Do Parcel Lockers Reduce Delivery Times? Evidence from the Field

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ABSTRACT

Common-carrier parcel lockers have emerged as a secure, automated, self-service means of delivery consolidation in congested urban areas, which are believed to mitigate last-mile delivery challenges through reducing out-of-vehicle delivery times and consequently vehicle dwell times at the curb. However, little research exists to empirically demonstrate the environmental and efficiency gains from this technology. In this study, we designed a nonequivalent groups pre-test/post-test control experiment to estimate the causal effects of a common-carrier locker in a multi-story residential building in downtown Seattle, WA. The causal effects are measured in terms of vehicle dwell time and the time delivery drivers spend inside the building, through the difference-in-difference method and using a similar nearby residential building as a control. The results showed a statistically significant decrease in time spent inside the building, and small yet insignificant reduction in delivery vehicle dwell times at the curb. The locker was also well received by the building managers and residents.

Keywords: Common-carrier Parcel Lockers, Residential Building, Last-mile Delivery, Dwell Time, In-building Time

1. INTRODUCTION

In recent years, explosive growth in e-commerce has spurred dramatic demand for deliveries in urban areas. From 2007 to 2018, e-commerce consumed more of the total U.S. retail market share each year, increasing from 5% to 14.3% (Ali, 2019). In 2020 alone, retail e-commerce sales grew 27.6% worldwide, and 31.8% in North America (Cramer-Flood, 2021). Since the advent of the COVID-19 pandemic and shutdowns in March 2020, online sales increased by over 30% in the U.S., despite a near-global recession that reduced consumer spending at brick-and-mortar retail in many countries (US Census Bureau, 2021; UNCTAD, 2021). Consequently, urban residential and mixed-use areas have seen dramatic increases in home deliveries. A single residential building in New York City can receive 60-100 packages per day (Dablanc, 2019), and census tracts spanning just a few blocks generate a delivery demand ranging from 200 to 600 packages per day (De Oliveira, 2017). Demand for package deliveries in residential areas spiked drastically during the COVID-19 pandemic, to the point at which major carriers such as UPS had to refuse delivery requests from retailers (Black & Homan, 2020).

Compared to commercial deliveries (in central business districts or industrial areas), residential delivery fulfillment exerts different pressures on public street space. An increased emphasis on direct-to-consumer deliveries gives consumers more power over how their orders are fulfilled (Savelsbergh & Van Woensel, 2016). An increasing tableau of carriers—postal and express parcel delivery companies, instant grocery and meal delivery services, and retailer fulfillment services—compete for limited and often congested street and curb space (Dablanc, 2019), and the uptick in small items ordered online has increased light goods vehicle traffic. In urban areas, delivery vehicles must compete for limited street parking not only with other commercial and service vehicles, but also with private and ridehailing vehicles.

These demands generate externalities in the so-called “last mile” of delivery— the final link from retailer to consumer. Limited parking availability can result in an average of one hour a day per delivery vehicle of wasted time cruising for parking (Dalla Chiara & Goodchild, 2020; Dalla Chiara et al., 2021). Traffic congestion, cruising for parking, missed deliveries and repeated delivery attempts in the last-mile account for as much as 28% of total transport costs and 25% of emissions from the overall supply chain sector (Chen & Conway, 2017; Urbanowicz-Pollock, 2019). Yet, street infrastructure has failed to keep pace with the rise in urban deliveries. In 2019, delivery companies paid the city of New York a combined $123 million in parking fines (Baker, 2020), mainly due to insufficient commercial load zones near delivery destinations. Little has changed since 2006, when carriers paid the city $102 million in parking fines over a year and averaged a combined 7,000 tickets per day (The Associated Press, 2006). Moreover, urban freight stakeholders estimate that up to 10% of first delivery attempts fail (Goodchild et al., 2019), creating the need for additional trips, mostly because the consumer is not home to receive the package. Package theft is also an increasing issue in urban areas. When residents are not home to receive their deliveries and there is no secure storage place, packages are left at the doorstep and might get stolen. A survey of 2,000 consumers in 2020 found that 43% had a delivery stolen from their front door that year (Roggio, 2021).

A potential solution to the last-mile delivery challenges that has emerged in the past few years is common-carrier parcel lockers. Common-carrier parcel lockers are automated multi-compartment storage systems that enable temporary storing of parcel deliveries from any carrier into a secure space until pick-up by the consumer. Delivery couriers deposit packages into any available compartment of an appropriate size in the locker. Upon delivery, consumers receive an electronic notification and a unique code that allows them to open the compartment and retrieve their packages at a convenient time. Parcel lockers may be placed in residential buildings, stores, transit stations, or neighborhood hubs, serving different groups of consumers.

Parcel lockers create a central delivery hub and allow couriers to deliver multiple packages to one location rather than multiple locations (Figure 1); e.g. instead of going to multiple destinations in a neighborhood, a courier can deliver all packages to a locker located in a nearby parking lot, or instead of going floor-to-floor and door-to-door in a large residential building, a courier can deliver all packages to a locker in the lobby of the building. This creates delivery density, and can potentially reduce the time spent inside a building and the vehicle dwell time— the time a delivery vehicle stays parked while the driver performs deliveries to nearby buildings. Reductions in dwell time and failed delivery attempts reduce time taken to perform deliveries, and hence lower costs for delivery firms, reduce delivery vehicle-miles traveled (VMT), and decrease traffic congestion and emissions. By providing a secure storage system, parcel lockers also effectively reduce failed delivery attempts and the need for additional trips. The World Economic Forum estimates that by 2030, parcel lockers could reduce global delivery costs by 2-12% and emissions by 5-18% (World Economic Forum, 2020). Yet, there has been no empirical analyses of impacts of parcel lockers on delivery times or traffic congestion.

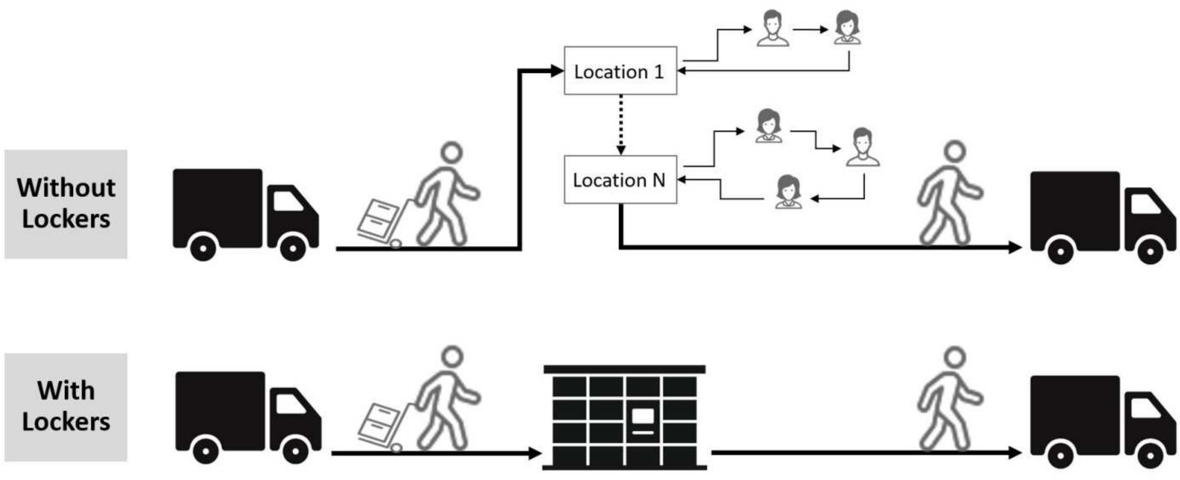


Figure 1: Schematic of an example delivery process with and without a parcel locker system

This study seeks to fill the above gap by quantifying the impacts of a common-carrier parcel locker on delivery times. We collected empirical delivery data on two multi-story residential buildings in downtown Seattle, one with and the other without a locker, and deployed a nonequivalent groups pre-test/post-test control experiment to estimate the causal impacts of a common-carrier parcel locker on delivery times, and more specifically, on vehicle dwell time and the time delivery couriers spend inside a building. Moreover, to assess the performance of lockers from the perspective of residents and building managers, we designed and conducted a short online survey of the residents of the building with the locker, and solicited feedback from the building managers.

By combining quantitative and qualitative data on operational delivery efficiency and user experience at a residential building, we determine and estimate the benefits of common-carrier parcel lockers for carriers, building managers and e-commerce users. This can inform delivery companies, urban planners, policy makers, and the broader urban freight ecosystem in designing a better urban logistics system and reduce externalities associated with the last-mile parking challenges.

The remainder of this paper is organized as follows. The next section provides a summary of previous research on common-carrier parcel lockers and pre-test/post-test experimental designs. The study context and research design are described afterwards, followed by the data collection process in Section 4. The 5th section explains the modeling framework and specifications, and the analysis results are presented in Section 6. The final section of the paper discusses the findings and provides recommendations for future studies.

2. LITERATURE REVIEW

This section provides a summary of previous research on common-carrier parcel lockers, and reviews prior studies that implemented the experimental design for establishing causal impacts of a treatment strategy.

2.1. Common-Carrier Parcel Lockers

Several studies on parcel lockers examined consumer views toward the adoption and use of lockers, especially those located in publicly accessible locations. Researchers in Brazil, Indonesia, Italy and the U.S. investigated the potency of public parcel lockers through surveys, focus groups, or interviews (Iannaccone et al., 2021; Nahry and Vilardi, 2019; Urban Freight Lab, 2018; Vakulenko et al., 2018; De Oliveira et al., 2017). While all studies found that most consumers— either young, middle-aged, or senior— still prefer traditional home delivery over the public parcel lockers, 60-70% of respondents in either study expressed an interest in using parcel lockers, citing security, more up-to-date package information, the ability to pick up packages at any time of the day and lower delivery costs as primary perceived motivations. The respondents also showed more willingness to use lockers if they were to be located in the walking distance of their home/work (Iannaccone et al., 2021; Nahry and Vilardi, 2019) or inside/near transit stations along their commute transit routes (Urban Freight Lab, 2018). In the Brazil study, respondents also stated their top three location picks for public lockers as supermarkets, stores and shopping malls (De Oliveira et al., 2017).

Existing operations research on common-carrier parcel lockers addresses large-scale routing and scheduling problems. Deutsch and Golany (2018) maximized total profit from deliveries by choosing the optimal number, location, and size of lockers in a city network, taking into account the cost to consumers travelling to the locker. In a typology of parcel lockers, Rohmer and Gendron (2020) identified two business models: carrier-owned lockers, such as those operated by Amazon or the United Parcel Service (UPS), and common-carrier lockers that are open to all carriers. They defined three primary operations research problems concerning lockers: network design and facility location, vehicle routing, and matching customer orders with lockers with appropriate capacity. Using a simulation of customer pickup at outdoor public lockers compared to home delivery, Arnold et al. (2017) demonstrated that self-pickup points can significantly reduce carriers' operational costs.

Another set of prior research on parcel lockers consists of aggregate analysis of economic and environmental benefits at the neighborhood or city level. Several studies, including an analysis of lockers provided by Polish postal service, InPost, concluded that, compared to other last-mile solutions such as common drop-off points, lockers generate the greatest reductions in VMT and carbon emissions (Iwan et al., 2016; Behnke, 2019). Van Duin et al. (2020) quantified the economic and environmental benefits of lockers in Amsterdam through an activity-based simulation model, and found that, compared to home delivery, lockers reduced emissions, primarily by limiting failed delivery attempts. In another study, Gatta et al. (2019) assessed the economic and environmental impacts of a potential locker-based crowdshipping service in Rome, where transit commuters (people traveling between home and work on transit) act as crowdshippers by delivering packages to parcel lockers located inside or near transit stations. The findings suggest that implementing such a service results in more than a thousand ton CO_2 reduction per year. A cost-benefit analysis of a prospective common-carrier parcel locker project for a residential complex in South Korea stated a benefit-cost ratio of 4.89 over a 10-year time horizon (Pham and Lee, 2019), with primary benefits stemming from travel time savings, along with vehicle cost and emissions reductions. Lachapelle et al. (2018) applied a clustering algorithm to land-use data from an Australian city to identify four typologies for neighborhoods with parcel lockers. Despite the apparent public benefits, few lockers were located in transit-accessible areas, and most were found in areas with considerable parking space.

In 2019, a common-carrier locker system was piloted in a 62-story office building in downtown Seattle, WA, one of the few tests of such systems in the United States (Goodchild et al., 2019). Researchers noted a 78% reduction in delivery times within the building, zero failed deliveries to the building, and a reduction in vehicle dwell times and idling. However, this study consisted of a small sample size, and was rather an observational study.

With the exception of the aforementioned pilot, existing research contains no experimental tests of individual common-carrier locker systems. Most existing research concentrates on the estimated network effects of lockers distributed throughout a city, aggregate efficiency gains for carriers, or generalized measures of emission reductions. Only a few studies examine delivery behavior at the block or building level, while these activities have critical effects on delivery time. Previous studies on improving last-mile delivery efficiency have identified dwell time at the curb and time spent navigating vertical space within a building as key performance measures (Goodchild et al., 2019; Kim et al., 2021).

Although these lockers have gained large acceptance in some European and East Asian markets, they remain largely untested in the United States. So, geographically, the existing literature on parcel lockers almost entirely focuses on countries where parcel lockers have become commonplace, such as Australia, Japan, Germany or Poland. Furthermore, research has been limited to privately-owned lockers, such those operated by Amazon or UPS, or government-run facilities such as Australia's Post lockers, rather than lockers that are carrier agnostic.

2.2. Causal Inference Experimental Design

Prior research has studied the impacts of lockers through either observational or simulated studies, and have not demonstrated a causal effect through experimentation. However, urban delivery times depend on several factors, such as the seasonality of deliveries, environmental conditions, or local traffic and construction operations, and ignoring those factors complicates identification of the causal effects of lockers on delivery times. Moreover, lack of a control group or randomization creates uncertainty over the contribution of selection bias and locker effects to reported differences in delivery times.

The gold standard for setting up such experiments is a Randomized Control Trial (RCT) where subjects are randomly assigned to treatment and control groups, and measured both before and after receiving a treatment. While RCTs have revolutionized economics and policy research in recent decades (Duflo, 1973; Banerjee, 2020), setting up such an experiment proves impossible in an urban transportation setting where researchers have no control over operators' schedules and routing (Handy et al., 2005).

A good alternative to RCT, is the difference-in-difference (DiD) method in a pre-test/post-test control group design. In this setting, subjects are divided into treatment and control groups with only one group receiving the treatment; yet for both groups observations are collected for two periods, before and after the treatment. To estimate the impact of the treatment, the average change over time in the control group is subtracted from the average change over time in the treatment group (Card & Krueger; 1994). This "double differencing" removes two sources of bias, from pre-existing differences between the members of the control and treatment groups, and from changes in the treatment group related to trends over time other than the treatment effect.

The DiD method has gained widespread credibility among researchers for estimating causal relationships when the treatment and control groups contain subjects that differ on one or more characteristics. However, such experiments are rare in the field of urban transportation, given the difficulty and resources required when implementing a pilot, collecting field data, assigning individuals to treatment and control groups, and controlling for confounding factors in the urban landscape. Handy et al. (2005) designed a quasi-longitudinal experiment to study the causal relationship between travel behavior and neighborhood characteristics, with the goal of investigating whether land use policies of bringing residents closer to destinations, will actually result in people driving less. Ge et al. (2017) conducted a pre-test/post-test control group design coupled with DiD analysis to test whether exposure to a real-time multi-modal transportation information display screen affects travel choices and perceptions of alternative modes to driving. A similar methodology was implemented by Wen et al. (2021) to measure the effects of ridehailing and carsharing service adoption on travel rate and car ownership. They designed a pre-test/post-test randomized encouragement experiment by sending mobility credits to randomly selected subsets of non-users to encourage them to join the mobility services, and applied DiD analysis to measure the effects of joining mobility services on travel behavior.

2.3. Study Contribution

Parcel lockers have emerged as a potential solution to the last-mile delivery challenges, and are believed to reduce delivery times and traffic congestion. However, to date, there has been no empirical analyses of impacts of parcel lockers on delivery times. This study presents a framework for a rigorous empirical analysis of the causal effects of common-carrier parcel lockers on delivery times. By collecting field data and applying a pre-test/post-test control group experiment, this study, for the very first time, estimates the impacts of a parcel locker system on delivery times, and more specifically, on vehicle dwell time and the time delivery couriers spend inside a building.

3. METHODOLOGY

3.1. Research Design

In this study, we have applied the DiD analysis framework to design a pre-test/post-test control group experiment for estimating the causal impacts of a locker system on *(a)* the time delivery vehicles stay parked at the curb (referred to as dwell times) and *(b)* the time delivery drivers spend inside the building (referred to as in-building time).

The treatment in this setting is installing a locker in a building. We selected two similar multi-story residential buildings in the same neighborhood as treatment and control buildings. In the treatment building a common-carrier parcel locker was installed, while the control building did not receive any intervention. The observational units are individual deliveries to buildings; so, in the remainder of the paper, the treatment and control group respectively refer to deliveries made to the buildings with and without the locker. Both buildings were observed in two time periods, before and after receiving the treatment (i.e. the installation of the locker). For each building, dwell times (through delivery vehicle arrival and departure times) and in-building times (through courier's entry and exit times to the building) were measured.

The main assumption for the DiD model to correctly estimate the treatment effect is parallel trends, meaning that in the absence of the intervention (i.e. treatment), the dependent variables for both the treatment and control groups should follow similar trends, or respond similarly to changes in the surrounding conditions. In this study, the treatment and control buildings have similar characteristics and sit only a few blocks from each other, being subjected to similar weather patterns, economic conditions, traffic disruptions or other outside factors.

We therefore assume that this assumption holds. The treatment and control buildings are described in the following subsection.

Figure 2 provides a simple schematic of the implemented DiD experimental design. In the pre-treatment period and in the absence of a locker, dwell times and in-building times for the treatment and control buildings follow parallel trends. The dashed line shows the hypothetical trend for the treatment group had there not been a locker, while solid line shows the observed trend. The impact of the locker will be estimated as the difference between the treatment and control groups in the average change in the outcome variable (dwell times and in-building times) between pre- and post-treatment periods.

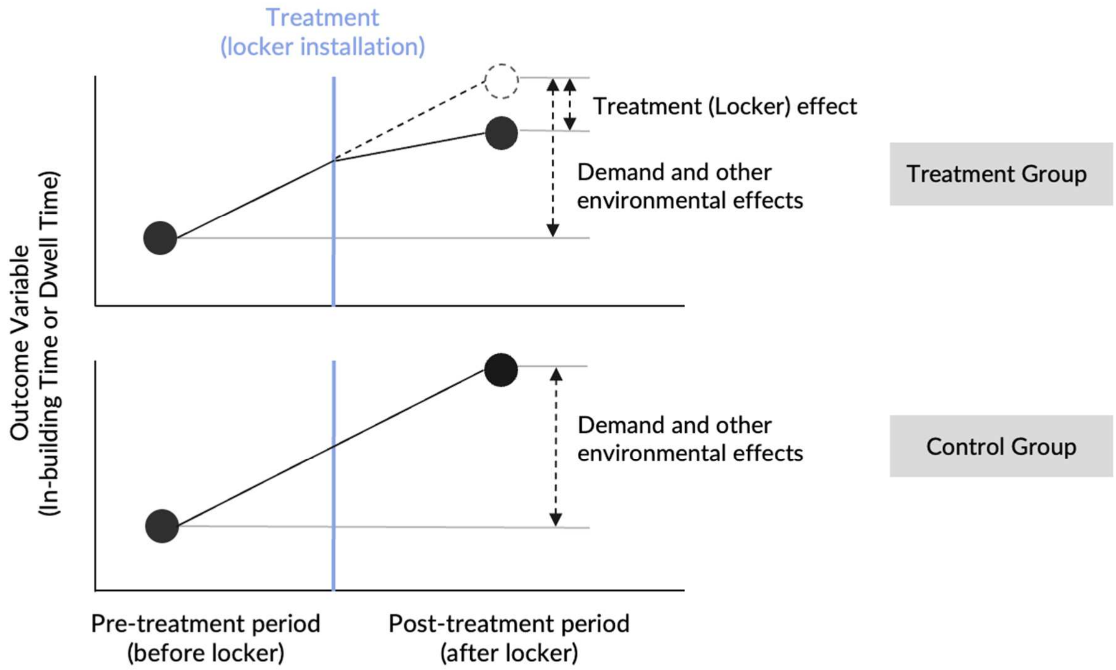


Figure 2: Schematic of the DiD experimental design implemented in this study

3.2. Treatment and Control Buildings

The building selected to receive the treatment (the locker system) for this study was a 26-story residential condominium with 133 units, in the Belltown neighborhood of Seattle, Washington. Near the building there are three commercial vehicle load zones (CVLZs, curb spaces dedicated to vehicles with a valid commercial permit and with a maximum allowed dwell time of 30 minutes) and three passenger load zones (PLZs, curb spaces dedicated for passenger pick-up/drop-off with allowed maximum dwell time of 3 minutes) that are used by delivery carriers.

In June 2020, we installed a parcel locker in the building lobby which started operating immediately. The installed locker had 8 large, 28 medium and 19 small compartments (Figure 3). The building has a mailbox area in the lobby and also a storage space on the 4th floor. Before the locker installation, delivery couriers usually left packages in the building lobby and/or walked throughout the building and went to different floors to make doorstep deliveries. The resident manager then picked up the packages left in the lobby and either took them to residents' doorsteps or placed them in the 4th-floor storage space, if a resident were not home to receive their packages. Upon installation of the locker, all residents were automatically registered in the locker operator's system by the building management. Carriers were also instructed to use the locker when delivering to the building. The locker company reached out to all the major carries and provided them with a code to access the locker. Instructions for carriers were also posted in the building lobby.

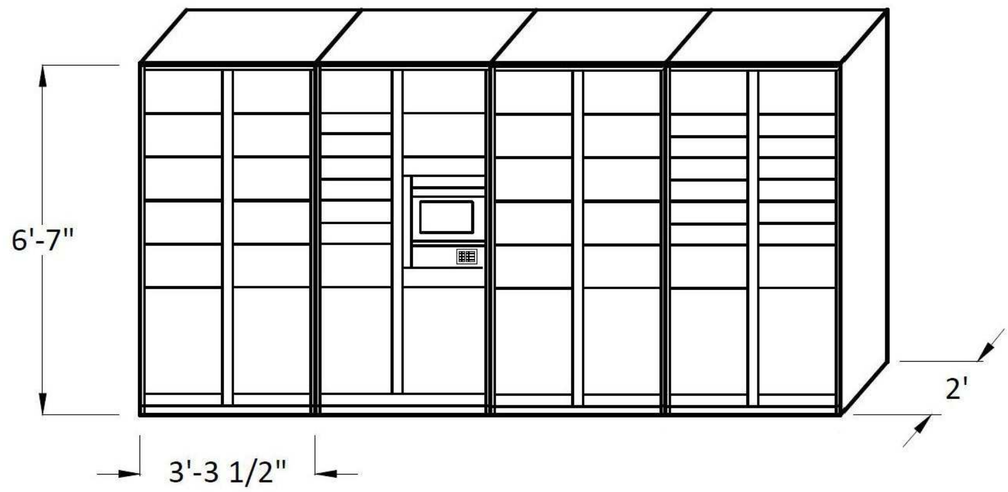


Figure 3: Schematic of the parcel locker installed in the treatment building

To select a control building, we used King County Metro's zoning and building characteristics database (King County GIS Open Data, 2021) to find candidate residential buildings with similar characteristics (e.g. floor area ratio, number of units, surrounding land use and parking spaces). We then reviewed the loading zone infrastructure and delivery process in the candidate buildings to determine the most similar building to our treatment building. The selected control building is a 27-story residential condominium with 111 units, two blocks away from the treatment building in the same Belltown neighborhood. There are three CVLZs and two PLZs around the building that are used by carriers delivering to the building.

The 220-acre mixed-use Belltown neighborhood is adjacent to Seattle's central business district, and as of the 2010 census, it is the most densely populated neighborhood in Seattle, with about 12,000 people living in a 0.3 square-mile area (US Census Bureau, 2010).

4. DATA

To collect data on vehicle dwell time and in-building delivery time, we designed and implemented a field data collection process. Moreover, for the treatment building, we designed and conducted a short online survey of residents and interviewed the building managers, to solicit feedback about the locker performance and changes in the delivery process.

4.1. Field Data

4.1.1. Data Collection

In order to collect data on deliveries to the study buildings, we designed and implemented a field data collection process that was performed in two time periods—before and after locker installation— for each of the control and treatment buildings, even though the locker was only installed in the treatment building. Field observations included information on delivery vehicle arrival and departure time, vehicle type, carrier, delivery driver's entry and exit times to the building, and type and volume of goods carried in and out of the building.

The data collection for pre- and post-treatment periods were conducted, respectively, in June-August 2020 and January-February 2021. A detailed data collection protocol was designed, and research assistants (RAs) were recruited and trained to collect data in the field. Data collection was done in three-hour shifts from 8:30 a.m. to 2:30 p.m. on several weekdays in the aforementioned periods.

For each shift, two RAs were deployed. The first RA recorded the time that commercial vehicles arrived at and departed from the blockfaces adjacent to and opposite to the study building, carrier, vehicle type (car, van or truck), blockface, parking space type (CVLZ, PLZ, paid parking, or no parking), and whether or not couriers delivered to the study building. Arrival time was defined as the time the commercial vehicle driver pulled into the curb space, and departure time as the time the driver turned on the engine to pulled out of the curb space. The second RA monitored the building entrance, recording the time each commercial vehicle driver entered and exited the building, carrier, types of goods, and estimated volume of goods carried in and out of the building. The second RA was also asked to track the drivers delivering to the building and record the curb space type and blockface where their vehicle was parked, so that it can be matched with the data collected from the first RA. RAs were instructed to only record commercial activity and ignore residents or visitors entering/exiting the building. All RAs were trained to recognize carrier logos and uniforms, parking signage, and visually estimate the volume of packages.

Field data collection recorded all commercial activities, including package delivery, service visits (e.g. plumbers or electricians) and meal/grocery delivery (e.g. DoorDash or UberEats). However, non-package delivery data was later removed from the analysis dataset.

4.1.2. Processing and Cleaning Data

The datasets from any two RAs in the same shift were matched based on time, carrier, blockface and parking space type, leaving out parking observations related to vehicles that did not deliver to the study building. Vehicle dwell time was then calculated as the time between vehicle arrival at and departure from the utilized parking space. In-building time was calculated as the time between a delivery vehicle driver's entrance to and exit from the study building.

Several steps were taken to clean the dataset. Two observations were deleted based on the RAs' notes: one where it was mentioned that the driver took a lunch break while staying parked at the curb, and another where the entry to the building was recorded but the exit was not observed. All volume measurements were standardized into meters cubed units. Multiple deliveries from the same vehicle were grouped together as one observation, with the in-building time and goods volume summed together. The goods volume carried in and out of the building were summed together to account for the extra effort required to maneuver and carry items. If a vehicle was present when the first shift started, the arrival time was assumed to be the start of the shift; similarly, if a vehicle stayed parked when the last shift ended, the departure time was assumed to be the end of the shift. A summary of collected data is presented in Table 1.

TABLE 1: Summary of Collected Field Data on Treatment and Control Buildings, Before and After Locker Installation

Variable	**Pre-Treatment**		**Post-Treatment**		**Total**
	Treatment Bldg	Control Bldg	Treatment Bldg	Control Bldg	
All Commercial Activities					
Days observed	5	10	8	4	27
Hours observed	45	51	48	21	165
Total deliveries	31	56	60	18	165
Total deliveries per day	6.2	5.6	7.5	4.5	N.A.
Package deliveries	19	39	43	15	116
Package deliveries per day	3.8	3.9	5.4	3.8	N.A.
Total parking events	121	135	187	56	499
Parking events per day	24.2	13.5	23.4	14.0	N.A.
Package Deliveries					
Package Volume					
Avg. package volume per delivery (m^3)	0.50	0.35	0.26	0.51	N.A.
Vehicle Type					
Car	1	3	2	3	9 (8%)
Van	10	18	20	6	54 (46%)
Truck	8	18	21	6	53 (46%)
Utilized Parking Space Type					
Commercial Vehicle Load Zone (CVLZ)	17	18	29	4	68 (59%)
Passenger Load Zone (PLZ)	2	5	7	2	16 (14%)
Paid Parking	0	13	2	9	24 (21%)
No-Parking	0	2	5	0	7 (6%)
Travel Lane	0	0	0	0	0

N.A.: Not Applicable (Total values are not applicable for variables that are defined as rates.)

Commercial entries to the buildings were recorded as either service visit, package delivery, mail/postal delivery, meal/grocery delivery, or other goods delivery. The vehicles captured in the study represented a broad cross-section of 165 deliveries to the two residential buildings. 59% of deliveries were package deliveries from UPS, Amazon, FedEx and other major parcel carriers. The remaining entries included 11% postal service stops, 5% service visits, 12% prepared meal deliveries, and 13% other goods including groceries, home appliances, or office supplies.

Since only packages are permitted in the locker, observations related to service visits and mail or meal/grocery deliveries, which accounted for about 30% of the total deliveries, were removed from the analysis dataset. The remaining 70% were all package deliveries and consisted of a total of 116 observations from the two study buildings.

4.1.3. Summary Statistics

Table 1 presents a summary of package volume delivered to the building, type of vehicles delivering to the building, and parking spaces used by delivery vehicles, for treatment and control buildings, before and after the locker installation.

The average volume of packages delivered in the two periods changed from 0.35 to 0.51 meters cubed at the control building, and from 0.50 to 0.26 meters cubed at the treatment building. The average volume increased by 45% from Summer to Fall in the control group and decreased by 48% in the treatment group.

The observed delivery vehicles included mostly light-duty vans (46%) and medium-duty trucks (46%), and a few passenger cars (8%). For the most part, delivery vehicles attempted to find authorized parking spots, although they used passenger and commercial loading zones interchangeably. 59% of the delivery vehicles parked in a CVLZ and 14% in a PLZ. Another 21% of the vehicles stopped in paid parking, but only 6% used no-parking, and no vehicles stopped in the travel lane. Utilized parking space type differed at the two buildings depending on the available spaces outside. 74% of vehicles at the treatment building parked in a CVLZ, compared to 41% at the control building. Only 3% of the deliveries to the treatment building stopped in paid parking, while 41% did so at the control building. However, the rates of unauthorized parking were similar at both locations.

4.2. User Survey Data

To assess the performance of lockers from the perspective of residents and building managers, and to solicit their feedback about changes in the delivery process, we designed and conducted a short online survey of residents of the treatment building and also spoke with the building managers.

The survey was conducted in March 2021, nine months after the locker was installed and started operating, and included questions on satisfaction and concerns about the locker performance and attitudes toward the locker as an urban delivery solution. The survey link was shared with the residents in an email sent by the building management. We also posted flyers containing a QR code to the survey link in the building common areas, such as lobby and elevators. To promote participation in the survey, a raffle prize of a $100 Amazon gift card was also offered.

The survey was open during the month of March, and in total 76 responses were received, which accounts for about 60% of the locker users (133 residents were registered to use the locker). After cleaning the dataset and removing repeated or low-quality responses, we ended up with 69 valid responses.

5. MODEL FRAMEWORK AND SPECIFICATION

The general model specification for the DiD analysis is presented in Equation 1. *Time* and *Group* are binary variables, taking 0 for pre-treatment period and control group, and 1 for post-treatment period and treatment group, respectively. Y is the outcome variable, β_0 is the regression intercept, β_1 is the time trend intercept for the control group (Group=0), β_2 is the difference between treatment and control groups before receiving the treatment (Time=0), and β_3 is the difference in outcome variable over time after receiving the treatment (Group=1, Time=1), which is assumed to be the causal effect of treatment on the outcome variable. Relevant covariates are also added to estimate the treatment effect more precisely by controlling for pre-existing differences between observations in the control and treatment groups.

$$Y = \beta_0 + \beta_1 Time + \beta_2 Group + \beta_3 \, (Time * Group) + \beta_4 \, Covariates + \varepsilon \quad (1)$$

We built two models for the two outcome variables of interest: vehicle dwell time and in-building delivery time. For the dwell time model, we added covariates to control for peak delivery period, vehicle type, and utilized parking space type. The covariates considered for the in-building time model were peak delivery period, vehicle type, and volume of goods carried in and out of the building.

The classical DiD model is estimated using linear regression. The model measures the change in the mean outcome variable for both treatment and control groups and subtracts the value for the control group from that of the treatment group. Both outcome variables in this study (dwell time and in-building time) are continuous, strictly positive, and right-skewed distributed. So, to estimate the DiD model parameters, we tried fitting a lognormal model and a generalized linear model (GLM) with gamma distribution and log-link function. The developed model specifications are described in Equations (2) and (3):

$$Ln(DwellTime_i) = \beta_0 + \beta_1 Time_i + \beta_2 Group_i + \beta_3 \, (Time_i * Group_i) + \beta_4 \, PeakHour_i + \beta_5 \, VehicleType_i + \beta_6 SpaceType_i + \varepsilon \quad (2)$$

$$Ln(BldgTime_i) = \beta_0 + \beta_1 Time_i + \beta_2 Group_i + \beta_3 \, (Time_i * Group_i) + \beta_4 \, PeakHour_i + \beta_5 \, VehicleType_i + \beta_6 \, Ln(GoodsVolume_i) + \varepsilon \quad (3)$$

Where:

- *i* denotes each vehicle (for dwell time model) or driver (for in-building time model) observation
- *DwellTime* represents the time (in minutes) that delivery vehicle *i* stays parked at the curb
- *BldgTime* represents the time (in minutes) that driver *i* spends inside the building
- *Time* is a binary variable denoting the time period of observation *i* (0 for pre-treatment and 1 for post-treatment)
- *Group* is a binary variable indicating the group that observation *i* belongs to (0 for control and 1 for treatment group)
- *PeakHour* is a binary variable showing whether observation *i* happened during the neighborhood's peak delivery period (1 for 9am-1pm and 0 otherwise). The Peak delivery period was determined as of 9am-1pm, based on the average number of deliveries observed in each hour.
- *VehicleType* is a categorical variable, taking values of car, van, truck, or other
- *SpaceType* is a binary variable indicating whether the vehicle parked in an authorized or unauthorized parking space (1 if the vehicle parked in no-parking or travel lane, and 0 otherwise)
- *GoodsVolume* is the total volume of goods (in meters cubed) carried in and out of the building.

In both models, the coefficient for the interaction term, β_3, represents the magnitude of the causal effect of the locker on the outcome variable of interest, adjusting for the modeled covariates. Given the logarithmic equations specified for dwell time and in-building time, the marginal effect of the locker on these outcome variables can be obtained using the exponentiated coefficient, $\exp(\beta_3)$. If all else being the same, the percentage change in the outcome variable mean value as a result of the locker installation can be estimated through Equation (4), where V represents the outcome variable.

$$\%\,\Delta = \left(\frac{\Delta \mathrm{V}}{\mathrm{V}}\right) * 100 = \left(\frac{\exp(\beta_3) - \exp(0)}{\exp(0)}\right) * 100 = \left[\exp(\beta_3) - 1\right] * 100 \qquad (4)$$

6. RESULTS

Our primary research questions in this study are:

- Did the common-carrier locker cause a change in vehicle dwell times for carriers delivering to the building?
- Did the common-carrier locker cause a change in time that delivery drivers spend inside the building to make a delivery?

The following subsections answer the above questions through descriptive analysis as well as regression models built for the DiD analysis. A summary of findings from the user survey is also provided to capture the perspective of residents and building managers of the treatment building toward the locker.

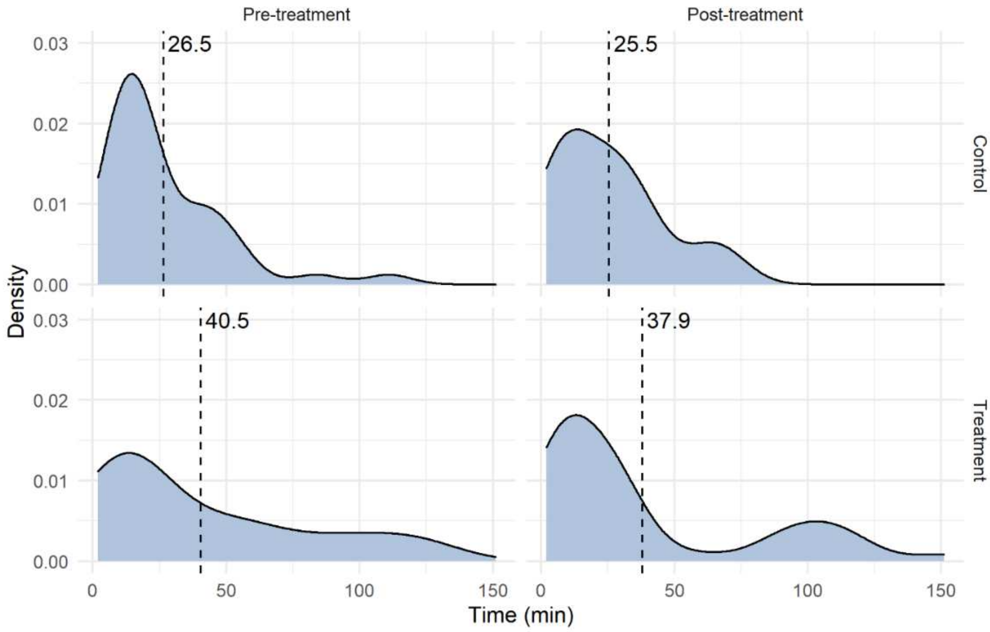
6.1. Descriptive Analysis

Table 2 and Figure 4 show in-building package delivery times and dwell times for all vehicles from which a package delivery was made to the building, recorded before and after locker installation. Since installing the locker only affected package deliveries, only dwell times and in-building time associated with package deliveries are included in the analysis.

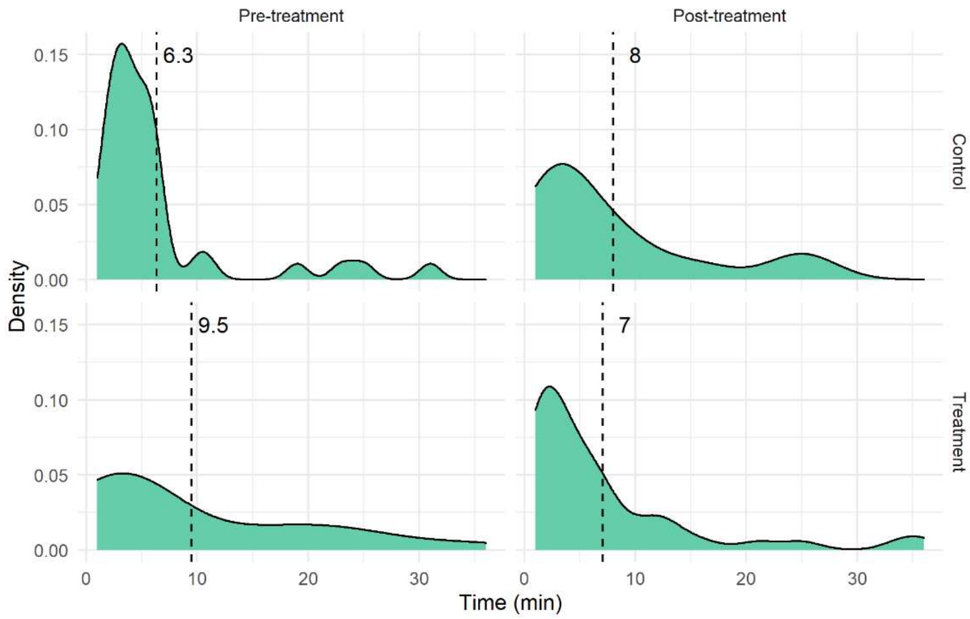
Delivery times are a function of several factors, including the volume and number of deliveries, which can change from month to month and day to day. So, to model the changes we look at the mean values and the trends for the study buildings. The treatment and control buildings share similar characteristics, and the pre-/post-treatment observation periods were the same for both buildings. So, in the absence of the locker, they are supposed to follow the same trends. However, as can be seen in Figure 4, on average, dwell times and in-building times decreased at the treatment building over the course of the study, while increasing or remaining the same at the control building. Examining the distribution means for the two buildings through a basic DiD estimate (Table 2) shows a small decrease in mean dwell times (1.6 minutes) for the treatment building compared to the control building. A larger drop in in-building times (4.2 minutes) is also observed for the treatment building relative to the control building.

TABLE 2: Summary of Mean Dwell Times and In-building Times

	Control Bldg		**Treatment Bldg**	
	Pre-treatment	Post-treatment	Pre-treatment	Post-treatment
Mean Dwell Time (min)	26.5	25.5	40.5	37.9
Mean In-building Time (min)	6.3	8	9.5	7
Dwell Time Difference (min)	-1		-2.6	
In-building Time Difference (min)	1.7		-2.5	
Dwell Time DiD	-1.6			
In-building Time DiD	-4.2			



(a) Dwell Time



(b) In-building Time

Figure 4: Distributions for dwell time and in-building time, before and after locker installation, for treatment and control groups

6.2. Regression Results

Using regression models, we tested the null hypothesis that dwell time and in-building time did not change for the treatment building compared to the control building.

6.2.1. Dwell Time

A model was fitted to the log of dwell times using Ordinary Least Squares (OLS) estimation. The model satisfied the assumptions for linear regression—the log of dwell times was approximately normally distributed, and we did not observe heteroskedasticity in the residuals.

TABLE 3: Regression Results for Dwell Time and In-building Time Models

Outcome Variable	**Dwell Time**	**In-building Time**		
Model Estimation Method	OLS	WLS	Gamma GLM	Gamma GLM, controlling for goods volume
Parameters	Coefficients			
Regression Intercept	1.16^{***}	0.64^{***}	0.47	0.44
Group: Treatment	0.33	0.13	0.42	0.37
Time: Post-treatment	0.15	0.39	0.53^{*}	0.43
PeakHour: 1	0.85^{***}	0.43^{**}	0.71^{***}	0.60^{***}
VehicleType: Truck	1.26^{***}	0.44^{*}	0.70^{*}	0.49
VehicleType: Van	1.31^{***}	0.75^{***}	1.00^{***}	0.91^{**}
SpaceType: Unauthorized	-0.79^{**}	/	/	/
Ln(GoodsVolume)	/	/	/	0.82^{***}
Treatment Effect	-0.40	-0.70^{*}	-0.92^{**}	-0.72^{*}
Locker Effect	**-32.97%**	**-50.3%**	**-60.12%**	**-51.45%**
Observations	116	116	116	116
Log Likelihood	-143.09	-151.08	-336.20	-331.68
AIC (Akaike Information Criterion)	302.18	316.17	686.39	679.36

Note: $^{*}p < .1$ $^{**}p < .05$ $^{***}p < .01$

The regression results are presented in Table 3. Dwell time decreased by 33% in the treatment group, controlling for the vehicle type, parking type, and peak delivery period. However, given the small sample size, the effect of locker on dwell time decrease was not statistically significant (p-value=0.275). Therefore, we could not reject the null hypothesis and the effect of the locker on dwell time remained inconclusive.

The coefficients for building and time period were positive but insignificant; showing that dwell times at the treatment building were generally longer than those outside the control building (regardless of the time period), and that dwell times increased from pre-treatment to post-treatment period. Other covariates though were found to have a significant effect on dwell times. Larger vehicles (vans and trucks) parked at the curb for longer compared to cars. Vehicles arriving during the peak delivery period (9am-1pm) had longer dwell times – perhaps because parking became less available during these times. Vehicles that parked in unauthorized spaces generally stayed for shorter time periods.

6.2.2. In-building Time

A similar lognormal model was fitted to the in-building times using the OLS. This model estimated a 25% decrease in in-building time, controlling for goods volume, vehicle type, and peak delivery period, but the treatment effect was not statistically significant (p-value=0.459). This estimate also fell within a wide 95% confidence interval, and the model suffered from heteroskedasticity of residuals due to the increasing variance of in-building time as volume increased. The Normal distribution plot also exhibited heavy tails, indicating that the log transformation of in-building time might not have been enough to meet the model’s normality assumption.

To correct for these problems, two additional models were fitted to the in-building times. A weighted least squares model (WLS), weighting each observation by the reciprocal of the residuals from the OLS model, and a generalized linear model (GLM) with a gamma distribution and log link function. The gamma distribution is commonly applied to model durations, such as waiting time which have similar probability distributions as those of in-building time (Ingvardson et al., 2018). The GLM framework is also reported to provide better interpretability of the coefficients for dealing with skewed positive data, compared to similar methods, such as log transformation (McDonald et al., 2000; Li et al., 2012).

Regression results for both Gamma GLM and WLS models, controlled for vehicle type and peak delivery period, are shown in Table 3. While both models appear to fit the shape of the in-building time distribution, the Akaike Information Criterion (AIC), a metric for model appropriateness, was lower for the WLS model, suggesting a slightly better overall fit. Both the Gamma and the WLS model corrected for the heteroskedasticity of the residuals observed in the OLS model, with the WLS model performing slightly better. The Gamma GLM model controlling for goods volume showed a higher p-value (0.089) for the treatment effect compared to the Gamma GLM without volume (p-value=0.024); however, the treatment effect was statistically significant in both models. Hence, since goods volume is an important predictor of in-building time, we also included a Gamma GLM with volume in the reported results.

Figure 5 compares the 95% confidence intervals for estimates of the treatment effect on in-building time for the three best models (WLS model and Gamma GLM models with and without controlling for goods volume) as well as the rejected OLS model. Although the small sample size creates some uncertainty and relatively wide 95% confidence intervals, all three models show consistent signs and small p-values for the treatment, suggesting that the locker significantly reduced the in-building time.

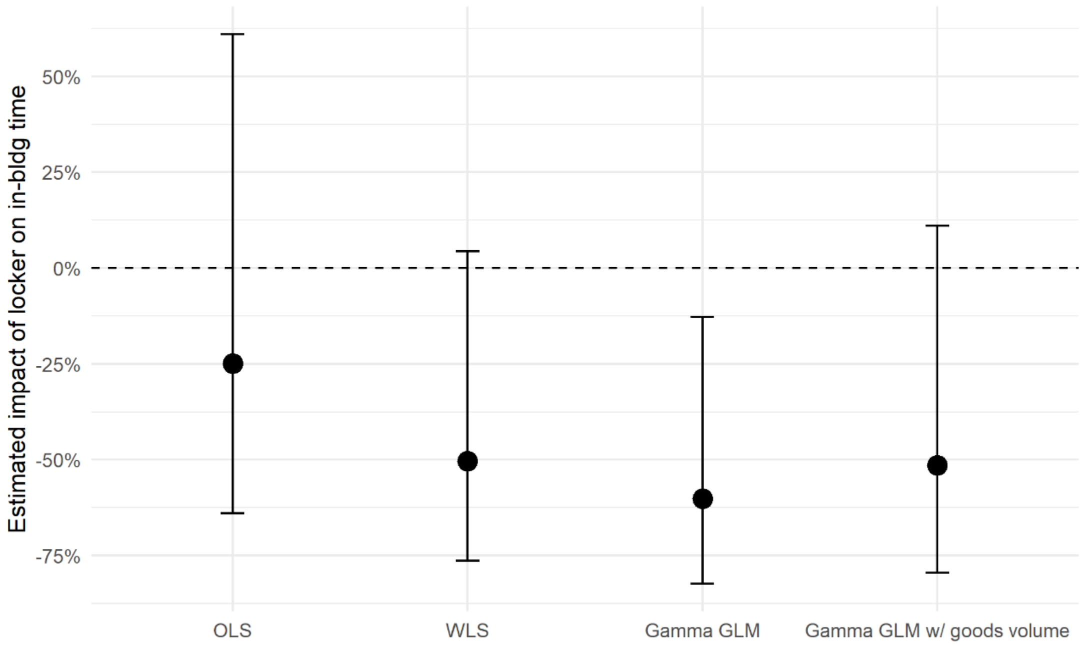


Figure 5: The 95% confidence interval for different in-building time regression models

Apart from the locker itself, the volume of packages, type of delivery vehicle, and time of day appeared to have significant impacts on in-building times. The positive coefficient for the peak hour indicates that in-building times rise during 9am to 1pm when many carriers are delivering to the building. Likewise, increasing the volume of packages carried in and out results in longer in-building times. Drivers of vans and trucks also took more time to deliver to the building. Compared to cars, vans and trucks are more likely to deliver larger volumes of goods which may also require making multiple trips into the building. If everything else is the same, switching from a car to a van increases the average in-building time by about 150% in the Gamma GLM model ((exp(0.91)– 1)*100).

The positive signs for the building and time period parameter coefficients imply that on average, drivers took longer to deliver inside the buildings during the post-treatment period, and that on average deliveries at the treatment building took longer, regardless of the time period. However, these parameters were insignificant in almost all three models.

6.3. Residents' and Building Managers' Feedback

The building managers expressed high levels of satisfaction with the locker. They noted that considering the time needed to register residents for the locker service, deal with sporadic locker issues, and address packages that are occasionally left in the lobby, still the workload of the resident manager is reduced by 90% post locker installation.

Residents also expressed high levels of overall satisfaction with the locker, reporting lower rates of missed delivery and lost/stolen packages since the installation of the locker in the building. They also expressed positive attitudes toward the locker as an urban delivery solution, reporting that on average the locker has made it easier for them to receive their online orders and that they believe lockers are a secure and more efficient way of urban delivery. A summary of user survey results is presented in Table 4.

TABLE 4: Summary of Locker User Survey Results Collected from Residents of the Treatment Building

Question	Responses (N=69)					
		Never	Once a month or less	A few times a month	A few times a week	
I missed a delivery and the package was returned	Before*	61%	33%	4%	1%	
	After**	92%	3%	1%	4%	
A package I ordered online was lost/stolen	Before*	70%	29%	-	1%	
	After**	90%	6%	1%	3%	
	Strongly agree	Agree	Somewhat agree	Somewhat disagree	Disagree	Strongly disagree
The building locker has made it easier for me to receive my online orders.	58%	28%	12%	-	1%	1%
Lockers are a more efficient way of urban delivery.	52%	33%	10%	-	-	4%
I'm concerned about the security of locker cells.	-	1%	3%	9%	38%	49%
	Very satisfied	Satisfied	Somewhat satisfied	Somewhat dissatisfied	Dissatisfied	Very dissatisfied
How would you rate your overall satisfaction with the locker service?	73%	20%	3%	1%	1%	1%

*The question was asked as: "BEFORE you had the locker in the building, how often did the following happen to you?"

**The question was asked as: "SINCE you had the locker in the building (i.e. summer 2020), how often did the following happen to you?"

7. DISCUSSION AND CONCLUSION

Managing the increasing flow of residential delivery requires creative technology solutions. Delivery consolidation through common-carrier lockers offers a potential solution to the last-mile delivery challenges through reducing delivery times. However, to date, no quantitative empirical evidence exists on the benefits of common-carrier parcel locker systems. While demonstrating effects with empirical data in a complex urban setting can be very difficult, it is an important and unavoidable step in evaluating and refining potential solutions.

The experimental study here presents one of the first attempts to rigorously and empirically test the causal effects of common-carrier parcel lockers on delivery times. After controlling for the volume of packages carried in and out of the building, time of day, and vehicle type, we found that the locker caused a drop of 50-60% in the average time spent inside the building. Although the exact magnitude of the locker effect varied across our models, all models showed a consistent and statistically significant decrease in in-building time.

The locker also resulted in reduced dwell time of delivery vehicles at nearby loading zones by 33%; although, the reductions were not statistically significant. Once parked their vehicle in a nearby loading zone, couriers often delivered not only to the study building, but also to several other buildings around the block. So, delivery to the study building only accounted for a fraction of the vehicle dwell time, and unless all/most buildings employ parcel lockers, the large time-savings from delivery tasks inside the study building will not result in significant reductions in the overall vehicle dwell time. It is also possible that delivery couriers use the in-building time savings on other curbside tasks, such as package sorting. Moreover, given our relatively small sample size, our model might have lacked sufficient power to detect the treatment effect for dwell times.

Overall, our findings demonstrated benefits to placing common-carrier lockers in residential buildings for all stakeholders in the delivery process. A decrease in delivery times gives carriers more time to complete their daily delivery journeys and lower their costs. The building managers stated that the locker reduced the workload of the resident manager by about 90% through eliminating the need to pick up packages from the lobby and deliver them to resident doorsteps. And 96% of residents reported satisfaction with the locker, and an improved e-commerce experience with much fewer missed or stolen deliveries.

We would like to highlight the fact that in this study the decision to install the locker in the treatment building was made by the building management and all residents were automatically registered in the locker operator’s system to start receiving their packages there with no opt-out option. However, in cases where there is such an option and/or an alternative for package delivery (e.g., doorstep delivery or delivering to a friend/neighbor), user adoption plays a key role. The success of lockers in reducing delivery times depend on the user adoption. If only a few people choose to use the locker, delivery consolidation will not happen, and delivery times will not improve significantly. This could pose a more critical issue in the case of neighborhood public lockers or lockers in commercial buildings where people self-select to become a user. On the other hand, if a group (e.g., an apartment building, an office building, or a neighborhood) collectively decides to adopt a locker, it might create a biased control group, because users in that case are a self-selected group that tends to be systematically different from non-users in their travel and online shopping needs and behaviors. Similarly, surveying locker users in those cases might not provide a realistic understanding of the system performance, due to the potential self-selection bias.

It should be noted that this research was carried out during the COVID-19 pandemic. During this time, residential areas saw dramatic spikes in package deliveries. So, some statistics and findings, such as the number of package deliveries per day, or average volume of goods carried in and out of buildings cannot be generalized to normal economic situations. Traffic congestion also dropped in most U.S. cities during the pandemic, possibly influencing dwell times and curb availability. It remains to be seen whether the consumer and delivery vehicle habits observed in this study will persist or rise/drop after the end of the public health crisis.

We also faced some restrictions on field data collection due to labor shortage, the evolving locker installation timeline, and disruptions from COVID-19 and hazardous air quality in Seattle in Summer 2020, which limited our pre-treatment sample size. Future studies could support and/or verify the conclusions presented here by obtaining a larger sample size, possibly from a more diverse range of buildings.

To develop a more robust estimate of the locker effect, we compared two residential buildings of similar characteristics. Future studies could investigate whether the time savings hold true for more buildings of various types, layouts and sizes, including commercial buildings, public facilities, or mixed-use establishments. Future research is also needed to estimate time savings associated with the public parcel lockers with users from multiple nearby locations. Such systems could offer great delivery time savings and reductions in carbon emissions, and demonstrating those impacts would be a natural extension of the findings from this research. To maximize the benefits of parcel lockers, this solution should be scaled to multiple residential buildings within a neighborhood, or public lockers be placed at various locations in urban areas to attract a wide range of users. Since implementing such large-scale operations could be difficult to conduct and cost-intensive, the impacts of such implementations could be pursued through simulation approaches, leveraging estimates from this study for validation or as an input for the extent of reduction in delivery times per locker system.

The results of this study provide the first empirical evidence that consolidating deliveries in a single secure location can reduce the time couriers spend delivering to a building and improve the e-commerce experience for users. From the consumer perspective, lockers provide a secure, convenient, self-service means to receive packages. So, if they are located in safe and accessible locations and are well operated, they have the potential to become commonplace. Reduced dwell time at the curb increases curbside parking turnover, which is especially valuable in urban core areas, and adds to the network capacity without the need for building new infrastructure. Lockers also eliminate failed delivery attempts, reducing delivery VMT and traffic congestion and emissions. So, we recommend cities to work with retailers, delivery firms, transit authorities and private property owners (e.g. buildings or parking lots) to incentivize and facilitate the implementation of lockers in large residential or commercial buildings that receive a high number of deliveries or in the congested urban areas where parking is limited. Some studies have also proposed transit-based locker-based crowdshipping strategies, where transit riders act as crowdshippers, placing packages in the lockers in/near transit stations, leveraging the trips that are already taking place (Simoni et al., 2020; Gatta et al., 2019). Reductions in delivery times have high efficiency gains for delivery firms and lower their costs, so lockers provide direct benefits to private companies. Retailers and transit authorities would also benefit from increased walk-in traffic and ridership generated by the locker pickup/delivery activities.

ACKNOWLEDGMENTS

This material is based upon work supported by the U.S. Department of Energy's Office of Energy Efficiency and Renewable Energy (EERE) under the Award Number DE-EE0008462. The views expressed herein do not necessarily represent the views of the U.S. Department of Energy or the United States Government.

The authors would like to thank the management of the treatment building for participating in this study by allowing for and helping with the installation of the locker, onboarding and training residents for the locker use, and distribution of the user survey. The authors also extend their thanks to the locker provider company for installing, operating and maintaining the locker over the course of this study.

REFERENCES

Ali, F. US E-commerce Sales Grow 15.0% in 2018. *Digital Commerce 360*, March 2019. https://www.digitalcommerce360.com/2019/03/13/us-ecommerce-sales-grow-15-0-in-2018/. Accessed Jan. 2021.

Arnold, F., I. Cardenas, K. Sörensen, and W. Dewulf. Simulation of B2C E-commerce Distribution in Antwerp Using Cargo Bikes and Delivery Points. *European Transport Research Review,* 10(2). 2017. https://doi.org/10.1007/s12544-017-0272-6.

Banerjee, A. V. Field experiments and the practice of economics. *American Economic Review*, 110(7): 1937-1951. 2020. https://doi.org/10.1257/aer.110.7.1937.

Baker, L. New York City hits UPS with $23 million in parking fines in 2019. *Freight Waves. FreightWaves,* February 2020. https://www.freightwaves.com/news/ups-hit-with-22m-in-nyc-parking-fines. Accessed Jan. 2021.

Behnke, M. Recent Trends in Last Mile Delivery: Impacts of Fast Fulfillment, Parcel Lockers, Electric or Autonomous Vehicles, and More. Logistics Management, 141–156. 2019. https://doi.org/10.1007/978-3-030-29821-0_10.

Black, T. and J. Holman, UPS restricts some Packages from Nike, Gap Amid Online Rush, *Bloomberg*. December 2, 2020. https://www.bloomberg.com/news/articles/2020-12-02/ups-restricts-some-packages-from-nike-gap-amid-online-rush. Accessed Jan. 2021.

Card, D. and A. B. Krueger. Minimum Wages and Employment: A Case Study of the Fast-Food Industry in New Jersey and Pennsylvania. *American Economic Review*, 84(4): 772-793. 1994.

Chen, Q., A. Conway and J. Cheng. Parking for Residential Delivery in New York City: Regulations and Behavior. *Transport Policy,* 54: 53–60. 2017. https://doi.org/10.1016/j.tranpol.2016.12.005.

Cramer-Flood, E. Global Ecommerce Update 2021. *eMarketer*, January 13, 2021. https://www.emarketer.com/content/global-ecommerce-update-2021. Accessed Mar.

2021.

Dablanc, L. E-commerce Trends and Implications for Urban Logistics. In *Urban Logistics: Management, Policy, and Innovation in a Rapidly Changing Environment*, M. Browne, S. Behrends, J. Woxenius, G. Giuliano, and J. Holguin-Veras, Eds. London: CPI Group, 2019, pp. 167–189.

Dalla Chiara, G., and A. Goodchild. Do Commercial Vehicles Cruise for Parking? Empirical Evidence from Seattle. *Transport Policy*, 97: 26-30. 2020. https://doi.org/10.1016/j.tranpol.2020.06.013.

Dalla Chiara, G., K. F. Krutein, A. Ranjbari and A. Goodchild. Understanding Urban Commercial Vehicle Driver Behaviors and Decision Making. *Transportation Research Record*. 2021. 2675(9): 608-619. https://doi.org/10.1177/03611981211003575.

De Oliveira, L.K., E. Morganti, L. Dablanc, and R.L.M. de Oliveira. Analysis of the Potential Demand of Automated Delivery Stations for E-commerce Deliveries in Belo Horizonte, Brazil. *Research in Transportation Economics,* 65: 34–43. 2017. https://doi.org/10.1016/j.retrec.2017.09.003

Deutsch, Y. and B. Golany. A Parcel Locker Network as a Solution to the Logistics Last Mile Problem. *International Journal of Production Research,* 56(1–2): 251–261. 2018. https://doi.org/10.1080/00207543.2017.1395490.

Duflo, E. Field experiments and the practice of policy. *American Economic Review,* 110(7), 1952-1973. *2020.* https://doi.org/10.1257/aer.110.7.1952.

Gatta, V., Marcucci, E., Nigro, M., Patella, S.M., and Serafini, S. Public Transport-Based Crowdshipping for Sustainable City Logistics: Assessing Economic and Environmental Impacts. *Sustainability 11*(1), 145. 2019. https://doi.org/10.3390/su11010145.

Ge, Y., P. Jabbari, D. MacKenzie and J. Tao. Effects of a Public Real-time Multi-modal Transportation Information Display on Travel Behavior and Attitudes. *Journal of Public Transportation*, 20(2): 40-65. 2017. http://doi.org/10.5038/2375-0901.20.2.3.

Goodchild, A., H. Kim, and B. Ivanov. Final 50 Feet of the Urban Goods Delivery System: Pilot Test of an Innovative Improvement Strategy. 2019. http://hdl.handle.net/1773/44473.

Handy, S., X. Cao and P. Mokhtarian. Correlation or Causality between the Built Environment and Travel Behavior? Evidence from Northern California. *Transportation Research Part D: Transport and Environment,* 10(6): 427–444. 2005. https://doi.org/10.1016/j.trd.2005.05.002.

Iannaccone, G., Marcucci, E., Gatta, V. What Young E-Consumers Want? Forecasting Parcel Lockers Choice in Rome. *Logistics 5* (3): 57. 2021. https://doi.org/10.3390/logistics5030057.

Ingvardson, J. B., O. A. Nielsen, S. Raveau and B. F. Nielsen. Passenger arrival and waiting time distributions dependent on train service frequency and station characteristics: A smart card data analysis. *Transportation Research Part C: Emerging Technologies,* 90: 292–306. 2018. https://doi.org/10.1016/j.trc.2018.03.006.

Iwan, S. K. Kijewska, and J. Lemke. Analysis of Parcel Lockers' Efficiency as the Last Mile Delivery Solution–The Results of the Research in Poland. *Transportation Research Procedia,* 12: 644–655. 2016. https://doi.org/10.1016/j.trpro.2016.02.018.

Kim, H., A. Goodchild and L. N. Boyle. Empirical Analysis of Commercial Vehicle Dwell Times Around Freight-attracting Urban Buildings in Downtown Seattle. *Transportation Research Part A: Policy and Practice*, 147: 320–338. 2021. https://doi.org/10.1016/j.tra.2021.02.019.

King County GIS Open Data. https://gis-kingcounty.opendata.arcgis.com. Accessed Jul 2021.

Lachapelle, U., M. Burke, A. Brotherton, and A. Leung. Parcel Locker Systems in a Car Dominant City: Location, Characterization and Potential Impacts on City Planning and Consumer Travel Access. *Journal of Transp. Geography,* 71: 1–14. 2018. https://doi.org/10.1016/j.jtrangeo.2018.06.022.

Li, H., D. J. Graham and A. Majumdar. The Effects of Congestion Charging on Road Traffic Casualties: A Causal Analysis Using Difference-in-Difference Estimation. *Accident Analysis and Prevention*, 49: 366–377. 2012. https://doi.org/10.1016/j.aap.2012.02.013.

McDonald, T.L., W. P. Erickson and L. L. McDonald. Analysis of Count Data from Before-after Control-Impact Studies. *Journal of Agricultural, Biological and Environment Statistics,* 5(3): 262–279. 2000. http://doi.org/10.2307/1400453.

Nahry and A. Farhan Vilardi. Consumer's Point of View on Parcel Lockers in DKI Jakarta. *MATEC Web of Conferences,* 270 (03003), 2019. https://doi.org/10.1051/matecconf/201927003003.

Pham, H. T. and H. Lee. Analyzing the Costs and Benefits of Installing Unmanned Parcel Lockers: Focusing on Residential Complexes in Korea. *Journal of International Logistics and Trade*, 17: 43–54. 2019. https://doi.org/10.24006/jilt.2019.17.2.002.

The Associated Press. Delivery Firms' Big Ticket Item: Parking Fines. *NBC News*. August 2006. https://www.nbcnews.com/id/wbna14602712. Accessed July, 2021.

Roggio, A. Porch Piracy is Growing. *Practical Ecommerce*, Jan. 2021. https://www.practicalecommerce.com/porch-piracy-is-growing. Accessed July, 2021.

Rohmer, S. and B. Gendron. A guide to parcel lockers in last-mile distribution–highlighting challenges and opportunities from an OR perspective. 2020.

Savelsbergh, M., and T. Van Woensel. 50th Anniversary Invited Article–City Logistics: Challenges and Opportunities. *Transportation Science,* 50(2): 363–761. 2016. https://doi.org/10.1287/trsc.2016.0675.

Simoni, M. D., Marcucci, E., Gatta, V., Claudel C.G. Potential last-mile impacts of crowdshipping services: a simulation-based evaluation. *Transportation*, 47(4), 1933-1954, 2020. https://doi.org/10.1007/s11116-019-10028-4.

UNCTAD. *Estimates of Global E-commerce 2019 and Preliminary Assessment of COVID-19 Impact on Online Retail 2020.* UNCTAD Technical Notes on ICT for Development. UN Conference on Trade and Development, 2021. https://unctad.org/system/files/officialdocument/tn_unctad_ict4d18_en.pdf.

Urbanowicz-Pollock, P.E. An International Analysis of Sustainable Urban Freight Transportation Planning Efforts. University of Texas at Austin, 2019.

Urban Freight Lab. Evaluation of Sound Transit Stations and Transit Oriented Development Areas for Common Carrier Locker Systems. 2018. Seattle, WA. http://depts.washington.edu/sctlctr/sites/default/files/research_pub_files/Evaluation-of-Sound-Transit-Stations-and-TOD-for-Lockers.pdf.

U.S. Census Bureau. 2010 Decennial Census. https://www.census.gov/programs-surveys/decennial-census/data/datasets.2010.html. Accessed March 2021.

U.S. Census Bureau. *Quarterly Retail E-Commerce Sales*. 2021. https://www.census.gov/retail/ecommerce/historic_releases.html. Accessed March 2021.

Vakulenko, Y., D. Hellström and K. Hjort. What's in the Parcel Locker? Exploring Customer Value in E-commerce Last Mile Delivery. *Journal of Business Research*, 88: 421–427. 2018. https://doi.org/10.1016/j.jbusres.2017.11.033.

Van Duin, J. H. R., B. W. Wiegmans, B. Van Arem, and Y. Van Amstel. From Home Delivery to Parcel Lockers: A Case Study in Amsterdam. *Transportation Research Procedia*, 46: 37–44. 2020. https://doi.org/10.1016/j.trpro.2020.03.161.

Wen, X., A. Ranjbari, F. Qi, R. R. Clewlow and D. MacKenzie. Challenges in Credibly Estimating the Travel Demand Effects of Mobility Services. *Transport Policy,* 103: 224–235. 2021. https://doi.org/10.1016/j.tranpol.2021.02.001.

World Economic Forum. The Future of the Last-Mile Ecosystem. 2020. https://www.weforum.org/reports/the-future-of-the-last-mile-ecosystem.