Commercial Vehicle Operations in Urban Areas: Identifying Policies to Reduce Negative Impacts

by

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A thesis submitted in conformity with the requirements for the degree of Master of Applied Science
Department of Civil Engineering
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Abstract

This thesis presents two methods to evaluate potential solutions to the problems caused by commercial vehicles cruising for parking and parking illegally. First, a policy evaluation tool is developed by combining a behavioural parking location choice model and a traffic microsimulation. This tool is applied to two scenarios that dedicate on-street parking spaces to commercial vehicles, and finds that both scenarios reduce the overall level of congestion. Second, a distance decay weighted regression model is estimated to identify the relationships between illegal commercial vehicle parking and the built environment. An increase in dedicated and off-street parking facilities are found to be related to reduced levels of illegal parking, while increased restrictions on current on-street spaces is found to be related to higher levels of illegal parking. Together, these methods can help policy makers develop new parking policies and measure their potential impacts on the transportation network.
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Chapter 1
Introduction and Background

1.1 Urban Commercial Vehicle Operations

Urban goods movement encompasses all shipments and services that move on the urban transportation network (Metrolinx, 2011). Urban goods movement is referred to as “the last kilometer”, as it represents the final link in the supply chain that connects raw materials to final goods and services. Efficient last kilometer operations are an important factor contributing to the growth and prosperity of cities. If commercial vehicles were unable to efficiently deliver groceries to stores and packages to homes and businesses, cities as we experience them today could not exist. However, as urban areas are growing ever larger and more densely populated, urban transportation networks are becoming more congested and urban commercial vehicle operations are becoming increasingly inefficient. In this last kilometre, commercial vehicle operators must navigate congested urban streets and search for appropriate parking. Spaces for vehicle loading and unloading are quickly disappearing in dense urban areas. Complete streets policies are setting increasing amounts of road and curb space aside for pedestrians and cyclists while ignoring the needs of commercial vehicles. This leads to increased competition for limited space between commercial vehicle operators, passenger vehicles, cyclists, and pedestrians and an increase in last kilometer delays. Last kilometre delays in central business districts (CBDs) are already one of the most expensive components of urban freight (O’Laughin et al., 2007). This cost is increasing over time. From 2006 to 2009 parking fines in Toronto increased 70%, and there is little evidence that illegal parking problems are being reduced. In Toronto, FedEx, UPS and Purolator paid an estimated $2.5 M in parking fines in 2009 (Haider, 2009).

The problem is significant and growing. The Toronto CBD, for example, receives a daily average of 81,000 packages from express delivery alone (Haider, 2009). Parking and loading spaces are already limited in the CBD because many buildings were constructed before the invention of the automobile. Increasing land values have resulted in the conversion of surface parking lots to high-rise buildings, which in turn are increasing the demands for goods delivery. Freight parking issues are common in other North American cities as well. The U.S. Department of Transportation (USDOT) together with the Federal Highway Administration (FHWA) and the Office of Freight Management and Operations prepared a series of case studies documenting best
practices for urban goods movement. Reports were prepared for Washington DC, Orlando, New York City, and Los Angeles. The purpose of these studies is to investigate initiatives aimed at mitigating congestion and improving efficiency of commercial vehicle operations (FHWA, 2009).

When confronted by increased competition and limited availability of loading facilities, commercial vehicle operators have two possible responses: search the area around the delivery destination for adequate parking (cruising for parking), or park illegally. Both of these behaviours have significant negative impacts on the urban transportation network. The following sections describe the problems that arise from each of these behaviours.

1.1.1 Cruising for Parking

In his 2005 book “The High Cost of Free Parking”, Donald Shoup notes that cruising for parking is not a new phenomenon. To prove this point, he includes an excerpt from a travel book in which the author details the same problem of cruising for parking as we observe today.

“We started out to view the town…. Round and round the blocks we drove trying to find a place to park…. Every curb was black with backed-in cars…” “There’s a place!” Alas! It was the wrong side of the street. So on we would go to the next corner hoping to be able to turn but invariably the traffic officer would firmly signal us, till time after time, we would find ourselves…in the very center of things, entangled in the traffic.” (p. 276).

Though the problem described is likely familiar to anyone who has driven a car in an urban area, the book the excerpt is from was written in 1926. Although the problem of cruising for parking was already apparent in the 1920s, it remains largely unaddressed and continues to cause problems on urban transportation networks today. Cruising for parking in urban areas creates three problems: increased congestion, increased air pollution, and wasting energy. Shoup estimates that vehicles cruising for parking around an average city block drive an additional 265 kilometres per day (Shoup, 2005). This adds up to over 96,000 VKT per year per city block spent cruising for parking. Assuming an average fuel economy of 8 litres per 100 kilometre, cruising for parking around one city block consumes over 7,700 litres of fuel per year. In terms of air
pollution, cruising for parking around the same block emits over 18 metric tons of CO₂ each year.

1.1.2 Illegal Parking

When commercial vehicles are unable to find adequate parking even after cruising to look for a spot, the only remaining alternative is to park illegally. Illegal commercial vehicle parking creates three problems on urban transportation networks.

The first problem is related to cost. In 2012 alone, CVs incurred over $27 million in parking fines in the City of Toronto. These fines are a major contributor to the high costs associated with the last mile of the supply chain (O’Laughlin et al., 2007) and are indirectly paid for by consumers in the form of higher prices for final goods and services. The City of Toronto recently increased the amount of parking fines during peak periods from $60 to $150 with the goal of reducing congestion caused by illegal on-street parking (City of Toronto, 2014). However, many CV operators treat parking fines as a “cost of doing business” in urban areas (Haider, 2009).

The second problem is congestion. It has been estimated that illegal CV parking in urban areas results in 476 million vehicle-hours of delay each year in the United States. This makes illegal CV parking the third leading cause of delay, behind only construction and crashes (Han et al., 2005). However, unlike construction, which is necessary to maintain existing infrastructure, and crashes, which are unintentional, illegal CV parking is an intentional and unnecessary source of congestion.

The third problem is safety. When any vehicle parks illegally in a bike lane, cyclists are forced to merge into the travel lane. This is a potentially unsafe manoeuver even in nearly free flow conditions, and can become more dangerous in the congested conditions frequently observed on urban arterials during peak periods. As any city cyclist will know, the occurrence of these conflicts is exceedingly common. In New York City, it has been observed that on average 14% of on-street CV loading events result in a conflict with a cyclist (Conway et al., 2013). Consider also that CVs have been found to cause a disproportionately high number of cyclist fatalities, in part due to these conflicts (Maclean and Graham, 1996).

Illegal CV parking is already causing significant problems in urban areas, and these problems will only be exacerbated by the increased employment and population density expected in major
urban centres over the next several decades. The Greater Toronto and Hamilton Area (GTHA) grew 9% between 2006 and 2011, and is now home to over 6.5 million people (Metrolinx, 2013). If the problems caused by illegal CV parking are not adequately addressed in the near future, our cities will become increasingly expensive and inefficient.

1.2 Research Questions and Objectives

A large number of potential policy measures have been recommended, but most are aimed at addressing location specific problems or are based on interviews and focus groups rather than analytical methods. For example, the FHWA has developed a series of case studies for major U.S. cities (Los Angeles, New York City, Washington D.C., and Orlando) to document prominent goods movement strategies (FHWA, 2009). Other studies have taken a more general approach and presented policies that may be more broadly applicable (Munuzuri et al., 2005; OECD, 2003; Visser, 2006) but have relied on expert opinion and driver interviews rather than quantified relationships.

Recent studies in Chicago and New York have begun to apply data driven approaches to analyzing illegal CV parking. The Chicago study estimated a regression model for CV parking citations, and identified several socioeconomic and land use factors that contributed to high densities of CV parking citations. Though complete information on the supply of parking was not available for this study, the authors found that alleyways were able to reduce the incidence of illegal CV parking (Kawamura et al., 2014). The New York study estimated the demand for and supply of parking in Manhattan, and found that many areas have CV occupancy rates well over 100%. This indicates a significant deficiency in the supply of CV parking facilities and is a likely a major contributing factor to illegal CV parking in New York (Jaller et al., 2013) This study gives credence to the claims made by CV operators that many times there is simply nowhere for them to park legally. However, most urban areas in North America are not as dense as Manhattan.

To date, policy makers have had very few tools to rely on when deciding which policies to implement to reduce the impact of commercial vehicle operations. Urban policy makers are in need of data and decision support tools to identify impacts of parking policy scenarios such as dedicated on-street parking for commercial vehicles, time restrictions, and pricing policy. Traffic simulation tools are increasingly popular for urban traffic analysis, however, they do not
currently provide sufficient representation of parking. Parking simulation models have been developed, but these models are for passenger parking, which is behaviourally different than truck parking. Econometric models of parking choices have also been developed, but again are limited to passenger cars (Habib et al., 2012).

A tool that allows for the testing of alternative policies would be useful to policy makers for several reasons. First, such a tool would allow policy makers to test several policies without needing to implement each on the actual transportation network to study its impacts. By using a simulation model, the impacts of alternative policies could be assessed without disrupting the transportation network. Second, a simulation based method allows policy makers to quantify the impacts of alternative policies. Quantifying the impact of a policy change on the transportation network would require a potentially expensive data collection effort before and after implementation. It is also possible that factors outside the control of policy makers could affect the results of such a study. Third, a policy analysis tool would be widely applicable and could be used in several urban areas, assuming urban commercial vehicle operations and the behaviour of the drivers is similar to Toronto. Some data collection would be required in each new location, but the level of effort required to collect this information would be much less than the effort required to test any policy on the actual transportation network.

There has also been limited research on the relationships between illegal commercial vehicle parking and the built environment. New policies are being adopted with little understanding of the underlying relationships. There are several questions that remain un-answered surrounding the relationships between illegal commercial vehicle parking and the built environment. Several of these questions will be addressed through this research. Such questions include:

- What features of the built environment are related to higher rates of illegal commercial vehicle parking?
- Are there current policies that may actually be leading to higher rates of illegal commercial vehicle parking?
- What policies may be beneficial in reducing the incidence of illegal CV parking?
- Is inadequate parking supply leading to an increase in the incidence of illegal commercial vehicle parking?
- Will creating additional parking supply reduce the incidence of illegal commercial vehicle parking?
This research has two aims. First, to develop a decision support tool to be used by policy makers to assess the effects of alternative policies on the efficiency of commercial vehicle operations and the impacts on the urban transportation network. This research also aims to answer the unresolved questions surrounding the relationships between illegal commercial vehicle parking and the built environment. A distance decay weighted regression model will be used to identify these relationships in order to improve upon previous research. The model attempts to predict parking citations using data on the supply of and demand for parking. A distance decay function is used to capture the spatial interactions between parking supply and parking demand. The significant variables and coefficient estimates resulting from this model can help to identify policy measures that are most likely to reduce the incidence of illegal CV parking.

1.3 Thesis Structure

The first chapter introduced the problems faced by CVs operating in urban areas and the negative impacts they can have on the transportation network. Chapter 2 presents a range of parking policies that have been used in an attempt to reduce cruising for parking and illegal parking throughout the world. Chapter 3 presents a truck parking selection model using data from a truck parking survey conducted in the summer of 2010. This chapter also introduces a traffic simulation model for a small study area in the Toronto CBD. The model specifically represents on-street parking, off-street surface parking lots, parking garages, truck loading docks, and alleyways suitable for truck loading/unloading. A binary logit model for parking selection is incorporated in this simulation environment that is capable of assessing the traffic impact of changes in parking policy on truck parking choice. The model is applied to test the impact of two simple truck parking scenarios on measures of effectiveness such as time to find parking, walking distance to the final destination, and total network travel time. Chapter 3 concludes with the results and conclusions of this research and suggests future research directions.

Chapter 4 presents research aimed at identifying the relationships between illegal CV parking, parking supply, and parking demand. Both an aggregate and a disaggregate model were estimated and are presented, along with the parking citation, parking supply, and parking demand data. A discussion of the results is included in each chapter where the research is presented.
Chapter 2
Potential Solutions

Many policies have been recommended and implemented to address the problems faced by and caused by commercial vehicles operating in urban areas. On-street parking is often the focus of policy makers, as curb space management policies can impact road congestion, business vitality, urban aesthetics, and pedestrian safety and comfort (Zalewski et al., 2011). Policy makers have generally responded to this problem by promoting parking turnover using increasingly strict time limits. Higher meter rates, on the other hand, are endorsed by those who believe time limitations are challenging to monitor and enforce. Shoup argues that increasing prices at parking meters can create curb vacancies by shifting a portion of drivers to less expensive off-street parking facilities (Shoup, 2006). This would reduce cruising for curb parking, which can reduce congestion. The generated revenue from parking meters can then be spent on public improvement in the metered neighborhoods. Pasadena is an example where charging market prices (off-street prices) for curb parking has reduced congestion and made the area safer and cleaner from the generated parking revenue (Kolozsvari and Shoup, 2003). Clearly, implementation of any passenger vehicle parking policy indirectly affects the operations of freight vehicle deliveries even if they are not the targeted group. Any policy that produces more vacant spaces on the curbside creates better opportunities for on-street freight parking.

In addition to the indirect effect of passenger vehicle parking policies on freight vehicles, loading zone regulations and freight restrictions directly impact freight deliveries. In response to recent freight vehicle operations issues, the Federal Highway Administration developed case studies in some of the major cities of the United States (Los Angeles, New York City, Washington DC, and Orlando) to document prominent goods movement strategies (FHWA, 2009). Freight parking strategies employed in these cities included time restrictions, pricing strategies, parking space management, and parking enforcement. The following sections present and discuss the benefits and potential problems with the most common urban parking policies for both passenger and commercial vehicles.
2.1 Time Restrictions

Time restrictions are a common policy measure where the periods during which stopping, standing, or parking are limited. These policies are typically in effect during peak traffic periods and apply to passenger vehicles and commercial vehicles alike. In Toronto, common time restrictions are in effect between 7:30–9:30 AM and 3:30–6:30 PM. These hours have recently been extended as part of the city’s Congestion Management Strategy (City of Toronto, 2014). The new restrictions will ban parking on major arterials between 6:00–10:00 AM and 3:00–7:00 PM in a bid to reduce congestion caused by parked vehicles.

Other cities are using time restrictions that apply only to commercial vehicles. The goal of such a policy is to separate commercial vehicles and passenger vehicles in urban areas temporally instead of spatially. In Manhattan, the New York City Department of Transportation (NYCDOT) is planning to implement delivery windows to designate curbside parking for freight vehicles in the morning and create better parking opportunities for passenger vehicles later in the day. They have learned that 65% of all deliveries occur before 12:00 PM and granting exclusive parking access to freight vehicles during these hours can reduce traffic congestion. A similar strategy is used in Philadelphia, where local businesses are encouraged to schedule the bulk of their deliveries before 10:00 AM (Zalewski et al., 2011).

Off-peak delivery is another time restriction that has received increased attention recently. Under an off-peak delivery policy, commercial vehicles are encouraged to make deliveries overnight instead of during the day. This policy has two main benefits: commercial vehicles are able to complete tours much more quickly due to spending less time stuck in traffic, and commercial vehicles are able to find adequate parking facilities much more easily. Even if commercial vehicles park illegally immediately in front of an establishment while making a delivery, the impact is dramatically reduced due to the reduction in overall traffic levels during the overnight period. Researchers estimated that, in Manhattan, shifting approximately 20% of freight traffic to off-peak hours would minimize the number of over capacity parking locations (Jaller et al., 2013). However, off-peak delivery policies are opposed by some who fear that the noise generated by commercial vehicles would be unacceptable in some areas. Courier groups are also opposed to off-peak delivery policies, because they interfere with the narrow time windows which couriers operate on (Haider, 2009). Some receivers are opposed to off-peak deliveries, as
they can result in increased costs stemming from overnight staffing requirements to receive the goods. Some measures, such as the use of trusted carriers and the installation of double doors, can alleviate some of these concerns. A pilot project in Manhattan found that many receivers are satisfied with off-peak deliveries, but require a financial incentive to initiate them (Holguín-Veras et al., 2005).

2.2 Pricing Strategies
Pricing strategies, in general, can encourage greater turnover of both passenger and freight vehicles to create better parking opportunities for newly arriving vehicles. The District Department of Transportation (DDOT) in Washington, D.C. has installed loading zone meters along K Street in response to all-day parking of commercial vehicles. The meters charge commercial vehicles $1 per hour and allow a limit of two hours for parking. The NYCDOT has also implemented a pricing strategy using the Muni-meter program that uses an escalating rate structure of $2 for one hour, $5 for two hours, and $9 for three hours (NYCDOT, 2004). This strategy has led to considerable reductions of dwell times (160 minutes to 45 minutes) and highlights the impact of different hourly pricing combinations (Zalewski et al., 2011).

The SFpark program in San Francisco dynamically adjusts the prices of on-street spaces and off-street facilities, with the goal of creating available on-street parking on each block. Over the first year in operation, SFpark has seen occupancy on overcrowded blocks fall after four of the six price increases (Pierce & Shoup, 2013).

2.3 Space Management
Commercial vehicle operators frequently lobby for an increase in dedicated on-street parking facilities. The underlying belief is that commercial vehicle operations efficiency can improve if ample curbside space is reserved for them. The NYCDOT encourages smaller jurisdictions to designate part of the curbside or even individual spaces to commercial vehicles. The DDOT and Downtown DC Business Improvement District in Washington, D.C. have also extended loading zones from 40 feet to 100 feet in length on K Street and moved commercial loading zones to the approach end of each block wherever possible. However, in an environment where competition for limited curb space is growing, there are limited opportunities to meaningfully increase the number of on-street spaces dedicated for commercial vehicle use. The City of Toronto Downtown Operations Study (DTOS) has recommended the implementation of dedicated
parking for couriers in 13 locations in downtown Toronto between 10:00 AM and 3:00 PM. The recommended locations, chosen with input from the Canadian Courier and Logistics Association (CCLA) are shown in Figure 1 (City of Toronto, 2013).

Figure 1: Dedicated courier delivery zones (City of Toronto, 2013)

2.4 Enforcement

Parking enforcement responds to lack of regard for parking regulations. For example, the Los Angeles Department of Transportation (LADOT) has initiated an enhanced parking enforcement program called “Tiger Teams” (FHWA, 2009d). The program deploys fifteen additional uniformed traffic control officials and ten additional tow trucks to enforce parking violations during peak hours. Washington D.C. has also adopted a similar program of parking enforcement on K Street in addition to its other curb-space management policies (FHWA, 2009a). The NYCDOT reports that enforcement is a critical component for a successful curbside management program. They implemented a pilot program incorporating enforcement in 2002 called THRU Streets (NYCDOT, 2004). This program consisted of the designation of THRU streets, where traffic flow was prioritized, and non-THRU streets, where accessibility was prioritized. On THRU streets, parking was made available on one side only. Enforcement was increased on
THRU streets, with the goal of reducing illegal parking and increasing curb clear time. On non-THRU streets, multi-space MUNI meters were installed on both sides of the street, creating approximately 150 additional freight parking spaces in the study area. This pilot program resulted in a decrease in travel times, an increase in network capacity, and increased the percentage of streets free of illegally parked vehicles. The Toronto DTOS has recommended a targeted enforcement strategy that includes:

- Increased surveillance levels;
- Establishment of an impound lot near the CBD for temporary storage of vehicles towed during peak periods;
- Increased presence of tow trucks;
- Awareness campaign to increase perceived risk of incurring a citation;
- Eliminating the reduction of parking fines at trial, thereby reducing the number of tickets that are challenged; and
- Increase in fines from $60 to $150 for peak period infractions.

2.5 Parking Information Systems

Various major metropolitan cities have recently incorporated innovative technologies to better manage the available scarce curb space. Such strategies range from using state of practice ITS technologies in projects like SFpark to sharing the available infrastructure.

San Francisco Municipal Transportation Agency (SFMTA) has initiated one the most comprehensive parking programs called SFpark. In addition to the dynamic pricing aspect discussed previously, SFpark collects and distributes real-time information on the availability of parking spaces on a spot-by-spot basis. This information is collected using embedded parking sensors (Figure 2) and distributed via a smartphone application. By providing this information, SFMTA hopes to reduce cruising for parking by directing vehicles directly to available spots.

Figure 2: SFpark sensor
Chapter 3  
Commercial Vehicle Parking Choice

3.1 Introduction

This chapter presents a tool that can be used to measure the impact of various parking policies on congestion. This tool is composed of a commercial vehicle parking choice model and a simulation of a small portion of the Toronto road network. The chapter includes a review of previous research on parking choice models and parking simulation, a presentation of the data used in the model, as well as a discussion of the results and implications of the final model.

3.1.1 Literature Review

This literature review is organized into two sections. The first presents previous research on parking choice models, while the second presents previous research on parking simulation.

3.1.2 Parking Choice Models

One of the earliest discrete parking choice models also happens to be the one of only two found to consider commercial vehicles. In 1982, Van der Goot estimated a multinomial logit model to predict parking choice, and separated vehicles based on trip purpose. One of Van der Goot’s purpose groups was “loading / unloading”. His model showed that walking time between the parking location and the trip destination, the occupation rate of the parking facility, and whether the spot was legal or illegal had a significant effect on parking choice for the loading / unloading trip purpose. With this model Van der Goot was able to accurately predict the parking alternative, defined as groups of similar spots, for loading / unloading vehicles with up to 64% accuracy (Van der Goot, 1982).

Almost all research into parking choice since Van der Goot does not consider commercial vehicles. It is revisited only once, in 2002 (Munuzuri, 2002). A possible explanation for this is that passenger vehicles make up a much larger proportion of the number of vehicles parking in a given area, so understanding their parking behavior was perceived by researchers as a more important topic.
Axhausen and Polak estimated two parking choice logit models, one in Germany and the other in the UK, in order to compare the results (Axhausen & Polak, 1991). The data used in this research were collected using a stated preference survey, which the researchers argued was superior to previous studies using revealed preference data. Their reasoning was that, given current technology, it was unfeasible to generate a complete set of individual parking locations that a driver could choose. To get around this problem, researchers had grouped similar spots together (Van der Goot, 1982). Axhausen and Polak argued that this would limit the usability of a model in testing policy alternatives such as varying pricing by masking the relationship between parking fee and distance to destination. Axhausen and Polak found that access time, parking search time, walking time between the parking location and final destination, parking type, and parking fee were all significant factors in selection of a parking location. Another important result from this research was that time spent searching for parking and time spent driving to the general location had significantly different parameters in both models. This suggested these two periods of a vehicle trip should be looked at separately in future studies. Lastly, the authors concluded that significant differences in the preferences for parking locations existed between drivers with different trip purposes. This is an important conclusion, as it verifies the need to consider commercial vehicles as a separate group.

Teknomo and Hokao applied a multinomial logit model in Indonesia using an RP data set (Teknomo & Hokao, 1997). Similar to other studies (Van der Goot, 1982; Axhausen & Polak, 1991), they found that walking time, trip duration, parking fee, and parking search time were all significant factors in selecting a parking location. Teknomo and Hokao also found that the parking location chosen is dependent on trip purpose, further supporting the findings of Axhausen and Polak.

Thompson and Richardson offered a parking choice model based on expected gain in utility (Thompson & Richardson, 1998). The main difference with this model was that unlike others that assumed the set of all parking choices was known, their model allowed for vehicles to compare the utility of parking in the current location against the likelihood that a better spot was available between their current location and the destination, without having information about the area in between.
Freight parking choice was finally revisited in 2002 with a very simple parking choice model (Munuzuri et al., 2002). Munuzuri et al. made a series of assumptions about the relative preferences of commercial vehicles, e.g. a loading space 20 meters from the destination is just as attractive as an illegal parking space directly in front of the delivery location. From these assumptions weighting functions are generated and calculated each time a vehicle approaches a destination. However, no basis or defense of the underlying assumptions is offered.

SUSTAPARK and PARKAGENT (Dieussaert et al., 2009; Benenson et al., 2008) were the first prominent agent-based parking models to be developed. These models are distinguishable from previous efforts in that they have the ability to consider parking preferences of individual vehicles (agents), and can track the movement of the individual agents through the network. This allows vehicles to interact with the urban environment on a micro scale level (Dieussaert et al., 2009).

The parking choice model in SUSTAPARK was based on an earlier model (Hess et al., 2006) with the notable difference of not considering the option of illegal parking. Researchers took advantage of the agent based nature of their model to apply different parking strategies to agents based on personal characteristics. Some strategies involved having the agents call a logit model, while others directed agents directly to parking locations.

PARKAGENT is notable in that it did not employ the use of a logit model for parking choice. Instead, they took advantage of the agent based nature of the model to direct parking choices by simple rules. Agents collected information on the occupancy of on-street parking facilities en route to their destination. Once the agents were within a certain radius of their destination, they would begin calculating the probability of a parking space being available between their current location and their destination. When the probability of finding another space between the current location and the destination reached a certain small value, the agent would park. This simple model was useful in the context of this study only because it was looking at overnight parking in a residential area where on-street parking was free of charge. This has an interesting similarity to commercial vehicle parking, where both types of drivers must find a parking location, do not have the option of changing modes, and have little control over the timing of the trip.
The most recent research done on parking choice modelling (Waraich & Axhausen, 2012; Waraich et al., 2012) has added the ability for agents to test numerous different parking search strategies, as well as re-plan their trips to increase the total utility of the trip. Re-planning is first implemented in (Waraich & Axhausen, 2012). This is done by iteration, where in each iteration of the simulation an agent will consider all available parking options and select the one that maximizes utility. Once every vehicle has selected a parking location, those agents with low total utilities will re-plan their trips. This may include trip time, travel mode, or trip destination. After a large number of iterations, a state of equilibrium is approached where no agent can increase their utility without increasing overall utility. However, this research did not contain a searching component. Agents were assumed to have complete knowledge of all possible parking locations in the destination area. This also meant congestion was not a factor on trip time or time spent searching for parking in this research. This is addressed in (Waraich et al., 2012) with the addition of parking search strategies. Each agent is assigned a parking strategy for each iteration, e.g. an agent may drive directly to a parking garage in the first iteration, and may search for on street parking in the second. This addition eliminates the assumption that the agents have perfect knowledge of parking facilities and better reflects reality by introducing the possibility for congestion into the network. These recent models however still do not consider parking choice for commercial vehicles.

3.1.3 Parking Simulation

Parking equilibrium models, which are common in the literature (Arnott & Inci, 2006; Lam et al., 2006; Shoup, 2006; Li et al., 2007; Gallo et al., 2011), are formulated to capture the relationship between various parking activity components such as price of parking and distance to final destination. One of the major drawbacks in such models is lack of regard for the dynamic nature of parking behaviour. These models neglect walking time (distance) and parking availability at different hours of the day. Walking distance (from parking spot to destination) is critical for those highly sensitive to time (such as truck drivers making deliveries). Similarly, representation of the supply of off-street parking can be crucial. Furthermore, the equilibrium models have crude presentation of cruising time which is highlighted as one of the most important features of parking behaviour by Ommeren et al. (2012).
In an attempt to fill in this gap in parking research, Benenson et al. (2008) propose an explicitly space sensitive dynamic model called PARKAGENT to simulate behaviour of individual drivers. This model is structured for two groups of agents (residential and visitor) in the city of Tel Aviv where future surface parking construction is expected. In this research drivers enter the simulation when within 250 m vicinity of their destination and lower their speeds to 25 km/h where they become aware of the need to park. This model is structured to evaluate the impact of additional parking facilities in the residential area but does not capture the impact of the type of parking facility.

Dieussaert et al. (2009) introduce SUSTAPARK which is a spatiotemporal tool simulating both traffic and parking behaviour in a cellular automata structured network. Their parking behaviour model uses a multinomial logit model which is a simplified version of that proposed by Hess et al. (2006). In this MNL structure, agents select their initial parking type from two possible choices (on-street and off-street parking) based on parking features such as search time, egress time, and expected fee which are input to a utility function. However, this initial choice is modified every 30 s according to the re-evaluated parameter values and new utility function. The utility function value for every agent would decrease as cruising time builds up to the point where parking off-street is a more suitable option.

Munuzuri et al. (2002) develop a dynamic parking model for freight vehicles in a microscopic traffic simulator called TRAMOS. In this model private and freight vehicles are assigned different available types of parking facilities, parking choice behaviour, and number of stops for each vehicle type. Private vehicles are assigned one stop whereas freight vehicles are assigned an itinerary of stops, each of which has a specified location and duration. The freight parking choice model is based on a weighting system for each parking facility type as a function of distance to delivery point. For example, at up to 15 m from the delivery point, the choice of loading zone parking has a higher decision weight than on street parking and is more likely to be chosen. The parking choice model for private vehicles, however, is simpler and only a function of the distance covered from the vehicle’s origin. Private vehicles are assumed to take the first parking facility when the distance they have travelled has reached a maximum threshold which is 1.25 times the width of the network. This proposed model is only tested on a simple network of four nodes and three links and sufficient analysis is not provided to assess policy.
Waraich and Axhausen (2012) extend MATSim to capture the influence of parking on daily (activity) plan features including travel time, travel mode, and destination choice. Their model reflects, for example, that insufficient or expensive parking may encourage drivers to change their mode of transport or time of departure. MATSim agents iteratively select, among possible daily plans with different utility scores, the one with the best final score (the “fittest alternative”). One of the disadvantages of the proposed model by Waraich and Axhausen (2012) is that it is not completely dynamic, meaning that perfect knowledge of parking availability is available before the trip is made. Clearly, this overlooks the possibility of cruising for parking in cases where drivers arrive to their destination and then start looking for a spot.

3.2 Data

The data collected for this research includes a survey of truck drivers, a count of truck parking events, and a complete inventory of parking supply in the Toronto CBD. The area for which the data were collected is bounded by Queen Street on the north, Simcoe Street on the west, Front Street on the south, and Victoria street on the east (Figure 3). All three of these pieces of data were collected in the summer of 2010, and are presented in the following sections.

3.2.1 Driver Survey Interviews

The interviews of truck drivers were conducted by a surveyor who targeted parked commercial vehicles on individual road segments on weekdays between the hours of 9:00 AM to 3:00 PM. The interviews collected arrival time, departure time, parking location, type of vehicle, the company that owned the commercial vehicle, the commodity delivered and the final destination of the delivery. The survey instrument is shown in Appendix A. Overall, 200 driver interviews were conducted. On average, approximately 10% of trucks parking in each segment were subject to a driver interview. A broad variety of commercial vehicle types and commodity types were covered in the survey, resulting in a reasonable representation of truck movements across the Toronto CBD. While conducting these driver surveys, the interviewer also observed the locations of trucks parking within the study area. 1,940 commercial vehicle parking events were observed during the data collection process. Further details of the data collection effort are presented in (Kwok, 2010).
### 3.2.2 Facility Inventory

This inventory consists of on-street parking, alleyways, loading zones, loadings bays, surface parking lots, and off-street public parking garages. The complete parking inventory and the area selected for simulation is shown in Figure 3.

![Figure 3: Study area with parking supply information](image)

A segment of the CBD was selected to be modelled using microsimulation, shown by the red dashed line in Figure 3. The study area is bounded by Queen Street on the north, Adelaide Street...
on the south, Victoria Street on the east, and York Street on the west. This area was selected for the following reasons:

- The area contains a mix of several street types. There are major two-way arterial streets (Bay, Queen, and Yonge), major one-way streets (Richmond and Adelaide), and small backstreets (York, Temperance, and Sheppard).
- The area is among the most highly developed areas in Toronto. The building stock consists mostly of high-rise buildings including the Bay Adelaide Centre (51 storey office complex), the Sheraton Centre (43 storey hotel), the Richmond Adelaide Centre (12 storey office complex) and several other 12 – 20 storey office towers. Retail and dining establishments are present at street level and office space is generally located above street level.
- The area is one of the most difficult areas for commercial vehicle drivers to operate in. This was established through consultation with the Canadian Courier Logistics Association as well as through driver responses to qualitative questions included in the driver survey.

3.3 Method

The modelling methods described in this chapter include a parking choice model and a parking simulation model. These models are described in the following sections.

3.3.1 Model Formulation

The parking choice model is an econometric discrete choice model of parking spot selection. A binary logit model is developed to determine the probability of parking at a location. The alternative is to reject the location in the hope of finding a better parking spot. This model can be written as (Ben-Akiva and Lerman, 1985):

\[ P_i = \frac{e^{\beta x_i}}{1 + e^{\beta x_i}} \]  

where \( \beta \) is a vector of estimated parameters and \( x_i \) is a vector of characteristics of the current parking location \( i \). The binary logit model is estimated with data from the driver interviews, in
which the selected parking location was identified. However, these interviews did not collect information on spots rejected by commercial vehicle operators. In order to estimate this model, a procedure to generate these rejected spaces was developed.

### 3.3.2 Choice Set Creation

The driver interview database only included observations of parking spots that were selected. For model estimation, records for parking spots that were rejected are also required. Such records were prepared by identifying the last two parking locations that driver would have passed and rejected en route to his chosen parking location, as follows. First, the address of the parking event and the address of the previous stop were found. Next, Google Maps was used to estimate the driving route from the previous stop to the selected parking location. From the parking inventory, the previous two appropriate parking facilities (i.e. facilities able to accommodate the vehicle type) that the driver would have passed en route to the parking location were identified (if such facilities existed). Since no information about parking availability/occupancy at the unselected parking facilities was available, (real-time occupancy information at all locations could not be collected during the parking survey), this procedure assumed availability of parking at the unselected parking facilities. Finally, the walking distance to the delivery destination and other relevant attributes of the selected and unselected parking spots were determined.

The assumptions made in the development of the estimation dataset may have implications for the model performance. For example, drivers may have selected a route to the destination other than the shortest path in order to improve the chance of finding parking. The driver may have considered and rejected more or less than two previous parking spots en route to the selected stops. Most importantly, not all prior spots en route were necessarily unoccupied. Improving upon these assumptions would have required additional detailed information from drivers during the interviews, which would have significantly added to respondent burden.

### 3.4 Results and Discussion

The binary logit model for freight vehicle parking location choice is sensitive to distance from the final delivery destination and parking facility type. No additional variables are included as no data on other parking location characteristics are available. The parameters of this model were
estimated using maximum likelihood estimation. The estimated parameters are summarized in Table 1.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>t-Stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Distance to destination (m)</td>
<td>-6.23E-03</td>
<td>-3.87</td>
</tr>
<tr>
<td>On street parking facility</td>
<td>-1.61</td>
<td>-4.11</td>
</tr>
<tr>
<td>Loading bay parking facility</td>
<td>2.21</td>
<td>2.09</td>
</tr>
<tr>
<td>Constant</td>
<td>2.12</td>
<td>6.09</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-84.35</td>
<td></td>
</tr>
<tr>
<td>Pseudo R-squared</td>
<td>0.3086</td>
<td></td>
</tr>
</tbody>
</table>

The final model achieved a pseudo-R squared value of 0.3086. The negative coefficient on the distance term shows that the further a parking space is from the delivery destination, the less likely it is that a commercial vehicle operator will choose to park there. The negative coefficient on the term representing on street parking reveals a preference against parking on street. Conversely, the positive coefficient on the term representing loading bays is positive, revealing a preference towards parking in loading bays. Other parking facilities did not enter the model as their coefficients were not statistically significant.

3.4.1 Application within a Parking Simulation Tool

To apply the results of this model, a simulation of the study area was created. Two scenarios were then developed within the simulation to test the outcomes of different policy scenarios. The following sections describe the structure and operation of the simulation as well as the impacts of each tested policy scenario.
3.4.1.1 Function of Parking Simulation Tool

A PM peak hour parking simulation model is developed for the study area in the Paramics traffic simulation software (Quadstone Paramics Ltd.), which models vehicle movements at a microscopic level. The PM peak hour was selected based on field observations showing that this is when the greatest degree of parking activity was occurring in the simulation study area. The Toronto CBD experiences greater levels of passenger travel activity in the PM peak hour because: A large number of workers are commuting out of the CBD at this time; a large number of people are entering the city to shop, eat or go to entertainment locations. While truck deliveries tend to peak in the midday period (Kwok, 2010) (presumably because they are trying to avoid congestion and access receivers during staffed hours) some of the greatest parking challenges are occurring in the PM period, when parking supply is reduced on some arterial roads, congestion is heavy, and competition for parking spots (from passenger cars) begins to increase.

The major inputs to this model are a detailed road network, parking facility locations and capacities, and truck and passenger vehicle demand matrices.

The Paramics road network for the study area was extracted from a larger network developed and calibrated for a previous project (Amirjamshidi et al., 2013). Parking facility locations were identified in a comprehensive inventory taken in the summer of 2010 (Kwok, 2010), and were coded into the simulation network.

The data for the development of truck and passenger vehicle demand matrices were retrieved from Toronto’s household travel survey (the Transportation Tomorrow Survey – TTS), City of Toronto intersection traffic counts, and the truck parking survey by Kwok (2010). TTS data were used to calculate the passenger vehicle trip generation and attraction for the study area. Truck trip generation and attraction was determined from the truck parking survey. The entry and exit points of in-bound and outbound trucks and passenger vehicles were distributed among the roads entering the study area using inter-section count data obtained from City of Toronto. Trips through the study area were calculated from the residual intersection counts after inbound and outbound trips had been subtracted. The model assumes no trips had both an origin and destination within the study area.
The parking choice model is integrated within the simulation model. The choice model is called each time a vehicle arrives at a potential parking facility, which is within 250 m of its final destination. This distance threshold is evident from the parking surveys which show that very few commercial vehicles parked further than 250 metres away from their destination (Figure 4).

![Cumulative Observations (%) vs Distance (metres)](chart)

**Figure 4: Distance from commercial vehicle parked location to destination**

The model then calculates the probability of selecting the targeted parking facility. Using a Monte Carlo simulation and the calculated binary choice probability, the vehicle decides whether to park in the facility or to keep driving to find a better parking opportunity. Once parked, vehicles dwell at the facility until they reach their parking duration time when they leave the facility and drive to their next destination outside the study area boundaries. The dwell time for each vehicle is calculated using Monte Carlo simulation, which relies on repeated random sampling. By generating a specific dwell time (for each vehicle) from a given cumulative distribution function and repeating the same process for many vehicles, the probabilities of the generated dwell times will approximate the observed data probabilities.

The cumulative percentage distribution function (CDF) of dwell time is calculated based on a curve fit to the observed data. This function is equal to \( f(x) = 0.183 \times \exp(6.045 \times x^{0.38}) \), where \( x \)
is a random variable between 0 and 1. Setting \( x \) to 1 makes \( f(x) \) equal 77 min which is the maximum dwell time in the observed data. When we randomly select \( x \) (between 0 and 1) and generate a dwell time for many vehicles, the PDF of the generated dwell times will be similar to the PDF of the observed data dwell times.

Figure 5 is a schematic of the simulation process applied simultaneously to each vehicle. The flowchart is interpreted in the following steps:

- The simulation model initiates at time \( T_0 \).
- Vehicles are traced if within 250 m of their final destination.
- Traced vehicles evaluate each parking facility they approach using the binary logit model, until one is chosen.
- When a parking facility is chosen, its capacity is reduced by 1 spot which is taken by the vehicle. Similarly, the capacity of the facility is increased by 1 when the vehicles reaches its dwell time and leaves the facility.
- The model stops tracing vehicles at the time they reach their dwell time and are dispatched from the parking facility to leave the network.
Initialize \( T = T_0 \)

Vehicle V is traced?

Vehicle V is parked?

Dwell time is reached?

Vehicle is in vicinity of destination?

Parking Choice Modeling

Parking facility chosen

- Enter parking facility
- Decrease parking facility capacity by 1

Parking facility not chosen

- Record vehicle attributes
- Parking search time
- Updated distance to destination

Termination?

- Yes
  - Extract outputs
  - Exit

- No
  - \( T = T + \text{time step} \)

Trace vehicle V
The model terminates when time reaches the simulation duration which is set to 1.5 hours with 0.5 hours of warm-up. The warm-up period leads to a preload at the parking facilities.

Four measures of effectiveness calculated in the model are average search time, average walking distance, average access time, and total network travel time. Vehicle search time is defined as the difference between the time a vehicle crosses a radius of 250 m of its destination to the time the vehicle finds a spot. Walking distance is defined as the distance between the final destination of the delivery and the parking location. Intuitively, lower values of both measures of effectiveness are more attractive to both parking authorities and users. Total network travel time (measured in minutes) is the sum of the travel time of all vehicles in the simulation starting from the moment a vehicle enters the study area and ending at the moment it exits. This does not include the dwell time of each vehicle because parked vehicles do not contribute to the congestion of the network. Finally, average access time is the summation of search time and walking time. This measure has been introduced to evaluate cases where vehicles park far from their destinations with a search time of zero but still have to walk from their parking location to their destination.

The integrated parking choice-simulation model is designed to evaluate various parking policies. To test the model, we apply the THRU Streets parking concept where traffic flow is prioritized on arterials and commercial vehicle access is prioritized on smaller streets. The two assessed parking policy scenarios are described below.

In Scenario 1, Sheppard and Temperance Streets are designated as access streets where access to parking facilities is given only to freight vehicles. Richmond and Adelaide Street are designated as THRU streets where freight parking is prohibited (Figure 6).
In Scenario 2, Sheppard and Temperance Streets are designated as access streets where access to parking facilities is given only to freight vehicles. Freight vehicles are permitted, however, to park elsewhere in the study area (Figure 7).

The results of the Scenarios 1 and 2 are compared to the base scenario representing the existing parking policy which allows parking of freight and passenger vehicles on all streets of the study area. To account for random variation in the model, 30 runs are executed for each scenario, and mean and standard deviation of each measure of effectiveness is provided. Table 2 presents the
measures of effectiveness for the base scenario and two THRU Street scenarios, for each vehicle type.

Comparison of the three scenarios shows expected differences between the search time and walking distances of both passenger and commercial vehicles. Scenario 1 results in lower freight search times compared to the base scenario, (although the difference is not statistically significant). This is due to the presence of more vacant spots in the access streets that are now available to freight vehicles. The freight vehicle search time standard deviation is also lower for Scenario 1 due to the exclusive access granted to freight vehicles. In Scenario 2, however, mean freight vehicle search time is further reduced to 55 s, a significant reduction. This happens because those freight vehicles with destinations on THRU streets that were forced to drive to the access streets in Scenario 1 can now drive directly to their final destination. In general, the standard deviation for search times is relatively high, indicating that some vehicles are able to find parking very quickly while some vehicles spend far more time searching for parking. This is consistent with the reality that if a vehicle does not find parking at a close distance the first time they pass their destination, they may spend significant time travelling around the block to make a second attempt.

Walking distances for freight vehicles, on the other hand, are higher for Scenario 1. This is due to the nature of the policy. Requiring freight vehicles to park on specific access streets restricts the drivers from parking at a location closer to their destination. Hence, drivers have to walk further to reach their final delivery/pickup locations. The mean freight walking distance in Scenario 2, however, is significantly lower. This happens because those vehicles that were restricted in Scenario 1 can now drive to their destinations and park at a closer location.

Mean access time (search time plus walking time) improves for freight vehicles, for Scenario 1, indicating that the savings in search time exceed the small additional walking time. Mean access time for Scenario 2 is less than half of that for the base scenario.

Passenger vehicles, as expected, experience different outcomes. Higher mean passenger vehicle searching time results in both Scenarios 1 and 2 (although the differences are not significant). This is due to a diversion of parking demand from the access streets to other locations where parking is harder to find. Mean walking distance also increases marginally for passenger vehicle
drivers, leading to access time increases for passenger vehicles for both Scenarios 1 and 2. These increases are not statistically significant. On the whole, the results of the three scenarios quantify an expected trade-off between measures of effectiveness of passenger and freight vehicles.

Total network travel time can be impacted in three ways. First, the cruising vehicles add to the total travel time. Second, the vehicles that are cruising for parking increase traffic volumes which lead to higher link travel times for all vehicles. Third, vehicles that park on-street decrease the capacity of the link by occupying segments of the rightmost lane. The proposed model is sensitive to the first two but not the third. The last column of Table 2 presents the mean of total network travel time, which is lower in Scenarios 1 and 2 compared to the base scenario.
Table 2: Impacts of simulated scenarios on the transportation network

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Search Time (min)</th>
<th>Walking Distance (metres)</th>
<th>Access Time (min)</th>
<th>Total Network Travel Time (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean  SD</td>
<td>Mean  SD</td>
<td>Mean  SD</td>
<td>Mean  SD</td>
</tr>
<tr>
<td>Freight</td>
<td>Passenger</td>
<td>Freight</td>
<td>Passenger</td>
<td>Commercial</td>
</tr>
<tr>
<td>Vehicles</td>
<td>Vehicles</td>
<td>Vehicles</td>
<td>Vehicles</td>
<td>Vehicles</td>
</tr>
<tr>
<td>Base Case</td>
<td>2.3</td>
<td>1.49</td>
<td>42.6</td>
<td>23.2</td>
</tr>
<tr>
<td></td>
<td>1.27</td>
<td>1.34</td>
<td>84.5</td>
<td>3.15</td>
</tr>
<tr>
<td>Scenario 1</td>
<td>1.13*</td>
<td>1.62</td>
<td>37.2</td>
<td>2.18*</td>
</tr>
<tr>
<td></td>
<td>1.05</td>
<td>1.41</td>
<td>85.1</td>
<td>2.63</td>
</tr>
<tr>
<td>Scenario 2</td>
<td>0.92*</td>
<td>1.74</td>
<td>32.1</td>
<td>1.36*</td>
</tr>
<tr>
<td></td>
<td>0.98</td>
<td>1.46</td>
<td>92.3</td>
<td>2.84</td>
</tr>
</tbody>
</table>

Note: Only values followed by an asterisk (*) are statistically different from the mean at the 95% confidence level
3.5 Conclusions

The integrated parking behaviour simulation model presented here is a new approach to parking policy evaluation. The model is able to capture important dimensions of parking activity such as walking distance, congestion impact, and parking search times that are commonly neglected in the literature, and usually not quantified at all in practical decision-making. With some effort the method can be applied in any jurisdiction for which a traffic simulation network and appropriate information about parking supply and demand are available. While the most crucial applications are in dense urban areas where the greatest competition exists for curb space, smaller urban areas with localized parking hotspots are also potential application areas.

To verify that the model provides useful and reasonable results, the model is applied to two scenarios for a small but busy study area in the Toronto CBD. These scenarios dedicate parking on some interior streets to trucks. Reductions in freight vehicle searching time occur in these scenarios, whereas freight vehicle walking distances depend on the parking policy for other streets in the network. Passenger vehicle search time and walk distances increase because some of their parking options are removed. All of these changes are intuitive, lending credibility to the model, and they quantitatively illustrate the trade-offs that arise in selecting among competing uses of curb space.

The model could be improved and further validated. First, parking spot availability/occupancy driver search time and walking distance were not collected in enough detail for the study area in the parking choice survey. Testing model outcomes against observed values for these critical measures would improve confidence in the model. Second, all trucks are assumed to make parking decisions that conform to a single simple choice function. Couriers, food deliveries and shredding trucks, as examples, all have very different constraints on their parking behaviour that could be represented with more detail if data were available.

This research could be further extended to evaluate the effectiveness of other parking policies discussed previously, such as time restrictions, parking information systems, pricing strategies, and new parking facilities, or requirements for new developments. However, some additional
data collection efforts may be required for evaluation of these policies. Additional data can be
integrated into the simulation by enhancing the parking choice models to include price variables
or prior knowledge of parking availability.
Chapter 4
Illegal Commercial Vehicle Parking Prediction Model

4.1 Introduction

This chapter identifies the relationships between illegal commercial vehicle parking and the built environment, represented by the parking supply and parking demand. This research attempts to go beyond the limited efforts previously discussed in Chapter 1 by using a distance decay weighted regression model to identify these relationships. The model attempts to predict parking citations using data on the supply of and demand for parking. A distance decay function is used to capture the spatial interactions between parking supply and parking demand. The significant variables and coefficient estimates resulting from this model can help to identify policy measures that are most likely to reduce the incidence of illegal CV parking. This chapter omits a review of previous research on modelling these relationships as the only relevant research was discussed previously in Chapter 1. This chapter includes a presentation of the data used in the model, a detailed description of all methods, as well as a discussion of the results and policy implications of the final model.

4.2 Data

This research draws on four sets of data: parking ticket data, parking supply data, employment data, and passenger trip data. To allow for the inclusion of parking supply data, the study area was limited to an area bounded in downtown Toronto by Queen Street on the north, Front Street on the south, Victoria Street on the east, and Simcoe street on the west. This study area captures what can be referred to as Toronto’s Central Business District (CBD). This area is approximately 800 metres by 800 metres (approximately half a mile by half a mile), and contains the highest employment density areas in Toronto. The study area is shown in Figure 8. Each of the data sets used in this research is described in the following section.
4.2.1 Parking Ticket Data

The parking ticket data used in this research were obtained from the City of Toronto Open Data Catalogue (City of Toronto, 2014). This data catalogue is part of a recent Open Government movement, and contains up-to-date information on everything from the locations of automatic external defibrillators to water main breaks throughout the city. The 2012 City of Toronto parking ticket database contains the following information:

- Date of infraction;
- Infraction code;
- Description of infraction;
- Amount of applicable fine;
- Time of infraction;
- Street address; and
A Freedom of Information Act request was submitted to obtain information indicating whether the each citation was issued to a vehicle owned by an individual or by a company. This information was used to segment the ticket data into personal vehicles and commercial vehicles. Though segmenting the data in this way could result in cars purchased for employee use being included in the commercial vehicle category, the number of non-delivery or service vehicles is likely small.

The ticket data set contains 2,373,687 records. Of this total, 630,280 records, or just over one quarter of all tickets issued (26.5%), are identified as commercial vehicles. The total fine amount for personal and commercial vehicles combined is $96,058,390. Parking fines issued to commercial vehicles make up 28.7% of this amount, or $27,615,375.

Figure 9 shows the temporal variation of CV parking tickets. Peaks are clearly visible at several times throughout the day: midnight, 10:00 AM, noon, and 4:00 PM. These peaks can be explained by a combination of time periods with more strict parking regulations and times of peak CV activity. The peak at 10:00 AM, for example, can be attributed to the large number of deliveries that occur during the AM peak period. The peaks at noon and 4:00 PM can be attributed to restrictions beginning at 11:30 AM and 4:00 PM, respectively.
These peaks are also visible if the area of interest is limited to the CBD, as shown in Figure 10. The peak at 4:00 PM is much more pronounced, which is likely caused by a higher proportion of streets in the CBD having peak period parking restrictions than streets in the rest of the city. There are also very few tickets issued between midnight and 6:30 AM. This could signal a lack of enforcement, a lack of commercial vehicle activity outside peak periods, or a relative abundance of available parking spaces during off-peak periods. The lack of CV activity during this time period is likely to change in the short term, as some operators begin making trips during off-peak periods to achieve time savings. Unless noise mitigation measures are taken by off-peak shippers, this increased activity is likely to spur increased enforcement related to noise restrictions.
Figure 10: Temporal distribution of CV parking citations issued within the Toronto CBD

In 2012, 120,840 tickets were issued in Toronto’s CBD, totalling $5,505,015 in fines. Of this total, 80,316 tickets, or 66% of all tickets, were issued to CVs. CVs accounted for a similar amount of the total fines, accruing $3,734,030, or 67.8%. These figures show that CVs account for a much higher share of parking citations in the CBD as compared to the same figures for the city as a whole (66% in the CBD, 26.5% in whole city). This can be explained partly by the larger number of CV trips that are destined for the CBD.

Table 3 shows the most frequent infractions for which CVs in the CBD are cited. The majority of tickets are issued to vehicles for parking, stopping, or standing during a prohibited time. This helps explain the peaks in Figure 10 that occur at noon and 4:00 PM, as parking during these times are generally prohibited. Vehicles occupying on-street spaces during restricted periods account for about 80% of all CV parking citations. The most common of the remaining citations include failing to pay for parking or parking a vehicle in a prohibited location, such as on the sidewalk or in front of a transit stop.
Table 3: Top CV Citations by Infraction

<table>
<thead>
<tr>
<th>Infraction Description</th>
<th>Frequency</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parking during prohibited time / day</td>
<td>42,390</td>
<td>52.78%</td>
</tr>
<tr>
<td>Stopping during prohibited time / day</td>
<td>17,234</td>
<td>21.46%</td>
</tr>
<tr>
<td>Standing during prohibited time / day</td>
<td>6,398</td>
<td>7.97%</td>
</tr>
<tr>
<td>Failure to display parking receipt</td>
<td>2,588</td>
<td>3.22%</td>
</tr>
<tr>
<td>Parking in travel lane</td>
<td>1,888</td>
<td>2.35%</td>
</tr>
<tr>
<td>Failure to deposit parking fee</td>
<td>1,682</td>
<td>2.09%</td>
</tr>
<tr>
<td>Stopping on sidewalk</td>
<td>1,227</td>
<td>1.53%</td>
</tr>
<tr>
<td>Standing in taxi cab standing area</td>
<td>1,131</td>
<td>1.41%</td>
</tr>
<tr>
<td>Standing at signed transit stop</td>
<td>1,053</td>
<td>1.31%</td>
</tr>
<tr>
<td>Other</td>
<td>4,725</td>
<td>5.88%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>80,316</strong></td>
<td><strong>100%</strong></td>
</tr>
</tbody>
</table>

4.2.2 Parking Supply Data

Data on the supply of parking were initially collected in August 2010, and were compiled to form a complete parking inventory for the Toronto CBD. This inventory is the same as was used in the parking simulation tool presented in Chapter 3, and includes all on-street spaces, off-street surface lots, alleyway loading zones, loading bays, parking garages, and private garages. The on-street portion of this inventory was updated in August 2013 to include detailed information on the timing of parking restrictions for on-street parking, standing, and stopping.

4.2.3 Employment Data

Data on the demand for parking were derived from two sources. For CVs, business establishment location, industry classification, and employment data were obtained from an Info Canada database. These data were used to calculate CV trips using a previously estimated freight trip generation (FTG) model. Establishment data were available for 213 addresses located in the study area, representing 5,000 unique establishments employing over 161,000 people. These establishments were found to generate over one thousand CV trips per day.
4.2.4 Passenger Trip Data

Passenger vehicle trips to the study area were obtained from the 2006 Transportation Tomorrow Survey (TTS). The TTS is comprehensive travel survey of individuals in the GTHA and is conducted once every five years. Data from the TTS were made available by the Data Management Group at the University of Toronto. Over 5,000 passenger vehicle trips were made to this area each day during the PM peak period.

4.3 Aggregate Model

The first attempt at finding relationships between illegal commercial vehicle parking, parking supply, and parking demand was made by aggregating these variables to the postal code level. This level of aggregation allows for easy visualisation of the data. The following sections present the data used in this model aggregated to the postal code level, the methods used, and the results and conclusions.

4.3.1 Data

ArcGIS was used to aggregate the existing parking citation and parking supply data to the postal code level. To allow for this aggregation, all parking citations first needed to be geocoded. This is the process by which addresses are translated into coordinates. The process used to geocode the large parking citation database is described in Appendix B. Freight trips, which were used to represent commercial vehicle parking demand, were also aggregated to the postal code level. The process used to estimate these trips is explained in the methods section. The aggregated data for parking supply, parking demand, and parking citations are presented in Figure 11, Figure 12, and Figure 13 respectively. The darker shades on each figure represent postal codes where there are more parking spaces, freight trips, and parking citations. It may be expected to find an easily visible relationship between these three variables. Postal codes with a large number of trips and few parking spaces should correspond to postal codes large numbers of parking citations. However, upon examination of these figures, no clear relationships appear between these three variables. In order to attempt to identify these relationships, a regression model was estimated.
Figure 11: Parking supply by postal code
Figure 12: Freight trips generated by postal code
Figure 13: Parking citations by postal code
4.3.2 Model Estimation

A linear regression model was used in an attempt to quantify the relationship between commercial vehicle parking citations, parking supply, and parking demand. The dependent variable in this regression model was commercial vehicle parking citations. The previously discussed parking inventory was used to represent parking supply, and a freight trip generation model was used to represent demand for parking. All variables were aggregated to the postal code level.

The freight trip generation model applied here uses parameters previously estimated by the Ontario Ministry of Transportation (MTO, 2007). In this model, the number of commercial vehicle trips to an establishment is estimated based on the industry classification of the establishment and the number of people employed at the establishment. The four industry classifications used are:

- Agriculture, construction, and mining;
- Manufacturing, transportation, communications, utilities, and warehousing (MTCUW);
- Retail trade, and;
- Office and services.

The parameter estimates are based on data from the Region of Peel Commercial Travel Survey, and are adjusted to reflect different commercial vehicle trip patterns observed in denser urban areas. Employment and industry classification data from InfoCanada was used in conjunction with the MTO parameter estimates in order to estimate the number of commercial vehicle trips generated by the establishments in the study area.
The functional form of the linear regression model used is shown in Equation 2 below.

$$T_i = \alpha + \beta_1 t + \beta_2 s_1 + \beta_3 s_2 + \cdots + \beta_n s_{n-1}$$

(2)

Where:
- $T_i$ = Parking citation density
- $\alpha$ = Constant term
- $t$ = Density of CV trips
- $s_1 \cdots s_{n-1}$ = Density of parking supply for each facility type
- $\beta_1 \cdots \beta_n$ = Estimated parameters

The independent variables included all information on parking supply, segmented by facility type, and the number of freight trips generated. The dependent variable used was the number of commercial vehicle parking citations. All variables were aggregated to the postal code level and converted to densities in order to control for postal codes of different sizes. The final model was constructed using only parameters that were found to be statistically significant at the 95% confidence level. The final model results are shown in Table 4.

Table 4: Results of aggregate OLS regression for commercial vehicle parking citations

| Observations | 274 |
| Adjusted R-squared | 0.68 |
| Dependent variable | Ticket Density |

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Coefficient</th>
<th>t-Stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>FTG Density</td>
<td>1.73</td>
<td>24.71</td>
</tr>
</tbody>
</table>

The model shows an adjusted $R$-squared value of 0.68, however only freight trip density was found to be significant. The positive coefficient signifies that, on a postal code level, higher rates of freight trip generation are related to higher numbers of illegal commercial vehicle parking citations.

A possible explanation for this result is that the relationships between the variables is being masked by aggregation. This problem is best explained through the following example. A postal code contains two establishments: a grocery store and an office building. The grocery store has ten parking spaces, generated ten commercial vehicle trips, and only two tickets are issued for vehicles parking illegally at that location. The office building has only 2 parking spaces, but still generated ten commercial vehicle trips, resulting in seven parking citations. On an individual
basis, the relationships between supply, demand, and parking citations can be clearly observed. However, once aggregated, the relationships become unclear. The postal code containing these two establishments would have twelve parking spaces, twenty commercial vehicle trips, and generate nine parking citations. To overcome this limitation, a disaggregate approach should be used.

4.4 Disaggregate Model

While a disaggregate model is needed to identify relationships between parking supply, parking demand, and parking citations, some consideration still must be given to the spatial relationships between the variables. A special many-to-many relationship occurs between parking spaces and trip destinations, which are the points where parking is demanded. Generally, all parking facilities can be used by a vehicle with any destination. This means that even though an establishment may have on-street parking directly in front of their door, it is not used only by CVs or passenger vehicles making a trip to that establishment. Similarly, those vehicles making trips to the establishment are not limited to the spaces directly in front of the establishment. They may choose from any number of parking facilities in a wide area surrounding the establishment. Therefore each establishment has an effective parking supply that is some portion of all the parking spaces in the area around it. It has been observed that passenger vehicles and CVs alike prefer to park as close as possible to their destinations (Shoup, 2006 & Nourinejad et al., 2014). It is then reasonable that spaces located closer to the establishment should be given more weight when determining the effective parking supply for an establishment. A similar relationship exists between parking citations and destinations. Not all citations issued to vehicles are parked immediately in front of their destination. A distance based weighting factor should then also be applied to the parking citation data used in this model.

4.4.1 Data

The final step before model estimation was to filter the data by day of week and time of day. Different travel patterns exist during weekdays than exist during weekends. In many areas there are also different parking restrictions between these two periods. In order to ensure that the model was not being forced to explain significantly different patterns that exist during different time periods, the data were filtered to include only weekdays. As parking restrictions are also
variable by time of day, the data should be filtered to include only certain time periods that have internally consistent parking restrictions. The time periods where these conditions exist are 7:30—9:30 AM, 12:00—1:30 PM, and 4:00—6:00 PM. Figure 10 shows that although high traffic levels occur in the AM peak period, not many CV citations are issued during this time. This may be due to the relatively few CVs on delivery during this time period. There are more citations issued during the mid-day period, but mid-day traffic levels are much lower than AM or PM peak period levels. This means that congestion caused by illegal CV parking is not a major concern. A large increase in the number of tickets issued occurs in the PM peak period, when heavy congestion occurs in the CBD. These factors make this time period potentially the most interesting and likely the time period where the resulting policy recommendations would have the largest impact.

4.4.2 Method

The following sections describe the formulation of accessibility functions to capture the relationships between the variables of interest and their application within a linear regression model.

4.4.2.1 Application of Accessibility Functions

A negative exponential relationship between parking spaces, parking citations, and establishments is assumed. The functional form for effective parking supply is shown in Equation 3 below.

$$E^i_{sj} = s_j \times e^{c \times d_{ij}}$$ (3)

Where:

- $E^i_{sj}$ = Effective value of parking spots at location $j$ to establishment at location $i$
- $s_j$ = Parking spaces at location $j$
- $c$ = Calibration coefficient
- $d_{ij}$ = Distance between location $i$ and location $j$

This distance decay function was applied to all variables used in the model. The distance between points was calculated as the grid distance. Several calibration coefficients were used, ranging from -0.001 to -0.1. The smaller the absolute value of the calibration coefficient, the further away a parking facility can be while still having the same impact on the effective supply
at an establishment. Little evidence exists for the choice of any particular value for the calibration coefficient over another, so models were estimated using several values.

### 4.4.2.2 Model Formulation

Addresses were used as the basic unit of analysis in the model. This unit of analysis was selected over other units, such as postal codes or intersections, because it is the most disaggregate. By using a disaggregate unit, hidden effects caused by aggregating locations with different characteristics which may drive different behaviours can be avoided. Conveniently, parking citations and employment data are both readily available at the address level. This makes the on-street parking supply the only variable of interest that is not already at the address level. On-street parking spaces were converted to the address level using Theissen polygons and a spatial join procedure. Theissen polygons are shapes drawn around each existing address such that the closest address to any point within a given polygon is the address at that polygon’s centre. A spatial join was then used to match each on-street parking space to the address from which the Theissen polygon it intersected was created. Finally, the distance decay function was applied to create a measure of accessibility to these spaces from all nearby addresses.

The functional form of the model to be estimated is shown in Equation 4 below:

$$E_t = \alpha + \beta_1 E_1 + \beta_2 E_2 + \ldots + \beta_n E_n$$  \hspace{1cm} (4)

Where:

- $E_t$ = Effective parking citations ($t$) after application of distance decay function
- $\alpha$ = Constant term
- $\beta_1$...$\beta_n$ = Estimated parameters
- $E_1$...$E_n$ = Variables after application of distance decay function

A list of independent variables that were tested for inclusion in the model is shown in Table 5.
Table 5: List and Description of Independent Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>tickets</td>
<td>Parking citations</td>
</tr>
<tr>
<td>cvtrips</td>
<td>PM period CV trips</td>
</tr>
<tr>
<td>paxtrips</td>
<td>PM period passenger trips</td>
</tr>
<tr>
<td>bizcount</td>
<td>Unique establishments at the location</td>
</tr>
<tr>
<td>employment</td>
<td>Employment</td>
</tr>
<tr>
<td>lzs</td>
<td>Loading zone count</td>
</tr>
<tr>
<td>lbs</td>
<td>Loading bay count</td>
</tr>
<tr>
<td>osl</td>
<td>On-street standing spaces</td>
</tr>
<tr>
<td>osp</td>
<td>On-street parking spaces</td>
</tr>
<tr>
<td>oss</td>
<td>On-street stopping spaces</td>
</tr>
<tr>
<td>sfs</td>
<td>Surface lot spaces</td>
</tr>
<tr>
<td>pgs</td>
<td>Parking garage spaces</td>
</tr>
<tr>
<td>restrictedspaces</td>
<td>On-street spaces where activity is restricted during PM peak</td>
</tr>
<tr>
<td>hydrants</td>
<td>Fire hydrants</td>
</tr>
</tbody>
</table>

4.4.3 Results and Discussion

All variables presented in the final model are effective values, which have been processed using the distance decay function previously described. Models were estimated using a range of calibration coefficients, $c$, in the distance decay function. It was found that a calibration coefficient value of -0.01 resulted in the best-fit model. This implies that a parking spot 100 metres away is worth a little more than one third of a spot located directly in front of an establishment when calculating the effective parking supply for that establishment. The final model was constructed using only parameters that were found to be statistically significant at the 95% confidence level. The final model results are shown Table 6.
Table 6: Results of OLS regression for commercial vehicle parking citations

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Coefficient</th>
<th>t-Stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Space Count</td>
<td>0.88</td>
<td>7.03</td>
</tr>
<tr>
<td>Business Count</td>
<td>1.41</td>
<td>19.6</td>
</tr>
<tr>
<td>Loading Bay Spaces</td>
<td>-9.19</td>
<td>-10.36</td>
</tr>
<tr>
<td>Surface Lot Spaces</td>
<td>-0.49</td>
<td>-4.84</td>
</tr>
<tr>
<td>Parking Garage Spaces</td>
<td>-0.05</td>
<td>-4.84</td>
</tr>
<tr>
<td>Constant</td>
<td>-14.58</td>
<td>-0.86</td>
</tr>
</tbody>
</table>

The model shows an adjusted $R$-squared value of 0.61. Positive coefficients were found for the number of restricted spaces as well as the number of establishments at an address, meaning an increase in restricted spaces or number of establishments at a single address will lead to an increase in the number of CV parking citations. Surprisingly, the business count was a much better predictor of citations than either the FTG models or raw employment. This could be due to the error terms already included in the FTG model. Another possible explanation is that any establishment, regardless of employment, will have a minimum number of deliveries. So if there are two locations with equal employment, the location with more unique establishments within it will attract more CV trips. Assuming all else is equal between the two hypothetical locations, the greater number of trips will generate a greater number of citations.

Negative coefficients were found for the number of loading bay spaces, surface lot spaces, and parking garage spaces. All other parking supply variables did not enter the model. This is notable, because it implies that increasing the number of available on-street parking spaces will have no effect on the incidence of illegal CV parking. Instead, policies should focus on increasing the availability of dedicated loading facilities for CVs and off-street parking facilities for passenger vehicles. A possible explanation for this result is that during the PM peak period CVs are unable to find available on-street spaces due to the large number of spaces occupied by passenger vehicles. In areas with parking garages and surface lots nearby, long term parkers will choose these facilities over on-street spaces. This results in more on-street spaces being available for CVs to park legally in front of their destinations. This is an important finding for courier groups in particular, who have been working to create more on-street parking dedicated for CV
use. If this model and explanation are accurate, their efforts may be better spent pushing for loading facility requirements in new buildings or increased on-street parking prices to entice passenger vehicles to use the less expensive off-street facilities where available.

4.4.4 Conclusions

This chapter examined the relationships between illegal commercial vehicle parking and the built environment, expressed in terms of the demand for and supply of parking in urban areas. New data were presented on CV parking citations, and it was found that 80% of CV parking citations were issued to vehicles operating during restricted periods. These restrictions are typically active only during peak periods when the full capacity of major arterials is needed to move vehicles. The large percentage of total CV tickets issued for these violations suggest that CVs are a major contributor to congestion on urban arterials in Toronto’s CBD.

This chapter also presented the estimation of a distance decay weighted linear regression model. The distance decay function was used to account for spatial interactions between parking citations, parking supply, and parking demand. Variables for effective parking citations, parking supply, and parking demand were created using this method. The resulting model found that restricted on-street spaces and high numbers of unique business establishments at a single location tend to increase the incidence of illegal CV parking. It was hypothesised that the number of unique establishments is a better predictor of CV citations than the estimated number of CV trips from the FTG model or employment because each establishment generates a minimum number of CV trips. This means locations with several unique establishments rather than one large establishment will generate more CV trips, resulting in more citations. The model also found that only loading facilities and off-street parking facilities contributed to decreases in the number of CV citations. The availability of on-street facilities was not found to have any ability to decrease the number of citations. These results can be used as an argument to shift policy away from increasing the quantity of on-street parking towards medium and long-term efforts to require loading facilities in new buildings. Another effective set of policies may include adjustments to on-street parking prices in order to shift passenger vehicles from parking at the curb to using available off-street parking facilities.
Chapter 5 Conclusion

This thesis focused on the problems related to commercial vehicles operating in urban areas and developed methods to identify what policies may be effective in mitigating the impacts of commercial vehicle operations. The first method involved simulating commercial vehicle parking behaviour and analysing how various parking restrictions would impact commercial vehicles, passenger vehicles, and overall network congestion. The second method focused on identifying relationships between illegal commercial vehicle parking, parking supply, and parking demand. Both methods represent tools that can help inform the decisions of policy makers when creating new parking policies in urban areas.

5.1 On Simulating Commercial Vehicle Parking Choice

Chapter 3 introduced a microsimulation based tool to measure the impacts of alternative parking policies on the transportation network. The method represented a new approach to parking policy evaluation. The method involves the integration of a behavioural parking choice model within a traffic microsimulation, and represents a new approach to parking policy evaluation. The model is able to capture several different aspects of parking activity, such as distance to destination, parking facility preferences of the driver, parking search time, and the impact of parking search on congestion. The model is tested through application to two scenarios with altered parking restrictions (Figure 14).

Figure 14: Scenarios tested with microsimulation tool
In the first scenario, commercial vehicles are given exclusive access to on-street parking spaces on two minor streets. However, they are restricted from parking elsewhere in the study area. In the second scenario, the exclusive commercial vehicle parking area is maintained, but the restriction from parking elsewhere is removed. The resulting impact on network congestion is summarized in Table 7.

**Table 7: Summary of impact of parking restrictions**

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Total Network Travel Time (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base Case</td>
<td>3542</td>
</tr>
<tr>
<td>Scenario 1</td>
<td>3497</td>
</tr>
<tr>
<td>Scenario 2</td>
<td>3439</td>
</tr>
</tbody>
</table>

In both scenarios, an overall reduction in total network travel time is observed. This signifies a reduction in total time spent searching for parking and walking from the parked location to the intended destination for both commercial vehicles and passenger vehicles.

5.2 On Identifying Relationships between Illegal CV Parking and the Built Environment

Chapter 4 focused on examining the relationships between illegal commercial vehicle parking, parking supply, and parking demand. New data on commercial vehicle parking citations were analysed, which revealed that commercial vehicles account for a disproportionately high share of parking citations in dense urban areas. It was also found that 80% of all commercial vehicle citations were issued during restricted parking periods. This suggests that not only is illegal commercial vehicle parking a more common problem in denser areas, but that it also has a larger negative impact during peak periods.

Chapter 4 also presented the estimation of two linear regression models. Each model used commercial vehicle parking citations as the dependent variable, and attempted to quantify its relationships with variables describing the parking supply and parking demand. In the first model, the data were aggregated to the postal code level to account for parking citations and parking spaces nearby, but not at the same address, as the intended destination. However, it was found that this aggregation may have masked the relationships the model was attempting to quantify. The second model employed the use of a distance decay based weighting function. This
function accounted for spatial interactions between parking citations, parking supply, and parking demand by creating measures of effective supply, demand, and parking infractions. The resulting model found that parking restrictions on existing on-street spaces and higher numbers of unique establishments are related to a higher number of parking citations, while the availability of dedicated loading facilities and off-street parking facilities are related to a lower number of parking citations. This result runs counter to conventional wisdom, which suggests that illegal parking can be solved by adding more on-street parking spaces. Instead, the model results suggest that creating dedicated commercial vehicle facilities, such as loading bays and loading zones, may result in a lower number of parking citations.

5.3 Recommendations for Future Research

The following are the major areas in which further research in this area may be useful.

- For the behavioural parking choice model, separate models should be estimated for each commercial vehicle type. In the current model, all commercial vehicles are assumed to make parking decisions that conform to a single choice function. Couriers, food delivery vehicles, and shredding trucks, for example, all have unique needs and likely make different choices when selecting a parking space. A larger data collection effort would be needed in order to estimate separate models for each vehicle type.

- A major assumption in the estimation of the choice model is made in the synthetic creation of a choice set of potential parking spaces for each vehicle. The choice set is determined by selecting the last two spaces a vehicle passed on the shortest path from their previous delivery to their chosen parking location. It is possible that in many cases the parking locations included in the choice set as being rejected by drivers may not have been available to them, and if they had been available, the driver may have chosen them. Creating a more realistic choice set could lead to a more accurate parking location choice model, though collection of the required data would be a significant challenge.

- Additional policies should be tested with the simulation tool, such as time restrictions, parking information systems, pricing strategies, and new parking facilities, or requirements for new developments. Some of these policies would be easy to implement,
while others would require additional data collection and significant alteration to the simulation network.

- In order to better identify the relationships between parking citations and the built environment, future studies should expand the boundaries to include areas outside of the central business district. The study area chosen for this research was limited based on the availability of a parking inventory. This forced the model to attempt to explain relatively small variations in the distribution of parking citations through relatively small variations in the built environment. The differences in parking citation distribution and the built environment between dense urban environments like the Toronto CBD and more suburban areas of the city may allow a model to better capture the relationships between key variables.
References


24. Off-Peak Freight Deliveries: Challenges and Stakeholders Perceptions


## Appendix A Commercial Vehicle Survey Instrument

**Questionnaire**

1.1 – Type of freight carrier
1.2 - TL, LTL or Package
1.3 - Type of freight carried
1.4 – Type of truck driven

2.1 – How long have you been driving for this company?

2.2 – How long have you been driving in downtown Toronto?

2.3 – How familiar are you with parking available in downtown Toronto?

3.1 – What type of fuel does your vehicle use?

4.1 – Currently, where are you parked relative to your destination?

4.2 – List the location(s) of the pickup/delivery or other activity accessed from this parking spot

4.3 – What is the approximate total weight of deliveries from this parking spot?

4.4 – What is the approximate total weight of pickup from this parking spot?

4.5 – What is the approximate total number of boxes/packages/items delivered and picked-up?

4.6 – Was any special handling equipment used? If so, please describe

4.7 – Did you have difficulty finding a legal parking spot? If so, how long did you spend searching for a spot to parking?

4.8 – Did you have to wait to use a loading zone at this stop? If so, how long did you wait?

4.9 – Do you idle or turn your engine off when making deliveries/pickups? If you do idle, for how long do you do so?

4.10 - Do you understand what the no stopping, standing, parking sign mean?

5.1 – What was the location of your previous stop?

5.2 – What will be the location of your next stop?

5.3 – How many pickups/deliveries/other purpose stops do you expect to have made by the end of today? How many of these are in downtown TO?

5.4 – What are your driving hours for today?

5.5 – What is the location of your depot?

6.1 – What times of the day are the easiest to park legally? The hardest?

6.2 – What makes it hard to park legally at the hardest time of the day? (Select three)

6.3 – Where are the majority of your parked locations at?

6.4 – How many parking tickets do you typically receive daily?

6.5 – Do you agree parking authorities are biased towards commercial vehicles in issuing tickets?

6.6 - Does your company have a parking policy? If so, what is it?

6.7 – What are major barriers for using loading and parking zones?

6.8 – Which area in the downtown is the most frustrating for you to park/load and why?
Appendix B: Parking Citation Geocoding Procedure

The original data set of parking citations issued in the City of Toronto in 2012 contained 2,746,149 records. This was reduced to a list of 2,743,697 complete records. 2,452, or 0.09% of records, were discarded because of typographical data entry errors. Contained within this list of 2,743,697 records were 229,326 unique addresses. This list of unique addresses was passed through GeoPinpoint, a geocoding tool, and resulted in a 93.3% match rate. The 15,363 unique addresses which remained unmatched by GeoPinpoint corresponded to 126,437 addresses in the original database. From the remaining unique addresses, 1,095 with more than 10 occurrences were selected. These addresses represented 86,370 records. An online geocoding tool was used to match these remaining records, but was not able to match records located at intersections. To match these remaining 7,625 records, a third online geocoder was used that allowed for the geocoding of intersections. The result of this process is 2,711,254 geocoded addresses, which represents 98.73% of the original complete database. The following instructions detail the steps used to prepare a table of addresses in Microsoft Access for geocoding and the methods used to geocode the finalized table.

Data Preparation

The 2012 parking citation data contains the following: Address, Intersection, Province, Tag Number, Date of Infraction, Infraction Code, Infraction Description, Fine Amount, and Time of Infraction. Our goal in geocoding these records is to obtain a spatial representation of these tickets, in order to organize them by postal code for further analysis. We will discard any record which does not have enough information to obtain a reasonably accurate location. Typical of large, manually entered records, the data contains many typos and inaccuracies. All of these erroneous entries should be removed. Assuming the typographical errors are randomly distributed due to human error while entering the data, deleting these records should not affect the overall sample. However, care has been given to avoid discarding incorrectly formatted records which occur many times, as removing these records would introduce bias into the data.

The data were imported into Microsoft Access to facilitate the preparation process. The following describes the Access Queries performed in order to clean the data.
Add municipality for all records:
UPDATE Ticket_Data_Original
SET municipality = “Toronto”;

Add province for all records:
UPDATE Ticket_Data_Original
SET province = “ON”;

Delete records with no address information:
SELECT [Ticket_Data_Original].*
FROM Ticket_Data_Original
WHERE [Ticket_Data_Original].[Address] is NULL;
DELETE Ticket_Data_Original.*
FROM Ticket_Data_Original
WHERE ((Ticket_Data_Original.Address) Is Null);

Delete any record beginning with ‘0’ or special character:
DELETE Ticket_Data_Original.*
FROM Ticket_Data_Original
WHERE ((([Ticket_Data_Original].[Address])<'1'));

Designate separator for intersections: This step is required to take advantage of the ability of some geocoders to return coordinates that match intersections.
UPDATE [Ticket_Data_Original]
SET [Ticket_Data_Original].[Address] = [Address] & ” && ” & [Intersection]
WHERE [Ticket_Data_Original].[intersection] IS NOT NULL;
Delete records with no number or designated intersection: There were 2201 records which had no intersection data and also no number address. These were deleted. Included in this was 299 street names, 61 street names which appear more than 5 times.

```
DELETE [Ticket_Data_Oringial].[Address]
FROM Ticket_Data_Original
WHERE [Address] NOT LIKE "*[0-9]*" AND [Address] NOT LIKE "* & & *";
```

Removed unnecessary spaces:

```
UPDATE [Ticket_Data_Original]
SET [Ticket_Data_Original].[Address] = Replace([Ticket_Data_Original].[Address], ", ", ", 1,1)
WHERE ((([Ticket_Data_Original].[Address]) Like "[0-9] [0-9]*")
```

Edited 769 records containing "CRCT", replaced with proper abbreviation, "CRES":

```
UPDATE [Ticket_Data_Original]
SET [Ticket_Data_Original].[Address] = Replace([Ticket_Data_Original].[Address], "CRCT", "CRES", 1,1)
WHERE ((([Ticket_Data_Original].[Address]) Like "* CRCT*")
```

Edited 205 records containing "LWN", replaced with "Lawn":

```
UPDATE [Ticket_Data_Original]
SET [Ticket_Data_Original].[Address] = Replace([Ticket_Data_Original].[Address], "LWN", "Lawn", 1,1)
WHERE ((([Ticket_Data_Original].[Address]) Like "*LWN*")
```

Edited 2520 records containing “CT», replaced with proper abbreviation, "CRT":

```
UPDATE [Ticket_Data_Original]
SET [Ticket_Data_Original].[Address] = Replace([Ticket_Data_Original].[Address], "CT", " CRT", 1,1)
WHERE ((([Ticket_Data_Original].[Address]) Like "* CT")
```
Edited 4526 records containing “TER”, replaced with “Terrace”:

UPDATE [Ticket_Data_Original]
SET [Ticket_Data_Original].Address = Replace([Ticket_Data_Original].[Address],
"TER", "Terrace", 1,1)
WHERE ((([Ticket_Data_Original].Address) Like "* TER*")) AND
(([Ticket_Data_Original].Address) Not Like "* TER[A-Z]*");

Edited 2904 records containing "BL", replaced with "BLVD": Special care must be taken not to change road names beginning in “BL”, such as Bloor St.

UPDATE [Ticket_Data_Original]
SET [Ticket_Data_Original].Address = Replace([Ticket_Data_Original].[Address],
"BL", "BLVD", 1,1)
WHERE ((([Ticket_Data_Original].Address) Like "* BL*")) AND
(([Ticket_Data_Original].Address) Not Like "* BL[A-Z]*");

Edited 3752 records containing "CRCL", replaced with "Circle":

UPDATE [Ticket_Data_Original]
SET [Ticket_Data_Original].Address = Replace([Ticket_Data_Original].[Address],
"CRCL", "Circle", 1,1)
WHERE ((([Ticket_Data_Original].Address) Like "*CRCL*"));

Edited 2521 records containing "GRV", replaced with "Grove":

UPDATE [Ticket_Data_Original]
SET [Ticket_Data_Original].Address = Replace([Ticket_Data_Original].[Address],
"GRV", "Grove", 1,1)
WHERE ((([Ticket_Data_Original].Address) Like "*GRV*"));
**Correcting other special characters:** At this point, there were 2,398 records containing a special character (not including the address delimitating “&&”). These 2,398 records represented 701 unique addresses. Sorting by addresses that appeared more than 10 times, there are 18 unique addresses which compromise 857 records. These 857 records consisted of hyphenated apartment numbers which required specific adjustments. An example is given below.

```
UPDATE [Ticket_Data_Original]
SET [Address] = Replace([Address], "10-60", "60")
WHERE [Address] LIKE "10-60 MENDELSSOHN ST*";
```

After these changes, the remaining 943 records which contained a special character were deleted, with the exceptions of:

- those containing a hyphen in the street name
- those containing an intersection delimitating “&&”
- those containing a period as a street type abbreviation

The queries used to perform these edits were:

```
DELETE *
FROM [Ticket_Data_Original]
WHERE [Address] LIKE "*[0-9a-zA-Z]*"
AND [Address] NOT LIKE "*[A-Z]-[A-Z]*"
AND [Address] NOT LIKE "*&*&"
AND [Address] NOT LIKE "*[A-Z].";
```

After performing the above-mentioned steps, the data set has been reduced from 2,746,149 to 2,743,697 records. Only 2,452, or 0.09% of records were discarded because of typographical data entry errors. Selecting only distinct Addresses, the table has been reduced from 2,744,640 to 229,326 records. This reduction allows for a faster geocoding process, which is described in the following section.
Geocoding

The first method used to geocode these addresses was GeoPinpoint. This program takes an Access Database as input and outputs the same database with added columns with x and y coordinates. The settings used in the GeoPinpoint geocoding procedure were:

- Use Un-Parsed Address Field
- Geocode By Municipal Boundary
- Geocode to Street Former Name
- Geocode to Street Alias
- Search Segment Information
- Use Constant for Prov/State: ON
- Use Intersection Delimiter

The first pass through GeoPinpoint resulted in:

- 15,363 unique, unmatched addresses
- 1,350 of which appear more than 10 times

In order to attempt to geocode these addresses, an online geocoder was used. The selected geocoder was located at http://www.gpsvisualizer.com/geocoder/, and was provided courtesy of Adam Schneider. The geocoder uses a Yahoo API and has a limit of 1,000 records per query. This geocoder also does not geocode intersections. All remaining unmatched addresses were matched using this method.

In order to match the remaining unmatched intersections, a second online geocoder was used. This geocoder uses the Google Maps API, and was located at: http://gmapssamples.googlecode.com/svn/trunk/geocoder/singlegeocode.html. The 53 unmatched intersections represented 7,625 records. All unmatched intersections were matched using this method.