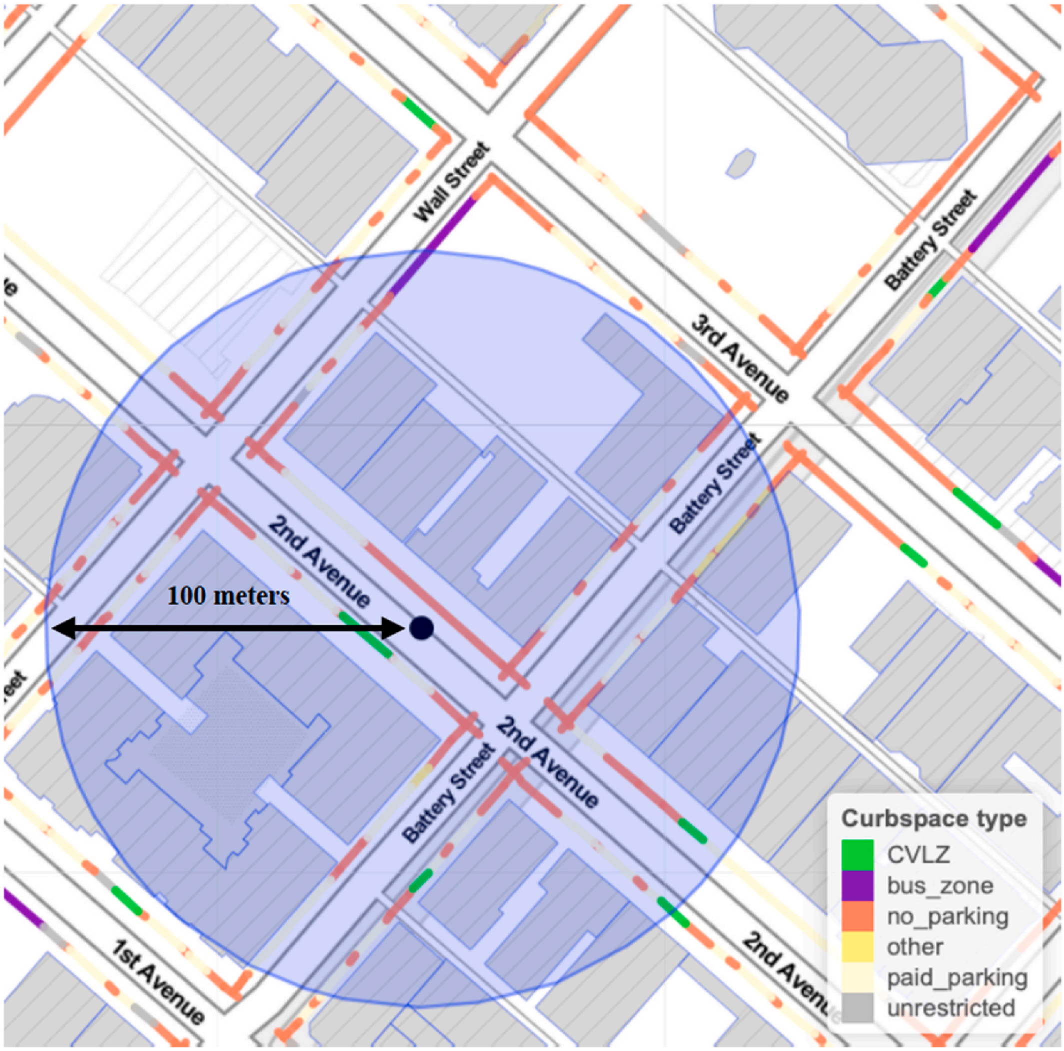

Fig. 2. A trip destination location (black dot), its respective buffer (blue area), and the curb-space parking allocation. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

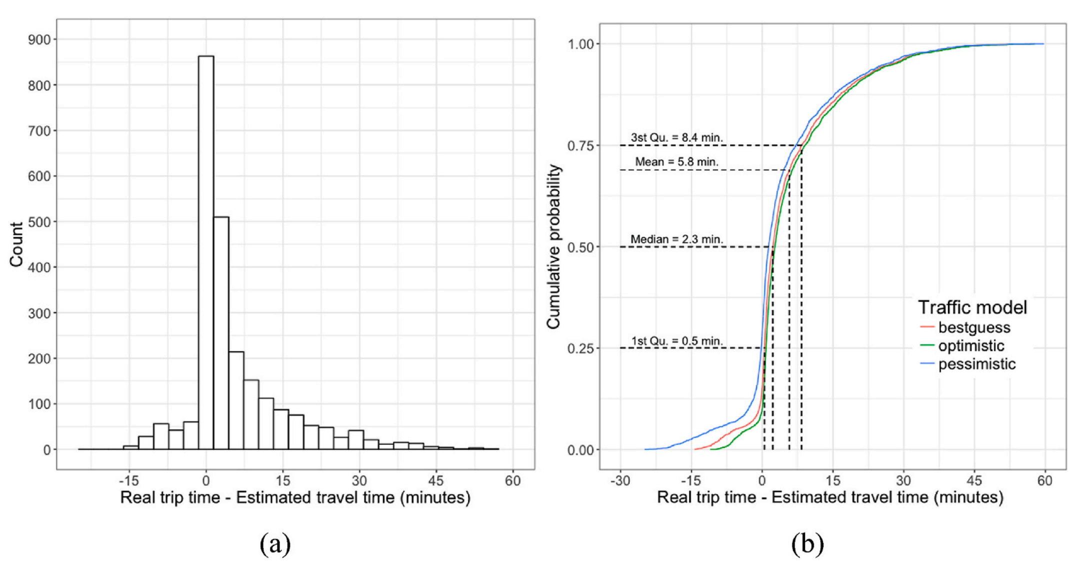

Fig. 3. (a) Empirical distribution of trip time deviations estimated by using the best guess traffic model; (b) cumulative distributions of the deviations from the pessimistic, optimistic, and best guess traffic models.

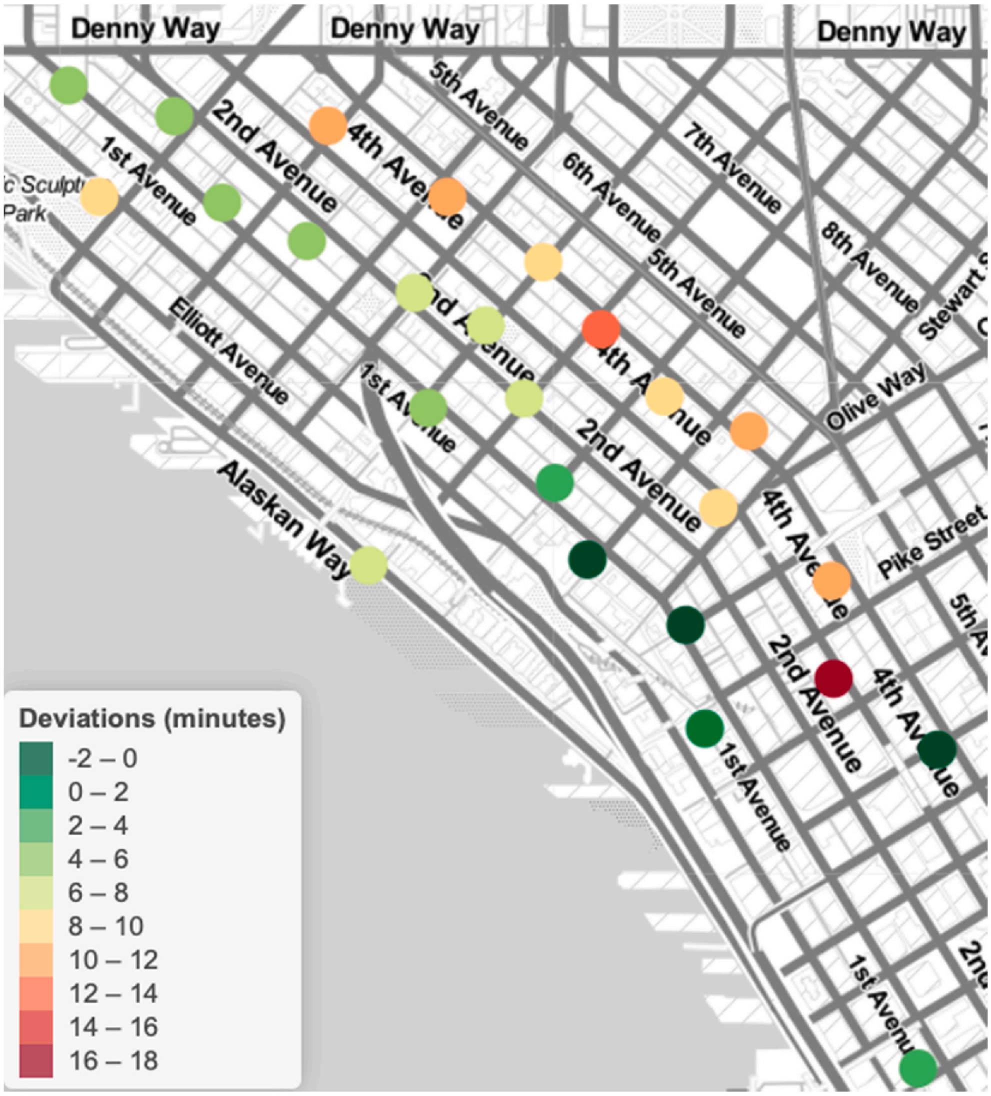

Fig. 4. Geographical distribution of trip time deviations. Each point is the center of a geographical cluster of trip destinations; the colors represent the mean cluster trip time deviation. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

at trip destinations might indicate that parking as well as public transit infrastructure influence trip time deviations.

5.3. Factors affecting trip deviations

To analyze the determinants of trip time deviations, we used regression analysis. The logarithm of the observed trip time was regressed over the logarithm of the estimated driving time and other variables. When controlling for driving time, the coefficient estimates of the other regressors could be interpreted as the changes in observed trip times caused by one-unit changes in the respective regressors, holding driving time fixed. Therefore, because trip time deviations were defined as the difference between trip times and the respective driving times, a variable's negative coefficient estimate reflected its potential ability to reduce trip time deviations.

We estimated three regression models. We first estimated an ordinary least squares (OLS) model (model I in Table 4). However, the OLS model did not account for possible dependencies between trips whose destinations were geographically close, which might cause unbiasedness of the coefficients (Bates et al., 2015). To capture this location effect, a mixed-effect random intercept model was used, in which observations with the same location cluster ID shared the same random effect (model II in Table 4). Moreover, because each driver performed multiple trips, we tested whether an additional random effect controlling for driver IDs would improve the model fit. The third model was a mixed-effect model with crossed random effects accounting for variations caused by location cluster ID and driver ID (model III in Table 4).

Using the sample data of 2477 observed trips, the regression coefficients of models I through III were estimated. For models II and III we estimated the coefficients by Restricted Maximum Likelihood (REML) using the Lme4 package (Bates et al., 2015) coded in R language (R Core Team, 2017).

Table 4 reports the regression estimation results (regressor coefficients are numbered 1 to 14).

As expected, driving time (regressor 2) significantly and positively affected trip time in all three models.

Regressors 3 to 6 described the curbside allocation near a trip destination. When multiplied by 100, the coefficient estimates could be interpreted as the percentage change in trip time caused by adding one parking lot of a given type near a trip destination, with driving time fixed. The signs of the estimated coefficients were consistent across all three models: an increase in curb space allocated to CVLZs, paid parking, or no parking zones decreased trip times, whereas an increase in bus zone space increased trip time, controlling for driving time. Regressors 3 and 4 were relatively significant in all three models, although their significance decreased when random effects for driver ID and location

Table 4
Regression estimation results.

Variable	Models					
	(I) Ordinary least squares		(II) Location random effects		(III) Loc. & driver random effects	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
1) Intercept	2.275 (***)	0.342	2.089 (***)	0.376	1.691 (***)	0.383
2) Driving time (log)	0.225 (***)	0.020	0.236 (***)	0.020	0.232 (***)	0.020
3) CVLZ	−0.065 (***)	0.005	−0.046 (***)	0.010	−0.013 (•)	0.009
4) Bus zone	0.031 (***)	0.004	0.014 (**)	0.006	0.008 (•)	0.005
5) Paid parking	−0.002	0.004	−0.006	0.004	−0.012 (***)	0.003
6) No parking	−0.001	0.001	−0.001	0.002	-0.6×10^{-4}	0.001
7) N. loading bays	−0.033 (**)	0.012	0.018	0.022	0.003	0.017
8) N. off-street parking	−0.055 (***)	0.018	−0.046 (*)	0.026	−0.039 (*)	0.022
9) Num. bus routes	−0.005 (***)	0.001	−0.0003	0.001	−0.0005	0.001
10) Paid parking occ.	0.003 (**)	0.001	0.001	0.001	0.0003	0.001
11) Building volume	-0.3×10^{-6} (***)	0.8×10^{-7}	-0.2×10^{-6} (**)	0.1×10^{-6}	-0.1×10^{-6}	0.1×10^{-6}
12) Num. stops per tour	−0.011 (***)	0.003	−0.009 (**)	0.003	−0.004	0.005
13) Departure time	✓		✓		✓	
14) Day of week	✓		✓		✓	
Random effects						
σ_{loc}	/		0.492		0.235	
σ_{driver}	/		/		0.423	
Summary Statistics						
Sample size	2477		2477		2477	
Log Likelihood	−3671.33		−3555.4		−3494.3	
AIC	7400.65		7170.9		7050.7	
BIC	7569.28		7345.3		7230.9	

Note: • p-value<0.15; * p-value<0.1; ** p-value<0.05; *** p-value<0.01.

cluster ID were added. The largest decrease was obtained when a CVLZ was added: adding one CVLZ reduced trip time by 1.3–6.5 percent, with driving time fixed. Interestingly, regressor 5 was insignificant in model I and II but became significant in model III. The changes in statistical significance when controlling for driver ID showed that different drivers might have different parking behaviors when choosing where to park the vehicle, with some of the effect of these variables being captured by the driver random effect.

While an increase in the number of private loading/unloading bays (regressor 7) did not influence trip times, an increase in number of off-street parking areas (regressor 8) decreased the deviations. Adding one off-street parking area decreased trip times between 3.9 and 5.5 percent, controlling for driving time. This reflects that parcel delivery drivers often prefer easily accessible on-street or off-street parking areas, but not private loading/unloading bays, which are often located in alleys.

Regressors 9 (number of bus routes) and 10 (parking occupancy) showed little statistical significance in models II and III. Interestingly, an increase in building volume (regressor 11) decreased trip time deviations. This could be related to the availability of better parking infrastructure near larger buildings.

The negative coefficient of number of stops per tour (regressor 12) showed that performing more stops along a tour reduced trip time deviations: a driver might perform more parking stops on a tour where less parking congestion was present, and less cruising was experienced.

We also controlled for time of the day and day of the week, but no estimated coefficients are shown for these variables as the associated regression coefficients are not statistically significant.

The mixed-effect models showed a better model goodness-of-fit. Moreover, the driver random effect explained more variability than the location random effect, reflecting that drivers differ in their parking and cruising behaviors.

6. Discussion and conclusions

Most of the scientific literature has studied the phenomenon of cruising for parking from the perspective of passenger vehicles, while urban logistics studies have often either ignored the presence of cruising or assumed that drivers park in the travel lane as close as possible to their destination without spending time searching for parking. Reviewing empirical studies on commercial vehicle parking, we found that the share of vehicles parking in the travel lane is small (2–3 percent); instead, commercial vehicle drivers prefer to pull over and park on the curb-side (either in commercial vehicle load zones or spaces reserved for other vehicles). This involves some form of parking search, and therefore cruising. However, only one paper has estimated commercial vehicle cruising time; Holguín-Veras et al. (2016) interviewed 16 drivers and reported average cruising times per trip of between 3 and 60 min. As evidenced by the limited sample size, this approach is time consuming and therefore unlikely to produce robust results.

This paper fills in that gap, by testing an approach using existing data to analyze the phenomenon of cruising for parking from the perspective of commercial vehicle drivers performing deliveries and pick-ups in urban areas. We developed a novel method to empirically estimate cruising times for commercial vehicles by using GPS data that is robust enough for analysis of the impact of transport infrastructure on cruising times. For a set of trip times obtained from GPS tracking of parcel delivery vehicles operating in downtown Seattle, we subtracted the respective estimates of driving time, i.e., the time it would take the vehicle to directly drive to a given destination without searching for parking, to obtain what we defined as *trip time deviations*, which we ultimately consider as a good estimator of cruising time.

We then analyzed the distribution of such deviations. Fig. 5 summarizes the main empirical findings. The empirical distribution of the estimated cruising times was centered at zero minutes and was right-skewed, with 85 percent of the observed trips having a positive deviation. The median deviation per trip was 2.3 min. Considering that the observed parcel delivery vehicles performed on average 30 trips per tour, the total trip time deviation experienced by a single driver in a day was 1 h and 10 min. Moreover, given that the average trip time was 8.21 min, trip time deviation accounted for 28 percent of total trip time. We draw two conclusions: (1) first, that the Google Maps Distance Matrix API is a reliable source of driving time estimates also for commercial vehicles, correctly predicting many of the observed trip times as the mode of the distribution is around zero; (2) the right-skewed shape of the empirical distribution of trip time deviations might indicates the presence of a positive cruising time.

Trip time deviations also showed a characteristic geographical pattern, given the sample GPS data obtained from Seattle. We observed

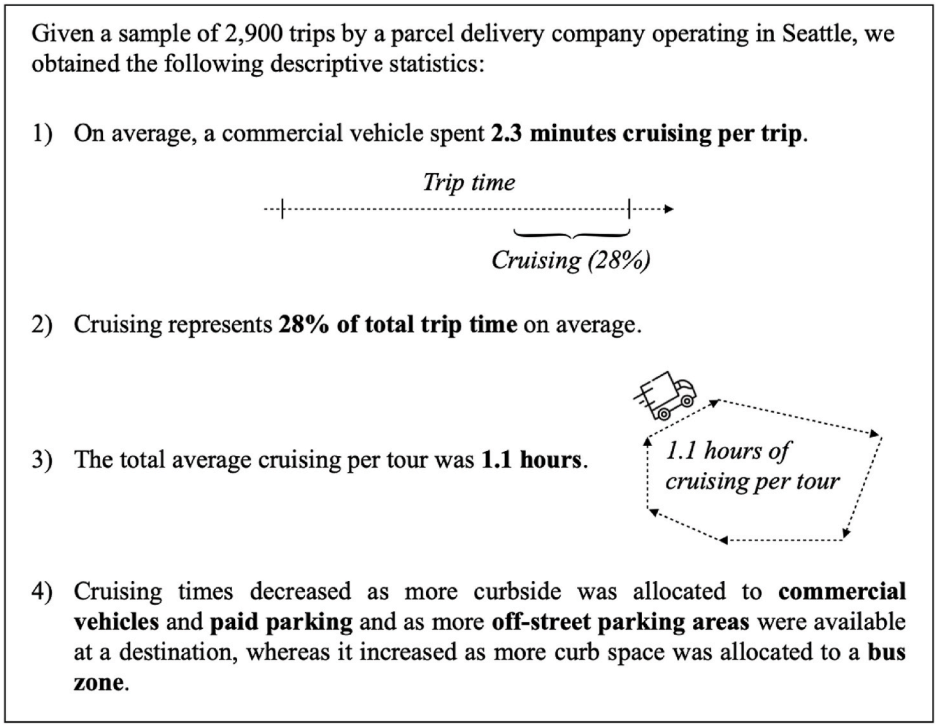

Fig. 5. Summary of empirical findings obtained from the sample data analyzed.

larger cruising time estimates in areas where larger portion of curb-space is allocated to bus zones, while shorter cruising times seems to be associated to areas where more curb-space is allocated to on-street parking and where more off-street parking areas are available.

Fitting a mixed effect regression model, some determinants of trip time deviations were identified. We found that the deviations were affected by the parking infrastructure available at a trip destination. Deviation decreased as more curbside was allocated to commercial vehicles and paid parking and as more off-street parking areas were available at a destination, whereas it increased as more curb space was allocated to a bus zone. The largest decrease was obtained when a Commercial Vehicle Loading Zone (CVLZ) – an on-street parking lot reserved for a single commercial vehicle loading/unloading - was added in the vicinity of a trip destination: adding one CVLZ reduced cruising time by 1.3–6.5 percent. The fact that the trip time deviations are statistically correlated to parking infrastructure allocated at trip destination reinforce the motivation of this study that such deviations are a good estimates of cruising times, as the cruising for parking phenomenon is associated with the lack of parking infrastructure.

Differently from most of other studies on cruising for parking, the current study proposed a novel method to estimate cruising time by using readily available and "big" data obtained from GPS vehicle tracking. The development of such a method is paramount to enabling the extension of cruising analysis to commercial vehicles, as traditional methods such as driver intercept surveys and traffic observations would result in too little data collected since commercial vehicles are only a small share of total traffic in urban areas. Moreover, as more carriers track their fleets using GPS, more data are available for future studies on commercial vehicle cruising, potentially comparing different types of commercial vehicles and their respective cruising behaviors. While it is clear this approach can be refined and improved, we have demonstrated that this approach demonstrates merit and should be pursued as a way to learn about cruising for parking, and prioritize curbside allocation improvements.

We acknowledge that cruising for parking is only part of the story. As discussed in Millard-Ball et al. (2019), cruising is a "self-regulating" phenomenon. In other words, we rarely observe large cruising times among passenger vehicles because when drivers perceive parking as scarce, they are more willing to walk longer distances, change travel mode, or even forgo travel. Similarly, commercial vehicles have "mechanisms" in place that help self-regulate cruising for parking. As mentioned earlier, one is parking in the travel lane, thereby avoiding the need to search for parking. Another, less explored mechanism is limiting the number of stops in a tour; for example, a commercial vehicle driver might choose to serve multiple delivery destinations from the same parking location, thereby avoiding the need to re-park the vehicle and eventually search for parking. The cost of that strategy is longer walking distances and parking dwell times, which in turn increases parking congestion. To have a complete view of commercial vehicles parking behaviors, all three behaviors must be considered: illegal parking behavior, cruising behavior, and willingness to walk. In this paper, we shed light on what is probably the least studied freight behavior: cruising behavior.

6.1. Policy implications

What then can be done to reduce commercial vehicles cruising for parking? One policy discussed above is allocating more curb-space to commercial vehicle load zones (CVLZs). Many urban areas not only often lack of enough CVLZs, but also those available often do not suit the needs of larger trucks: they are too small, and they require unsafe maneuvers to access them (Alho & de Abreu e Silva, 2014). Using sample data from a parcel delivery company, in the current study we found that by adding one CVLZ, cruising time would be reduced by up to 6.5 percent. While these results are specific to the times and places of data collection, further studies could quantify cruising times to determine how much curb-space should be allocated, and where, much the same way annual parking studies are currently used to allocate and price private vehicle parking (for instance the City of Seattle Department of Transportation, 2020, has a performance-based approach to parking pricing).

Pricing is a well-established mechanism for managing parking demand for personal vehicles (Ottosson et al. 2013; Shoup, 2006), and it is therefore often considered, though not widely accepted or implemented, as a strategy for managing commercial vehicle parking (Institute of Transportation Engineers, 2018). Currently, commercial freight carriers either do not pay for using CVLZs or pay for a permit: a one-time fee which grants them access to all CVLZs for a given time. For instance, in Seattle a permit costs US$ 250 for the right to use the city's CVLZs for a year (City of Seattle Department of Transportation, 2019a). However, the question of whether pricing would reduce commercial vehicles' cruising is not an obvious one. For passenger vehicles, higher prices reduce parking demand by having some drivers park in sub-urban areas, in off-street parking garages, changing mode of transport or even forgoing the trip. Lower demand guarantees that some curb-space will always be open, and fewer drivers will have to search for parking. However, commercial vehicle drivers are often not the ones deciding their trip destination. Instead, they respond to demand for freight deliveries and pick-ups of urban businesses and households (Holguín-Veras et al., 2015). Therefore, even by pricing CVLZs, it is not clear whether, or to what extent that might change parking demand and therefore significantly affect cruising. CVLZs pricing may reduce parking dwell times and increase parking turnover, but no evidence can confirm this hypothesis at this time.

Providing real-time parking occupancy information to drivers, although not an easy to achieve, could potentially reduce cruising, especially if integrated with carrier routing systems. In an ongoing study the authors are testing the first parking information systems for commercial vehicles in Seattle (Pacific Northwest National Laboratory, 2019) to gather evidence of this effect.

Another approach to reducing parking cruising for commercial vehicles is to change modes of moving freight in urban areas, such as using cargo cycles or delivering by foot, which would eliminate the need to use curb-space, and therefore cruising.

It is the hope of the authors that this work will pave the way for further studies into commercial vehicle cruising for parking and for further research into policies to address the pressing issue of lack of available curb-space for commercial vehicles in urban areas to reduce commercial vehicles' cruising, driver walking, and illegal parking.

Declaration of competing interest

None.

CRediT authorship contribution statement

Giacomo Dalla Chiara: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing - original draft, Visualization. **Anne Goodchild:** Conceptualization, Supervision, Funding acquisition.

Acknowledgments

This material is based upon work supported by the U.S. Department of Energy's Office of Energy Efficiency and Renewable Energy (EERE) under the Award Number DE-EE0008462. The views expressed herein do not necessarily represent the views of the U.S. Department of Energy or the United States Government. We would like to thank the City of Seattle Department of Transportation for the data support and the management of the parcel delivery company for providing the trip data.

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