Examining the Effects of Common Carrier Lockers on Residential Delivery

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Abstract

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In recent years, e-commerce has dramatically increased deliveries to residential areas. The rise in delivery vehicle activity creates externalities for the transportation system, including congestion, competition for parking space, and emissions. Common carrier lockers have emerged as a way to manage these effects by consolidating deliveries, but they remain largely untested in the United States. This thesis examines the effects of a common carrier locker placed in a residential building in downtown Seattle, Washington. An experimental design with on-street data tests the effect of the locker on dwell times and time that delivery people spend in the building. Data collected by the locker provider gives insight into the e-commerce behavior patterns of residents. Finally, a simulation model was constructed to obtain the optimal configuration of box sizes in similar lockers. The results show that the locker had a statistically significant effect on time spent within the building, but not on dwell times or curb productivity. However, dwell times for similar vehicles in this sample decreased somewhat. The simulation demonstrated that time-based policies and flexible locker designs can prove to be effective strategies for managing demand.

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1 Introduction

In recent years, explosive growth in e-commerce has spurred dramatic demand for deliveries in dense urban areas. Worldwide retail E-commerce sales grew 27.6% in 2020, and 31.8% in North America [1]. At the same time, rapid urbanization is taking place, and online shipments require delivery to residential locations and dense urban hubs. The increased emphasis on direct-to-consumer deliveries gives customers in residential areas more power to dictate when, where, and how their orders will be fulfilled [2].

These e-commerce trends demand that operators to deliver to many consecutive addresses, often within highly specific time windows, amid traffic congestion and limited parking. These demands cause numerous problems in the so-called "last-mile" of delivery: the final link from retailer to customer. For freight operators, friction in the last mile can disrupt vehicle routing and scheduling. Researchers estimate that up to 15% of all first delivery attempts fail [3], sometimes because the customer is not home to receive the package. From the perspective of city planners, last-mile freight challenges include illegal parking behavior, congestion, and increased vehicle miles travelled and emissions. In 2006, UPS, FedEx and other delivery companies paid New York City $102 million in parking fines annually and averaged a combined 7,000 tickets per day[4][4][4] [4], [3]. Some researchers estimate that up to 25% of emissions from the overall supply chain come from last-mile delivery [5]. To combat congestion, much last-mile research concentrates on reducing vehicle dwell time, or time stopped at the curb [3]. Shorter dwell times increase the availability of parking space, reducing congestion and emissions from parking cruising.

Residential and mixed-use areas pose particular challenges for urban freight. In recent years, the range of couriers delivering to residential buildings has grown more diverse, expanding from traditional express carriers to include retailer-owned fulfillment services such as Amazon Prime, instant-grocery services such as Instacart, and meal-delivery services such as Doordash. Customer expectations regarding delivery speed, time windows, and ease of return have exponentially increased [6]. In contrast to the bulk shipments to commercial buildings, residential e-commerce activity in urban centers consists of repeated, small-batch deliveries. Delivery vehicles range from light-duty vans to cargo bikes and the private passenger vehicles of gig workers. The annual delivery schedule is highly peaked. As many as 20% of all deliveries fall during the holiday season from November to December [7]. This can make it difficult to plan permanent parking infrastructure or last-mile solutions to accommodate deliveries throughout the year.

In the past several years, common carrier parcel lockers have emerged as a solution to the last-mile delivery problem for online orders. A common parcel locker is a secure central hub from which a consumer can receive packages from any carrier. Delivery drivers can deposit packages into any open box in the locker. Upon delivery, customers receive an electronic notification and unique code that allows them to retrieve the package. Although these lockers have gained acceptance in some European and East Asian markets, they remain largely untested in the United States [8].

The purpose of this research is to determine the impact of e-commerce deliveries and common parcel lockers on the transportation system for residential buildings in an urban mixed-use setting. Specifically, I examine the effects on three areas: carrier operations, parking infrastructure, and consumer behavior. The results can be used by policy makers to develop incentives and management plans for lockers in residential areas, either in public or private space.

The focus of the study is a locker installed in Seattle's Belltown neighborhood as part of a Department of Energy-funded study on urban goods delivery efficiency. Belltown represents a typical dense mixed-use neighborhood close to downtown. The 26-story residential building that received the locker reported several inefficiencies with its previous delivery process. Some carriers delivered packages individually to the 133 apartments, moving door-to-door throughout the building. Others deposited packages in a storage room, where the building manager had to sort through them and ensure residents received their items. The goal for the locker was to consolidate these arrivals, improving package security, reducing the building manager's workload, and improving timeliness of deliveries.

From the operations perspective, I aim to determine whether the installation of this common carrier locker caused a change in the time that delivery drivers spend inside the building or stopped at the curb (dwell time). The effect on parking infrastructure was measured through vehicle dwell times in loading zones outside the building, and a curb productivity calculation. Data from the locker provider provided descriptive insights into the usage cycles, seasonality, and demand patterns of customers. This e-commerce consumer information can aid urban planners in designing freight infrastructure and policies to accommodate seasonal demand patterns.

This study aims to answer these questions through a variety of datasets and research methods. I compared the building with a locker installed to control buildings using a nonequivalent groups design and difference-in-difference estimation, with manually collected parking data. To obtain insight into consumer behavior, I analyzed anonymized data recorded by the locker provider and described users by characteristics such as the number and type of packages they receive.

The remainder of the thesis is organized as follows. Chapter 2 describes the existing literature on parcel lockers and residential delivery. Chapter 3 outlines the methodology, including difference-in-difference estimation, curb productivity calculation, and simulation. Chapter 4 provides results, and Chapter 5 consists of discussion and policy implications.

2 Literature Review

2.1 E-commerce delivery to residential areas

In recent years, urban residential and mixed-use areas have seen dramatic increases in delivery demand. In New York City, as of 2017, census tracts spanning just a few blocks could generate demand ranging from 200-600 packages per day [9]. A 2017 study of a 300-unit upper-middle-class apartment building in New York City, conducted using concierge package receipts, estimated the rate of package deliveries at 1.5 per week per household, or around .5 per resident [7]. Deliveries were relatively consistent on weekdays but declined by around 14.4% on weekends. The months of November and December alone accounted for more than 20% of the deliveries. A single New York City residential building lobby can receive 60 to 100 packages per day [6]. Such a rate of delivery exhausts building managers and concierges, prompting some apartment buildings, especially in China and Europe, to routinely install common parcel lockers.

Compared to commercial delivery, residential fulfillment exerts different pressures on public street space. An increasing tableau of carriers, comprising not only postal and express parcel delivery companies, but now instant grocery and meal delivery services and retailer fulfillment services such as Amazon Prime, compete for street space [6]. The uptick in small items ordered online has increased light goods vehicle (LGV) traffic, and the behaviors and needs of these vehicles are not well understood. Compared to commercial areas, mixed-use or residential districts offer few spaces for commercial vehicles to park, and the spaces that exist are often occupied by residents. E-commerce trends toward smaller delivery time windows and on-demand delivery drive carriers to deliver smaller batches of packages compared to B2B deliveries. In addition, customers expect easy and free returns, potentially increasing demand for residential package pickups.

Common carrier lockers could permit carriers to consolidate some single package deliveries, leading to reduced congestion and emissions. In New York City, for example, one study found that increasing packages per stop from 1 to 5 could reduce the required stops per day by as much as 500 [9].

2.2 Last-mile logistics and Common Pick-up Points

In the field of urban logistics, the last mile in the supply chain is the smallest unit of analysis, but perhaps the most critical [10]. Congestion, missed deliveries and other obstacles in the last-mile from retailer to consumer account for as much as 28% of total transport costs and 25% of emissions from the overall supply chain [5], [10]. Contrary to the popular view of urban freight, many last-mile activities take place outside the vehicle. A study in London found that drivers spent up to 62% of the time for urban delivery tours walking, with an average distance of 105 meters from the vehicle to each customer [11]. Drivers parked for up to 77% of the tour and drove at an average of only 7 kilometers per hour in the delivery area. Therefore, streamlining the flow of activities in and around buildings is of paramount importance. Urban Freight Lab researchers coined the term “Final 50 feet” to describe the supply chain segment beginning when delivery vehicles pull into a parking space and ending when consumers receive goods [12]. The researchers identified reducing failed deliveries and dwell time in curbside loading zones as the top two strategies for streamlining the Final 50 feet [12].

Despite the impacts of increased last-mile pressures, the effects on urban planning, mobility, and transportation in dense urban centers remain underexamined [13]. The University of Washington's Urban Freight Lab has led research in this area with a number of studies in downtown Seattle. In one report, researchers found that only 13% of buildings in downtown Seattle maintain loading bays, forcing 87% of deliveries to curb and alley space [12].

A broad category of proposed solutions, from the perspective of logistics and business management, centers on consolidating online orders into centralized, secure pickup locations [14]. This strategy can eliminate the need for carriers to deliver to multiple addresses in the same building, ride freight elevators, or search for customers to sign for a package—activities that consume up to 61% of the total delivery time in the last mile [12]. In Europe and Australia, some retailers have experimented with common pick-up / drop off points (CDPs): convenience stores, post offices, or other local hubs that store packages for consumers. A feasibility analysis of common pick-up and drop points in the United Kingdom found that CDPs were successful for areas with failed delivery rates exceeding 20% [15]. In France, carriers ship up to 20% of parcel deliveries to households to common pick-up points in dense urban areas, suggesting the rising popularity of common distribution points for online orders [16].

2.3 Common Carrier Locker Systems

While research into common distribution points lays a foundation for solving the last-mile problem, a research gap still exists in understanding the performance of common parcel lockers. Most operations research addresses larger scale routing and scheduling problems rather than individual locker characteristics [17]. For example, Deutsch and Boaz maximized total profit from deliveries by choosing the optimal number, locations, and size of lockers, taking into account the cost to consumers of travelling to the locker [18]. In a typology of parcel lockers, Rohmer and Gendron (2020) identified two business models: carrier-owned parcel lockers such as those operated by Amazon or the United Parcel Service (UPS) and common carrier lockers [17]. The latter category consists of lockers operated by third-party service providers, postal services, or transit agencies and made available to a number of carriers. The authors defined three primary operations research problems concerning lockers: network design and facility location, vehicle routing, and matching customer orders with lockers with appropriate capacity. These goals focus primarily on business success, and not benefits for residents or the general public.

Most existing parcel locker research concerns 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 generated the greatest reductions in vehicle miles travelled (VMT) and carbon emissions [19], [20]. Van Duin et al. (2020) quantified the economic and environmental benefits of lockers through an activity-based estimation model [21]. Compared to home delivery, lockers reduced emissions, primarily by limiting failed deliveries. Lachapelle et al. applied a clustering algorithm to land-use data from an Australian city to identify four typologies for neighborhoods with parcel lockers [22]. 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, the University of Washington's Urban Freight Lab conducted a pilot of a common carrier locker system in downtown Seattle, one of the few tests of such systems in the United States [8]. Researchers noted a 78% reduction in delivery times within the building, 0 failed deliveries to the locker, and a reduction in vehicle dwell times and idling. Common parcel lockers also produced travel time savings in residential areas in South Korea [23].

2.4 Consumer Behavior With Respect to Parcel Lockers

Another subset of research examines parcel lockers from the consumer perspective through survey, focus group, or interview-based methodologies. Lockers shift some delivery costs from carrier to consumer [21]. Carriers must continue to satisfy their customers, so the more user-friendly and convenient common carrier lockers are, the more quickly they will become widespread. An online survey of 15-64 year-old locker users in Jakarta, Indonesia found that most customers still preferred traditional home delivery over the locker, citing timeliness and convenience [24]. However, some favored lockers for their lower delivery costs and more up-to-date package information. Researchers in Brazil used a stated preference survey to understand customer demand for automated delivery stations (lockers) [16]. 63% of respondents said they would use the system, naming safety and security as primary concerns. Customers stated their preferred location for the locker as supermarkets (26%), followed by stores (22%), and shopping malls (21%). An intercept survey of Link light rail riders in Seattle found that customers at two stations received online orders on average once or twice per week [25]. The majority of these respondents preferred to receive orders via home delivery, but 63% of people at one station, and more than 40% at two other stations, said they would consider switching to a common carrier locker in the transit station. With a focus group of 26 Swedish customers, Vakulenko and Hellstrom (2018) found that if participants had one positive experience with the locker, they were likely to continue using it, generating a cycle of positive interactions [26], [27]. They characterized parcel locker benefits as either functional, emotional, social, or financial. In another study, researchers asked Polish Generation Y consumers if they would switch to locker delivery for environmental reasons [28]. They found that young people did not necessarily perceive the lockers as more eco-friendly, but that they were willing to pay more for sustainable delivery. Rather than sustainability, Generation Y consumers cited lower delivery cost and ability to pick up orders at any time of day as the primary advantages of lockers.

A critical question for researchers studying consumer attitudes toward lockers concerns access mode and maximum tolerable travel distance. Common drop-off points can only reduce congestion and emissions if customers walk, bike, or chain trips together to collect their packages [15]. The same holds true for lockers. Nahry and Vilardi estimated the maximum distance consumers would travel to reach the locker to be 3.86 kilometers [24]. In one survey, a majority of the Generation Y consumers picked up their parcels by car on the way to another destination, while 44% walked [28]. Similarly, in the survey of Brazilian consumers, 59% said they would use private vehicles to collect packages [16]. Van Duin et. al noted that lockers only reduced emissions if consumers did not need to travel more than .94 km in urban areas, or 6 km in ex-urban areas, to retrieve their packages [21]. If lockers are to provide a sustainable alternative to door-to-door delivery, most consumers must be willing to complete their portion of the last-mile via a low-emissions travel mode.

2.5 Research Gaps and Study Contributions

With the exception of the 10-day Urban Freight Lab pilot, existing research contains, as of this writing, no known examples of experimental tests of the effectiveness of individual common carrier locker systems on last-mile delivery [8]. Most existing research concentrates on the network effects of lockers distributed throughout a city, aggregate efficiency gains for carriers, or generalized measures of emissions reductions. Geographically, the existing literature almost entirely focuses on countries where parcel lockers have become commonplace, such as Australia, Japan, Germany or Poland. No existing studies examine how parcel lockers change delivery driver behavior at the block or individual building level, although these decisions have the most critical effects on the time required for deliveries. Furthermore, research has largely been limited to privately owned lockers, such those operated by Amazon or the United Parcel Service (UPS), or government-run facilities such as Australia Post lockers, rather than common lockers.

This study seeks to fill these gaps by quantifying the effects of locker systems on delivery vehicle dwell time, volume carried into specific buildings, and time spent inside the building. In a study of ridehailing pick-ups and drop-offs in Seattle, Goodchild et al. (2019) provided a framework for measuring the effects of various strategies on curbside congestion by developing a metric for vehicle productivity and comparing dwell time distributions [29]. This study will borrow from these methodologies in conjunction with a nonequivalent groups pre-test / post-test design to pinpoint the causal impacts of a single common parcel locker on delivery time and dwell time.

Another goal of this study is to fill the gaps in understanding individual-level consumer e-commerce behavior in the United States. In particular, more research is needed in the area of modeling customer demand for lockers. If proven effective, lockers could be placed in transit stations or other public areas. Accurate and timely consumer behavior data can help transportation planners to manage these spaces to maximize public benefits and avoid negative externalities. In conjunction with surveys and other data sources, automated locker data can fill a gap in objective measures of e-commerce behavior. For example, studying the time packages remain in the locker can inform efforts to nudge customers, promoting greater turnover of locker boxes. Separating seasonal cycles from long-term trends in package demand can help planners or building managers actively manage the locker. Segmenting customers through clustering can inform marketing efforts and give a clearer picture of customer demographics. However, few, if any, studies have addressed these aspects using objective data from locker providers. Besides maximizing efficiency for carriers, understanding customer behavior can inform cities of the use, sizing, and placement of public locker systems that would result in the greatest reductions in congestion and emissions.

3 Methods

3.1 Site Selection

The Urban Freight Lab, in conjunction with the City of Seattle, selected an eight-block stretch in Seattle's Belltown neighborhood as a study area for several Department of Energy-funded projects on technological improvements for delivery efficiency. Belltown is a dense urban neighborhood adjacent to Seattle's downtown, consisting mostly of mid- to high-rise residential buildings. The area experiences significant delivery activity in its passenger and commercial vehicle loading zones. As part of the project, Royal Crest Condominiums, a residential building with 133 units, welcomed a common carrier locker in June 2020. Two nearby buildings, Market Place Tower and Grandview Condominium, in the same eight-block study area, were selected as controls. These buildings were selected based on their similarity to Royal Crest Tower in terms of floor-area ratio, number of residents, and composition of nearby loading zones. For each building, I defined four blockfaces adjacent to or opposite the building as the study area. To maintain the independence of observations, study areas were chosen so that the loading zones for each building did not overlap.

Figure 1: Map of Study Buildings in the Department of Energy Project. Market Place will receive an active locker in the future, but for this study was included as a control building.

3.2 Pre-Test / Post-test Design

A key goal of this study was to identify whether installing a common parcel locker caused any change in delivery and dwell times around the residential building. Previous observational studies of common carrier lockers have not demonstrated a causal effect through experimentation. Doing so proves difficult because other effects, such as the seasonality of deliveries or local construction operations, could interfere with the effect of the locker on delivery times. The gold standard for this situation 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. However, this proves impossible in an urban setting where researchers lack control over delivery operators' schedules and routing.

Because of this difficulty, the difference-in-difference model (DID) has gained widespread credibility among built environment researchers for estimating causal relationships for treatment and control groups with individuals that have different characteristics [30], [31]. Observations are collected for two periods, before and after the treatment takes effect. One group receives the treatment and the other receives no intervention. Then, the average change over time in the control group is subtracted from the average change in the treatment group. This "double differencing" removes two sources of bias, from preexisting differences between the members of the control and treatment groups, and from changes in the treatment group related to trends other than the treatment effect.

Several assumptions must hold for the model to correctly estimate the treatment effect. The most crucial is parallel trends. In the absence of the intervention, both the treatment and control sites should change in tandem with one another. In other words, they should respond similarly to changes in the surrounding temporal or environmental conditions. In this study, this is a reasonable assumption, given that the treatment and control buildings sit only a few blocks from each other, and are subject to similar weather patterns, economic conditions, traffic disruptions or other outside factors. The model must also represent an accurate relationship between the dependent variable and the covariates. Finally, the error term must have expectation zero and be distributed independently of the covariates.

Difference-in-difference was used to measure the causal impact of the locker on delivery vehicle dwell times and time that drivers spent inside the building. The treatment group consisted of deliveries to Royal Crest Tower. The control group included the two nearby buildings, Market Place and Grandview. The pre-treatment period was defined as Summer 2020, and the post-treatment period consisted of measurements taken in the first two weeks of February 2021.

3.3 Data Collection

For each group, the dependent variables were measured during two periods: Summer (July – September) and Winter (February), before and after the locker installation. Data collectors were trained to recognize prominent carriers and parking signage, and on how to estimate the volume of packages. Data collectors stood outside the buildings for 3-hour shifts from 8:30 a.m. to 2:30 p.m. on weekdays. One data collector recorded the time delivery vehicles arrived and departed from four blockfaces adjacent to and opposite the study buildings, the carrier, vehicle type (car, van or truck), blockface, and parking space type (commercial loading zone, passenger load zone, paid parking, or no parking). Dwell time was defined as the time the driver pulled into the space until the time they turned on the engine to pull out of the space. If a vehicle was present when the data collector arrived, or remained after the last shift, the arrival or departure time was assumed to be the start or end of the shift, respectively.

Simultaneously, a second data collector observed the building entrance, recording the time in and out of the building, carrier, type of goods, and estimated volume of goods carried in and out of the building (in meters cubed). The observations included delivery vehicles, service vehicles (such as plumbers or electricians) and on-demand delivery services (such as DoorDash or Uber Eats couriers). The two datasets were manually matched based on carrier, parking, and time variables. After residents began to consistently use the lockers, post-treatment data collection was completed from February 1 to 12, using the same procedure. A summary of data collected is presented in Table 1 below.

Table 1: Manual Data Collection Summary

	Pre-Treatment					**Post-Treatment**				
Building	Deliveries	Parking Events	Days Observed	Parking Events per day	Deliveries per Day	Deliveries	Parking Events	Days Observed	Parking Events per day	Deliveries per day

Royal Crest	32	121	5	24.2	6.4	60	187	8	23.4	7.5
Market Place	90	146	11	13.3	8.18	42	80	4	20	10.5
Grandview	56	135	10	13.5	5.6	18	56	4	14	4.5

3.4 Data Pre-processing

The vehicles captured in the study represented a broad swath of deliveries, from maintenance visits, to prepared meal delivery, to package deliveries from express carriers. Two observations were deleted: one lunch break and one entry where the exit was not observed, and departure time could not be determined. If a driver from the same vehicle entered the building multiple times, the observations were grouped together as one, with time inside summed together. The final sample included 297 deliveries to the study buildings. Deliveries were categorized as either package, service, documents and mail, or other, based on data collectors' observations. Parcel deliveries accounted for 188 observations (63.3% of total deliveries). Only these 188 observations were used for regression models and difference-in-difference estimation, as the locker only serves packages. Some deliveries to the building were observed in which the drivers parked their vehicles outside the study area. These observations lacked corresponding parking information, and therefore were excluded from the model.

3.5 Data Analysis and Model Specification

The classical difference-in-difference model is estimated using linear regression. The model simply measures the change in the mean delivery time for both groups and subtracts the mean change in the control group from the mean change in the experimental group. The null hypothesis is that the treatment did not produce any change in the dependent variable (delivery and dwell times).

Several authors have extended this methodology to models that are better suited for non-normally distributed outcome variables [32]. Both variables in this study were continuous, strictly positive, right-skewed distributions, so both a lognormal and a generalized linear model with gamma distribution and log link function were fitted. The gamma family, which includes the exponential distribution, is commonly used for durations, such as waiting times, with distributions similar to those of dwell time and time inside. MacDonald writes that the GLM framework provides better interpretability of the coefficient compared to similar methods, such as log transformation, for dealing with skewed, positive data [32]. As an example in the transportation engineering domain, Li, Graham, and Majundar used a difference-in-difference GLM with a negative binomial distribution to estimate the effects of congestion pricing on traffic causalties [33]. These authors also reported that adding covariates can more precisely estimate the treatment effect by further controlling for preexisting differences between members of the control and treatment groups. For this study, covariates were added to adjust for volume of goods carried into the building, vehicle type, parking type and other variables known to affect delivery times.

Typically, both models yield similar results, but different interpretations. The log normal coefficients reference the change in the conditional geometric mean given an increase in the independent variable, whereas the GLM estimates the change in the arithmetic mean [34]. However, as was the case in this study, they sometimes disagree. Wiens (1999) noted that the presence of outliers, the assignment of an arbitrary cutoff value for censored observations, and non-constant variance can produce disparate results [34]. The delivery dataset contained several outliers with times inside of more than 1 hour, and some short stops of less than 1 minute that were assigned a value of 1. The data also displayed heteroskedastic residuals, which I corrected for through weighted least squares regression. In accordance with Wiens' recommendation, I present results for several models (ordinary least squares, weighted least squares, and gamma glm) as well as plots to visually evaluate the treatment effect.

Initial models were constructed incorporating both the residential and commercial control buildings into one control group. However, differences between the buildings and a large imbalance between the treatment and control classes made it difficult to isolate the treatment effect. To remedy this problem, two sets of models were run: one with both control buildings, and one comparing Royal Crest to only its residential counterpart, Grandview.

For dwell time, the general model was specified as:

$$\begin{aligned}\ln(Dwell_i) = {} & \beta_0 + \beta_1 Time_i + \beta_2 Treat_i + \beta_3\,(Time_i * Treat_i) + \beta_4\,Peak_i + \beta_5 Vehicle_i \\ & + \beta_6 Illegal_i + \varepsilon\end{aligned}$$

Where *Time* is a binary variable denoting whether observation was measured in the pre- or post-test period, and *Treat* is a binary variable indicating whether the observation belonged to the treatment or control group. Many factors, apart from the delivery process at the Royal Crest building, could affect dwell times. Carriers often park in one location, stage packages, and deliver to many addresses by walking.Covariates were selected based on factors known to affect delivery vehicle dwell times, namely traffic congestion, vehicle type and legality of parking [35]. However, variables at other buildings the driver walked to from the same stop, such as delivery processes in those buildings, or changes to the drivers' routes, could not be easily measured and incorporated into this model. So, it was still difficult to detect a drop in dwell times as a result of the locker, given the number of outside factors that could influence driver behavior. *Peak* is a binary variable of 1 if the vehicle parked between the peak delivery hours for the area of 9 am to 1 pm, and 0 if the observation fell outside this range. *Vehicle* is a set of indicator variables for whether the vehicle was a car, van, truck, or other. *Illegal* indicates whether a vehicle parked in an illegal space (no parking or paid parking), or a loading zone—either a Passenger Loading Zone (PLZ) or Commercial Loading Zone (CVLZ)).

For time inside the building, the model was specified as:

$$\ln(Timein_i) = \beta_0 + \beta_1 Time_i + \beta_2 Treat_i + \beta_3\,(Time_i * Treat_i) + \beta_4 \ln(Volume_i) + \beta_5\, Peak_i + \beta_6\, Vehicle_i + \varepsilon$$

Where *Timein* is the time in minutes that the delivery person spent inside the building, and *Volume* is the net estimated volume of goods carried inside and out, in meters cubed. The volume in and out were added together to account for the extra effort required to carry larger items either in or out.

In both models, the coefficient for the interaction term (*Time * Treatment*) represents the magnitude of the causal effect of the treatment on the response variable, adjusting for the covariates in the regression. The exponentiated coefficient can be interpreted as the ratio of the arithmetic mean for the treatment group / the arithmetic mean for the control. Thus, the following formula was used to obtain the marginal effect of the treatment, adjusted for the other covariates in the model:

$$effect = \left(e^{\beta_3} - 1\right) * 100$$

3.6 Curbspace Productivity

Another key research question examines whether the common parcel locker encouraged a more efficient use of public curbspace. Much debate exists on what constitutes a productive curb, so it was necessary to define a new metric based on similar research into passenger loading. To measure the impact of the locker on parking congestion and public space, I developed a metric of curbside productivity for delivery vehicles. This metric measures how many goods can be delivered in a certain volume for the same amount of curbspace. Previous research from Fehr + Peers and the Urban Freight Lab calculated similar metrics for passenger vehicles, but adapting the computation for goods is an emerging research area [36], [29]. I defined the curb productivity as follows:

$$Productivity_{space-type} = \frac{total\ volume\ of\ goods}{curb\ length * total\ dwell\ time} = \frac{m^3}{m * hr}$$

Where the space type was either Commercial or Passenger Loading Zone. The total dwell time includes the dwell time for all vehicles in the study period summed together, so if 10 vehicles parked for 5 min each, the dwell would be 50. To make the results easier to interpret, I multiplied the formula by the length of a typical on-street parking space (20 feet, or 6 meters), giving:

$$\frac{m^3}{m * hr} * 6\ m = m^3\ per\ hour\ per\ space$$

I compared the curbspace productivities for all buildings before and after the locker implementation.

There are several major limitations to this approach. It only measures productivity for the study building – it does not include volume delivered to other buildings. However, this fits the study goal of measuring the impact on outside parking congestion for an intervention inside a particular residential building. In addition, the metric is heavily influenced by overall volume and does not take into account the relative value of the goods. Finally, it fails to take into account possible externalities, such as congestion and emissions, from spacing out deliveries. For example, one vehicle delivering one unit of goods and stopping for 5 minutes yields the same result as 10 vehicles delivering one unit of goods each and each stopping for the same length of time. Although the economic productivity is the same, the second scenario produces greater emissions and competition for parking. This metric should therefore be viewed as a starting point for future research.

3.7 Locker Usage Metrics

Apart from the operational benefits of common parcel lockers, this study also sought to understand e-commerce consumer behavior and interactions with the locker system. Specifically, I sought to map out daily and seasonal consumer demand patterns, categorize distinct subsets of the user population, and identify the main factors influencing customer e-commerce behavior.

Seven months of data from the locker provider created a comprehensive and timely window into this behavior. The original dataset provided by Parcel Pending consisted of package deliveries to the 55-box Royal Crest Tower locker. The data included a delivery and pickup timestamps, carrier ID, user ID, and box number. The dataset spanned 224 days from June 1 through December 31 and included 133 residents. I calculated locker usage metrics both for overall deliveries and per user. Deliveries were identified by grouping the individual package delivery data in five-minute intervals. All packages delivered by a single carrier in a single interval were considered part of one delivery. An anonymized user ID attached to each package delivery allowed me to calculate metrics specific to each user. These are listed in Table 2 below.

Table 2: Locker User Metrics

Variable	**Description**	**Data Type**
Package Count	The total number of packages the user received over the days studied	Integer
Number of Deliveries	The total number of deliveries received in the studied time period	Integer
Days with Delivery	The percentage of days on which the user received **at least one** delivery	Percentage

Deliveries per Day	The total number of deliveries to the user / the number of days studied	Decimal
Max packages in one day	The maximum number of packages received on a single day	Integer
Packages Per Delivery	The total number of packages / the total number of deliveries	Decimal
Packages Per Day	Total number of packages / days in the study	Decimal
Large Ratio	Total number of large packages / overall package total	Percentage
Medium Ratio	Total number of medium packages / overall package total	Percentage
Small Ratio	Total number of small packages / overall package total	Percentage
Morning Pickup Ratio	Number of packages picked up before 12 pm / total number of packages	Percentage
Weekend Pickup Ratio	Number of packages picked up on Saturday or Sunday / total number of packages	Percentage
Average Pickup Time	Pickup Time – Delivery Time for each package / number of packages received	Decimal Minutes

3.8 Clustering Users by Household Characteristics

A key research question concerns how e-commerce usage varies within residential buildings. The Parcel Pending data contain no demographic information, but I derived the size and behavior of households from the user account structure. When users register for the service, they are associated with an ID for their apartment unit. A user can have multiple occupants under one account, but each has a specific occupant ID tied to the property ID. I counted the number of users under each apartment ID, the total packages received, and the average pickup time for all members of the household.

I scaled these three features, calculated the Euclidean distance between them, and input the distance matrix into a K-means clustering algorithm. K-means attempts to minimize the variation within clusters and maximize the distance of points in one cluster to those outside it through an iterative process. The algorithm places K random centroids in the dataset, computes the Euclidean distance from each point to each centroid and attaches each point to its nearest centroids. It then updates the centroid using the average of the distance to the points in the cluster, and converges when the cluster assignments do not change. To choose K, I examined the "elbow plot," showing the sum of squared errors against cluster size, and chose the number of clusters where the marginal reductions in the error decreased significantly.

A major limitation of this approach is that some occupants, especially minors, might not be listed on the Parcel Pending account. Furthermore, the data do not specify the relationship between occupants — for example whether they are family members or unrelated roommates. However, in the absence of other demographic information from the building, this method provides some insight into e-commerce behavior across household types.

3.9 Factor Analysis

Factor analysis is a method often used in psychological or survey-based research to pinpoint underlying "factors" that explain variables collected empirically [37]. The technique identifies common sources of variance among several variables and groups them together. The direction of causality is assumed to move from the underlying factor to the observed variables. In this study, I used factor analysis to model the drivers of customer demand patterns and construct a simplified model of consumer behavior from a complex array of observations. Factors with a sum of squared loadings above 1 were retained. The factors were estimated using the minimum residual method.

3.10 Time Series Analysis

Another research question concerned how locker usage varied according to time of day, day of the week, and month of the year, or season. Delivery patterns are known to be highly seasonal, with peaks around holidays, yet little public information exists on the magnitude of these changes for specific types of buildings [35]. More insight into the seasonality of e-commerce demand can assist urban planners and building managers with developing infrastructure such as lockers.

In this thesis, I examined two time series: the number of packages delivered each day, and the daily locker occupancy rate. The occupancy rate was calculated as the number of packages remaining in the locker at the end of the day (midnight). The number of packages remaining at the end of any given day (d) is the cumulative sum from day 1 to day d of the number of deliveries (D) minus the number of pickups (P) for every day (i).

$$\sum_{i=1}^{d} (D_i - P_i)$$

To construct the time series, I removed the first days of data, consisting of test deliveries before the locker reached stable usage, and the last incomplete day. I also removed duplicate records of less than a second apart resulting from errors in the Parcel Pending dataset. I grouped package deliveries by day and merged these data with a sequence of all days from the beginning and end of the study period to include days with 0 deliveries.

I then decomposed each time series through Seasonal Trend Decomposition using Loess (STL) [38]. The trend component (*T)* was obtained through Loess (Local Regression) Smoothing, which consists of fitting a polynomial to the time series data. To calculate the weekly Seasonal Component (W) the series was detrended by subtracting the trend value for each day from the total number of packages for that day. From the detrended data, each subset of each period (for example, all Mondays) was Loess smoothed to obtain the weekly seasonal component. The remainder (R) is the leftover value after subtracting the seasonal and trend values from the original number of packages per day. STL loops through several iterations of smoothing to obtain optimal estimates.

3.11 Simulation Models

A final set of research questions aimed at configuring the number of different-sized locker boxes to maximize usage and turnover while keeping rejected packages to an acceptable level. The goal was to develop a general model of online package delivery activity so that building managers or city planners could choose an appropriate locker for future projects to efficiently use public space. The three types of simulation models described below captured different aspects of the locker's functionality.

3.11.1 Discrete Event Simulation

Package occupancy and turnover in the locker was modeled through discrete event simulation, as an M/M/3 queue. To avoid seasonal and time-dependent effects, I narrowed the scope of the simulation to a typical week during the busy fall season (mid-September through November), excluding the weekend. This season was chosen because it represents a moderately busy time after users adjusted to the new locker system, but before the unusually high-volume holiday period. Planning for mid- to high-volumes ensures that building managers are less likely to encounter rejected packages and allows the locker to adapt to unexpected peaks in deliveries.

The locker's three box sizes (small, medium, and large) represented the servers. In accordance with queuing theory, delivery driver arrivals and the service time (representing time packages spent inside the locker) were modeled as a Poisson process, with times as exponentially distributed random variables [39]. Both distributions carry the "forgetfulness" property. That is the probability of another package arriving does not depend on the time that the last package arrived. Similarly, the time packages remain in the locker is determined by individual customers' behavior and does not depend on the previous states of the simulation.

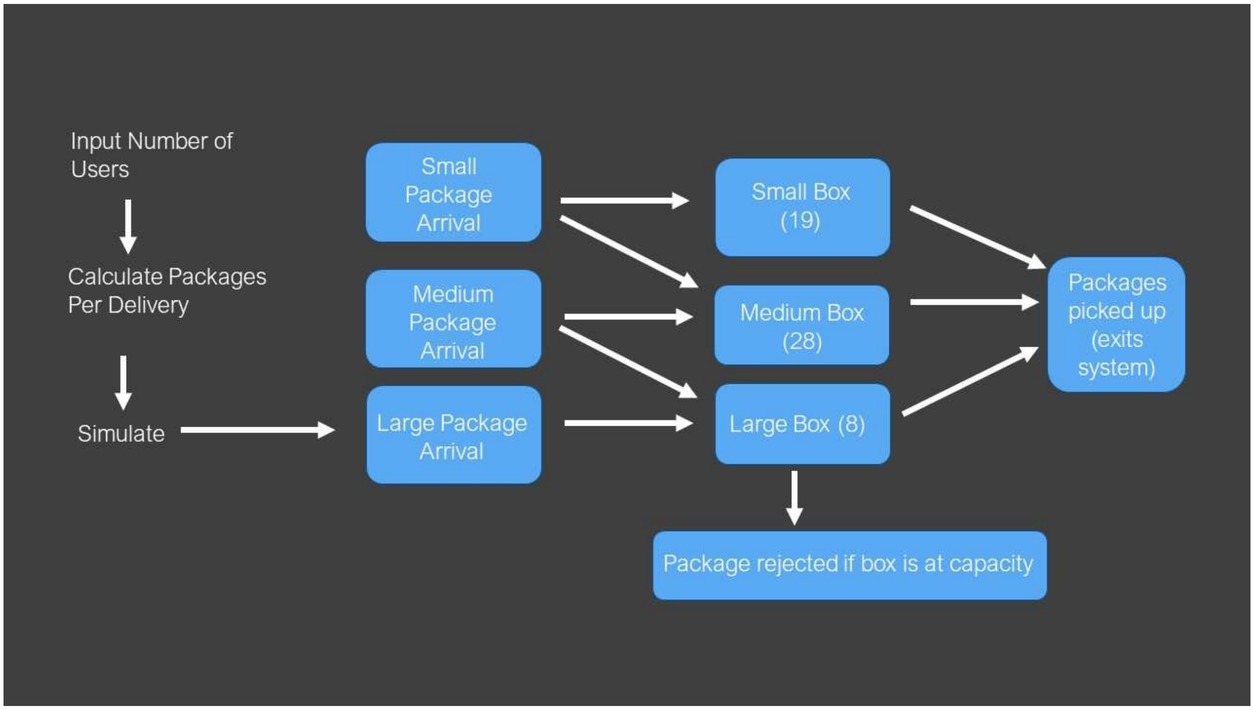
Packages arrived in bulk, with batches according to a zero-truncated Poisson distribution with a mean of 3.8 packages per delivery, determined by the Parcel Pending data. The rate for the arrival distribution came from the average number of packages arriving per minute at Royal Crest during the specified time frame. The rate for the service time was set to 1 / the average difference between the time the package was picked up and the time it was delivered. The queue length was set to 0, meaning that if a package encountered a server at full capacity, the package was rejected. Small packages were allowed to enter either small or medium boxes. Similarly, medium packages could enter large or medium boxes. The full range of simulation parameters with values from the Royal Crest data is presented in Table 3, and the flow of the simulation is shown in Figure 2 below. Comparisons with the groundtruthed on-street data are provided in the same table to lend credibility to these parameters. The simulation was implemented in the R programming language using the Simmer package.

Table 3: Discrete Event Simulation Parameters

	Delivery interarrival times (mins)	Packages per Delivery	Pickup Time (hours)*	Size Distribution
Mean	**43.7**	**3.8**	**10.96**	**10% small** **40% medium** **50% large**
STD	53.1	3.2	16.37	
Shape / distribution type	Exponential	Zero-truncated Poisson	Exponential	
On-street data average	54.39	3.6	--	--
On-street data STD	51.57	2.8	--	--

**pkgs left more than 1 week excluded*

Figure 2: Discrete Event Simulation Model



The above model depends on three key parameters. However, most building managers or policy makers begin their planning knowing only the number of people the locker will serve.

Therefore, the following assumptions simplified the above model to receive the number of users as an input. For urban residential populations similar to that of Royal Crest, it was assumed that as population increases the relative demand for different sizes of packages would remain the same. A factor derived from the average packages Royal Crest users receive per day was used to obtain the packages per day for a given population. It was also assumed that the rate of deliveries would not change—large carriers have set routes and would economize on fuel and labor costs by bundling more packages with each delivery. In reality, the arrival rate likely would change somewhat, especially for Amazon Prime or other services that promise delivery in tight time windows, but modeling interactions between package per delivery and arrival rate was too complex for the scope of this project. The package per day figure was divided by the number of deliveries possible in one business day with the interarrival rate to obtain the packages per delivery. The calculation is shown below:

$$people * \frac{.28\,pkg}{people * day} * \frac{1\,days}{10\,deliveries} = pkg\ per\ delivery$$

Measuring the success of the simulation was approached as a simulation optimization problem. A key question was optimal for whom? Many stakeholders hold different, and possibly competing, goals for the locker. The company that provides the service might seek to maximize new users, while building managers are more concerned with keeping the lobby from overflowing with packages. As this thesis focuses on urban planning, the problem was approached from the perspective of city planners with the hope that the solution would apply to both the private and public sphere. From this view, a key goal would be to ensure the locker was a productive use of public space — that is it occupied no more space than was necessary and continuously served residents. However, if the locker was too small, it would become a public nuisance by letting packages overflow into the building lobby or onto the sidewalk. Therefore, the objective function (O) represents the average locker occupancy measured in 1-hour intervals over the 120-hour (5-day) simulation period. A constraint of no more than 5 rejected packages in the entire week was established. Based on conversations with the building manager, this was viewed as a reasonable constraint. However, it can be adjusted to meet the needs of future buildings. The objective was:

$$Max: O(p,b) = \sum_{h=1}^{8} \frac{p_h}{b}$$

$$\textit{Subject To: } p_{reject} \leq 5$$

Where O is the occupancy, determined by the packages p at hour h, divided by the number of boxes b. For each run of the simulation, the output values were averaged over 10 simulated weeks to avoid the effects of unusually high or low delivery days.

Two analyses were performed using the simulation output. In a sensitivity analysis, each parameter was varied in steps of 20%, from between 60% and 140% of its observed value at Royal Crest. All other parameters were held constant, and the corresponding change in the objective function was recorded. For the second analysis, the parameters were fixed at their Royal Crest values, and several configurations of locker boxes were tested to see which yielded the optimal value in the objective function (highest occupancy) given the constraints (no more than 5 packages left in the lobby). I aimed to include lockers with 3 to 5 towers (1 more and 1 less than the current Royal Crest locker), with a diverse range of box-size configurations. All models chosen are real options in use in other buildings. The following 6 configurations were tested:

- 4 Towers: 37 small, 19 medium, 8 large
- 4 Towers: 19 small, 28 medium, 8 large (current configuration)
- 4 Towers: 13 small, 21 medium, 10 large
- 4 Towers: 19 small, 8 medium, 12 large
- 3 Towers: 19 small, 18 medium, 6 large
- 5 Towers: 25 small, 25 medium, 10 large

3.11.2 Monte Carlo Simulation

The Monte Carlo simulation uses a different approach to answer the question of how many packages to expect given a certain number of users. Currently, this information can be difficult or time-consuming for the locker provider and building manager to collect. Rather than modeling the deliveries through time, the Monte Carlo simulation takes the average of a large number of random draws from a sample to estimate expected values for packages received in a typical day. The user data described above served as the input for simulations of packages expected on a typical day from September through November, given different sizes of user populations. The simulation assumed that each individual from the Parcel Pending data had an equal probability of being selected, randomly generating groups of users with similar characteristics to those of the Belltown locker users. The simulation followed the algorithm below, with each run repeated 10,000 times to generate the distributions of expected packages for user populations of n = 50, 100, 200 and 300:

```
For each day in 10,000 simulated days:
    1. Randomly select 1 day
    2. Randomly select n users from the 127 Parcel Pending users
    3. Add up all the packages of each size delivered to each selected user that day
    4. Return the number of packages of each size delivered that day
```

3.11.3 Failure Time Model

To further explore the effect of different box configurations on locker efficiency, I constructed a failure time model for the Royal Crest locker. The model defines failure as the day when the number of packages remaining at the end of the day exceeds the number of available boxes of a suitable size. For each number of boxes, the simulation runs as follows:

```
1. Start with 0 packages
2. While: total packages in locker is less than or equal to available boxes:
    1. Randomly sample a daily change in packages
    2. Add to total packages in locker
    3. If the total goes negative, set it to 0
   End if: packages in locker exceed number of available boxes
```

4 Results

4.1 Descriptive Changes in Dwell Times and Delivery Operations

The final dataset of 297 vehicles consisted mainly (51%) of package deliveries but included 9% service visits, 11% postal service stops, and 11% prepared meal deliveries. Another 14% of deliveries represented B2B services such as commercial dry cleaning, grocery delivery, or office supplies — mostly observed at the commercial building (Market Place). A seasonal decline in package volume was also observed, dropping 9% in the control and 19% in the treatment group. The delivery vehicles observed included 20% passenger cars, 42% light-duty vans (Ford Transit or similar) and 36% medium-duty trucks (DL-23 or similar).

On average, dwell times and time spent in the building decreased by similar amounts at Royal Crest and Market Place over the course of the study, while increasing or remaining stable at Grandview. Table 4 shows the before and after times recorded for all vehicles, and for parcel service and postal deliveries, along with the basic difference-in-difference estimate. All times are shown in minutes.

Table 4: Changes in Time inside and dwell times

All Deliveries								
	Time – Period 1	**Time in – Period 2**	**Dwell – Period 1**	**Dwell – Period 2**	**Dwell Difference**	**Time inside Difference**	**Dwell DID**	**Inside DID**
Treatment	8.75	6.5	31.7	30.2	-1.5	-2.25	-.1	1.08
Control	11.2	8.03	28.3	26.9	-1.4	-3.17		
Parcel and Postal Deliveries Only								
Treatment	10.25	6.61	44.65	36.2	-8.45	-3.64	-5.29	-2.48
Control	9.02	7.86	34.44	31.27	-3.17	-1.16		

The changes in time inside and dwell times varied significantly depending on the type of delivery, as seen in Figure 3. Only package deliveries saw notable drops in dwell time or time inside at the treatment building. Times significantly increased for postal and service vehicles in the treatment group, but this was due to a few outliers with dwell times far longer than most other vehicles. Given the small sample size, the average times were highly sensitive to these outliers. Examining the distributions for the four groups (shown in Fig. 4) in the difference-in-difference design shows little to no change in dwell times for the treatment category. However, a small drop in time inside is observed relative to the changes in the reference groups.

Figure 3: Differences in times across carriers and delivery categories

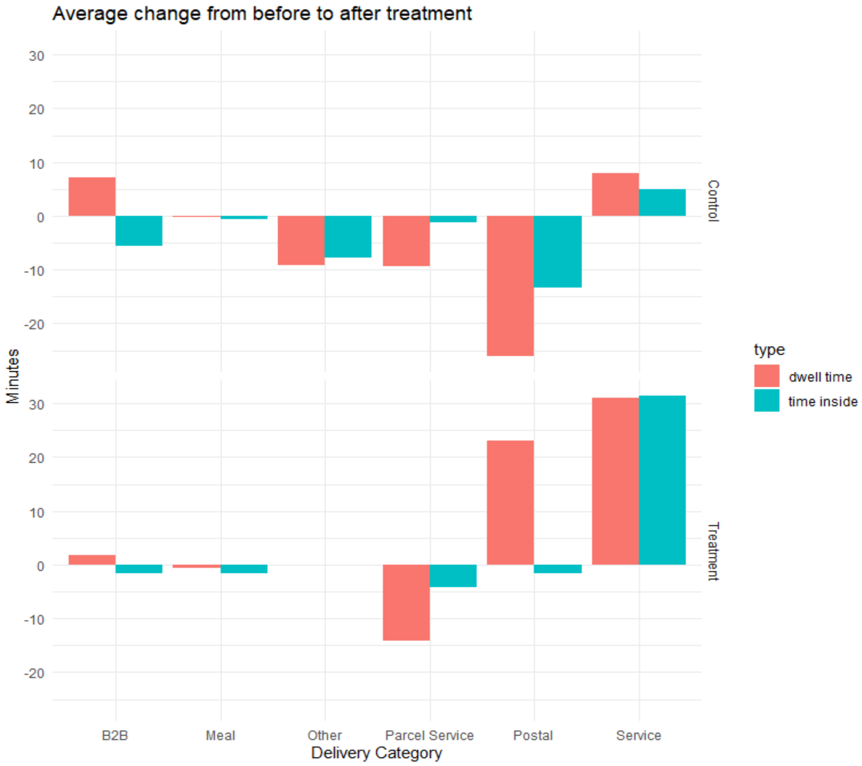
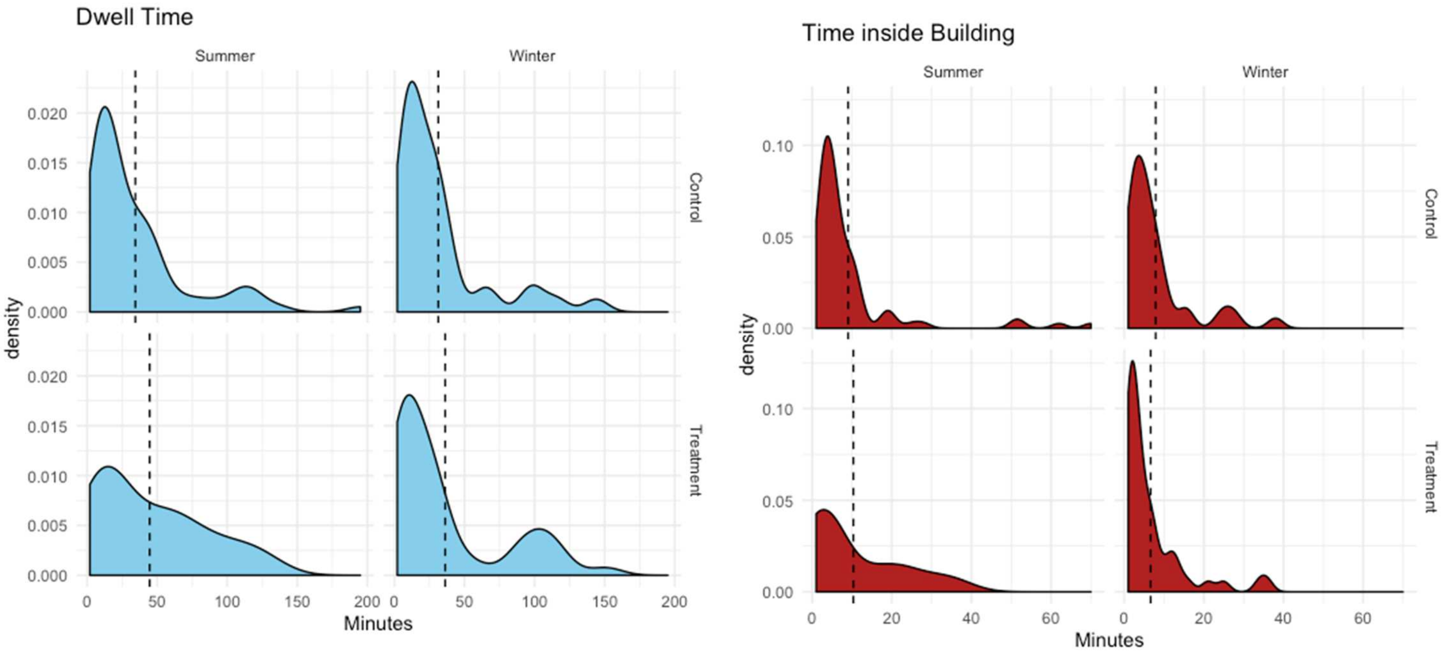


Figure 4: Dwell Time and Time inside distributions for each group – Package deliveries only



Simple differences between the sample groups were calculated to obtain a rough estimate of the treatment effect. For parcel and postal deliveries, the difference in difference of the average time spent in the building between treatment and control was -2.84 minutes. This means that the time in the building went down by almost 3 minutes on average at Royal Crest, even controlling for similar nearby buildings. When examining only parcel and mail deliveries, the difference-in-difference for dwell time was -5.29 minutes. Dwell times at Royal Crest decreased by 19%, while decreasing only 9% in the control group. The dwell time decrease was only true for trucks, however, while times remained constant for cars and vans. Trucks parked outside Royal Crest saw dwell times decrease by 36.4%, from an average of 48 minutes to 30.5 minutes. The difference-in-difference in the average dwell times for trucks was 18.1 minutes.

4.2 Testing the Difference-in-Difference Hypothesis through Regression Modeling

Using regression models, I tested the null hypothesis that dwell time and time spent in the building did not change. A model was fitted to the log of dwell times using Ordinary Least Squares (OLS) estimation. As shown in Table 5, dwell time decreased by 32.69% in the treatment group, holding the vehicle type, parking, and peak hour constant. However, given the small sample size, the 95% confidence level for this estimate ranged from a decrease of 67.8% to an increase of 37.4%. Other models incorporating the commercial building or using Weighted Least Squares estimation did not produce meaningful differences in the results. Therefore, I could not reject the null hypothesis and the effect of the locker on dwell times remained inconclusive.

It is possible that the locker had less visible effects on dwell time compared to time inside because outside factors such as events in other buildings on the carriers' routes might not have been captured in the model. The variability in dwell times is also much higher compared to time inside. Even if a driver saved a few minutes inside the building they might be parked for an hour or more, and simply use the time savings to stage packages, spend more time at other buildings, or complete additional tasks.

Outliers might also have biased the estimate for dwell times. The dwell time observations contained 10 outliers with times greater than 1.5 times the interquartile range. These were largely

UPS and USPS vans and trucks that parked for one to two hours at a time and deliver to numerous locations. These were valid measurements and important data points for measuring packages deliveries, so they were retained in the model. The inside times also contained 9 outliers above 1.5 times the interquartile range. However, these were closer to the mean compared to the dwell time outliers, except for two mail carrier who spent nearly 160 minutes in the building.

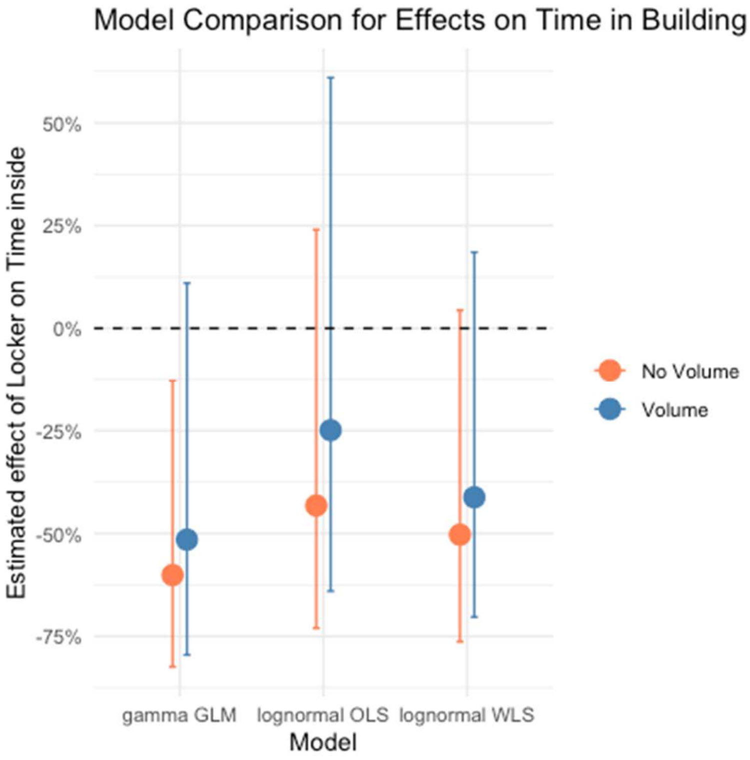
Table 5: Dwell time DID results

	Lognormal – Grandview Only	Lognormal – All Buildings
P-Value	.265	.62
Treatment Effect	-32.69%	-14.8%
Sample Size	116	188

A similar model was fitted with OLS to estimate the effect of the locker on the natural logarithm of time spent inside the building. This model estimated a 25% decrease in time inside when controlling for volume, vehicle type, and peak hour, but the estimate also fell within a wide 95% confidence interval. However, this basic model suffered from heteroskedasticity of residuals (seen in Figure 5) due to the increasing variance of time spent inside when volume increased. The normal plot (Figure 6) also exhibited heavy tails, indicating that the log transform of time inside might not have been enough to meet the model's normality assumption.

To correct for these problems, two additional models were fitted. A weighted least squares model weighted each observation by the reciprocal of the residuals from the OLS model. This model estimated a 41.23% decrease for the treatment effect, controlling for volume. A generalized linear model with a gamma distribution and log link function estimated an effect of 51.45% when controlling for volume, which was significant at the 90% confidence level. Figure 4 compares the confidence intervals and estimates for each model, with and without adjusting for volume of goods. The Akaike Information Criterion (AIC), a metric for model appropriateness, was lower for the WLS model, suggesting a better overall fit. However this is just one measure of model performance, and all three models appear to fit the shape of the time inside distribution. Although the small sample size creates some uncertainty, taken together, these models show consistent signs and large effect sizes for the treatment (seen in Table 6). This suggests that the locker significantly reduced the time spent inside the building.

Figure 4: Model comparison and 95% confidence intervals for locker effect on time spent in building



Models were also run with both residential and commercial buildings in the control group. Incorporating the commercial building resulted in lower estimates for the treatment effect in all cases. However, the difference in the delivery process and composition of the units in the control building possibly violates the parallel trends assumption for difference-in-difference modeling. Because of this, the models with the commercial building were not included in the results.

Table 6: Time Inside DID model comparison

Time inside - Grandview only (n = 116)	
Without Volume	**With Volume Control**

Model	Gamma	WLS	OLS	Gamma	WLS	OLS
P-value	.0238*	.067 .	.154	.089 .	.142	.459
Effect	-60.12%	-50.3%	-43.2%	-51.45%	-41.23%	-24.9%

Detailed regression output and coefficients for the three significant models is shown in Table 7 below. Vehicle type had one of the strongest associations with time inside and dwell time. Switching from a car to a van, for example, increased the average time inside by 148% in the gamma model with volume (his percentage was calculated according to the formula for log-linear regression coefficients on page 17). Peak hour (9am-1pm) and volume also had strong positive correlations with the time spent in the building. These results were expected — During peak hours, delivery vehicles face more traffic congestion and competition for parking space, and might linger in the space for longer. Larger volumes are more difficult to maneuver in and out of the building, and could require multiple trips, regardless of whether a locker is available.

Table 7: Detailed Regression Results for Time Inside

	Dependent variable:		
	Time Inside *glm: Gamma – Link = Log*		Time Inside *Weighted Least Squares*
	(1)	(2)	(3)
Location	0.37	0.42	0.13
	(0.28)	(0.27)	(0.27)
Time Period	0.43	0.53^{*}	0.39
	(0.31)	(0.30)	(0.28)
Peak Hour	0.60^{***}	0.71^{***}	0.43^{**}
	(0.22)	(0.21)	(0.18)
Truck	0.49	0.70^{*}	0.44^{*}
	(0.37)	(0.35)	(0.23)
Van	0.91^{**}	1.00^{***}	0.75^{***}
	(0.36)	(0.35)	(0.23)
ln(Total Volume)	0.82^{***}		

	(0.31)		
Treatment Effect	**-0.72***	**-0.92****	**-0.70***
	(0.42)	**(0.40)**	**(0.38)**
Constant	0.44	0.47	0.64***
	(0.39)	(0.38)	(0.24)
Observations	116	116	116
Log Likelihood	-331.68	-336.20	-151.08
Akaike Inf. Crit.	679.36	686.39	316.17
Note:			$^{*}p < .01^{**}p < .05^{***}p<0.01$

Figure 5: Residual Plots – Gamma (left) and WLS (right)

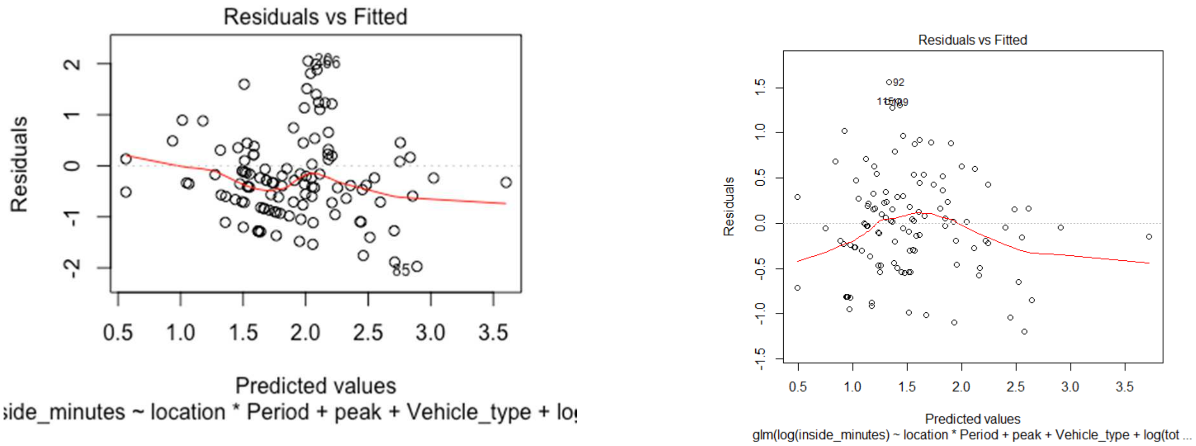
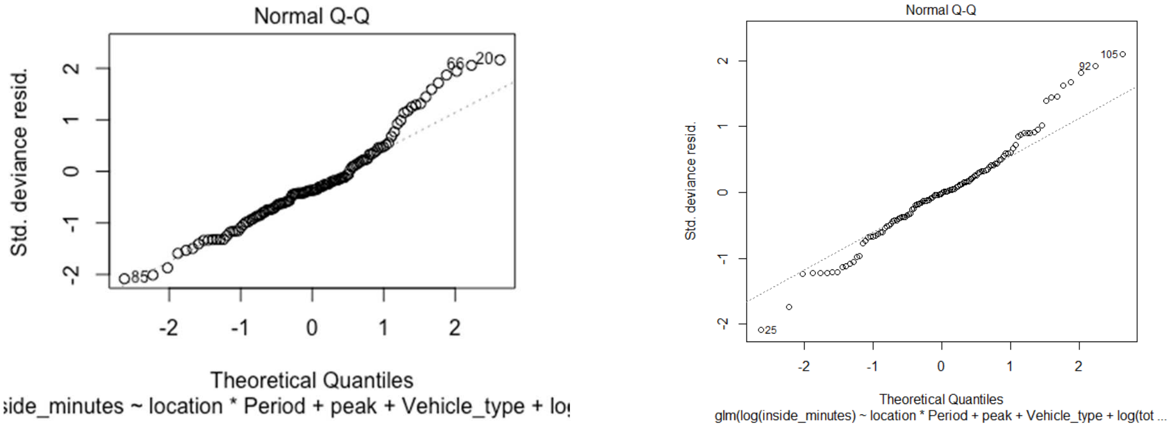
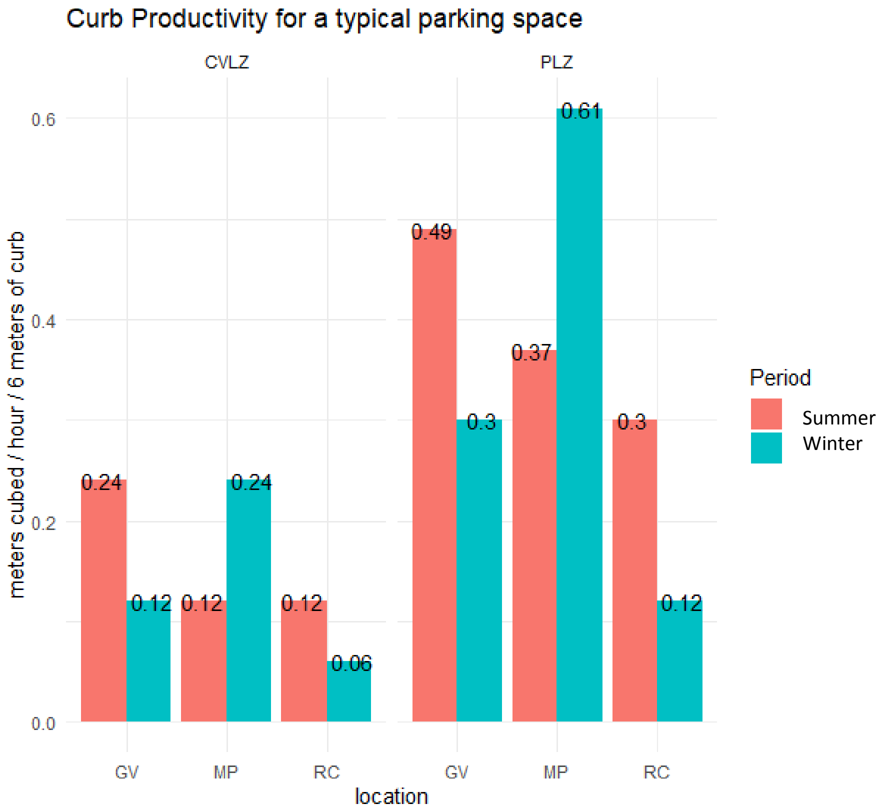


Figure 6: Normal Plots for Gamma (left) and WLS (right)



4.3 Curbspace Productivity

Figure 7: Curbspace Productivity for all buildings before and after the locker installation



The locker did not appear to have much impact on curbspace productivity (shown in Figure 7: Curbspace Productivity for all buildings before and after the locker installation). The productivity declined from Summer to Winter by 50% at both Grandview and Royal Crest, for both CVLZs and PLZs. This is likely because both of these buildings saw average delivery volumes decrease, but their average dwell times and deliveries per day remained roughly the same. For Market Place, curbspace productivity increased, supporting the assumption that this building might have either violated the parallel trends assumption or significantly deviated from the other buildings in its existing characteristics. The figure above shows the changes for each type of building and space.

4.4 Locker Usage Data and Consumer Behavior

4.4.1 Temporal Trends in Locker Usage

The 214-day time series for the number of package deliveries from June 1 to December 31 (Figure 8) exhibits a strong weekly seasonal component with a daily variation of 5 to 15 packages on average. Deliveries are spread evenly throughout the weekdays, with a slight dip on Wednesday (33.3) and slight increase on Fridays (36.4), on average. On weekends, deliveries drop to an average of 25.8 on Saturdays and only 16.7 on Sundays.

Weekend deliveries accounted for a minority of all deliveries, but an increasing percentage compared to a similar study from previous years [7]. 18.1% of deliveries were made on weekends. 11.3% of all deliveries were made on Saturdays, and 6.8% on Sundays. The average pickup time on weekends was 5.98 hours, 13.7% longer than the weekday average. Amazon and USPS operate 7 days per week, providing the most consistent service. Amazon alone accounted for the majority of weekend deliveries (57.6%), and USPS for 25.8%. UPS and Fedex only made 7.5% and 7.8%, respectively, of weekend deliveries. This pattern likely reflects the fact that on-demand delivery services such as Amazon Prime deliver around the clock, while traditional express carriers are mostly active on business days.

I observed a long-term positive trend in weekly adjusted deliveries from summer to winter 2020, consistent with typical e-commerce holiday shopping patterns. Deliveries peak in mid-October, and again during the holiday ordering season in December. Fig. 11 shows the results of the time series decomposition – including the raw input data, the overall trend, the weekly cycles, and a remainder representing leftover random noise.

Figure 8: Daily package delivery time series decomposition

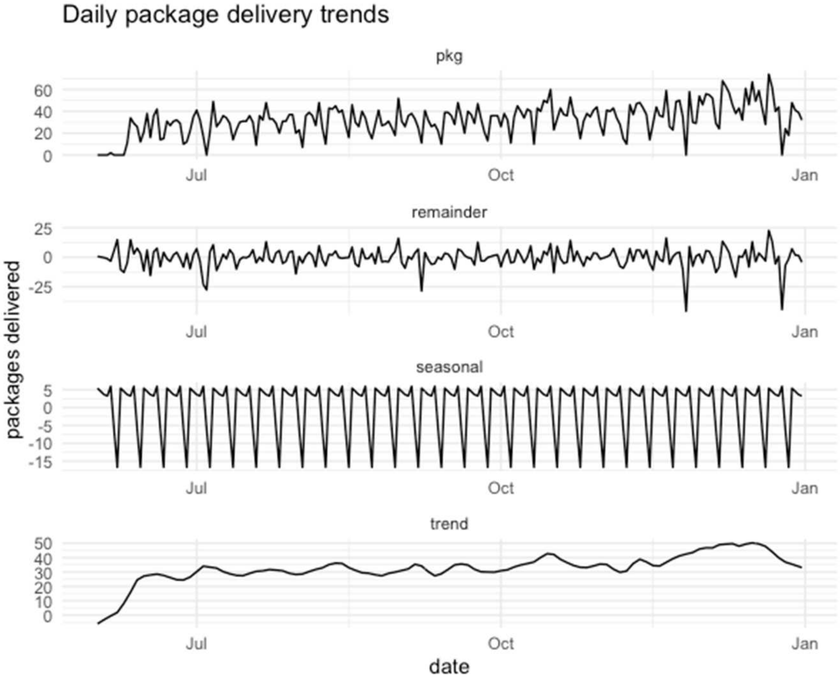
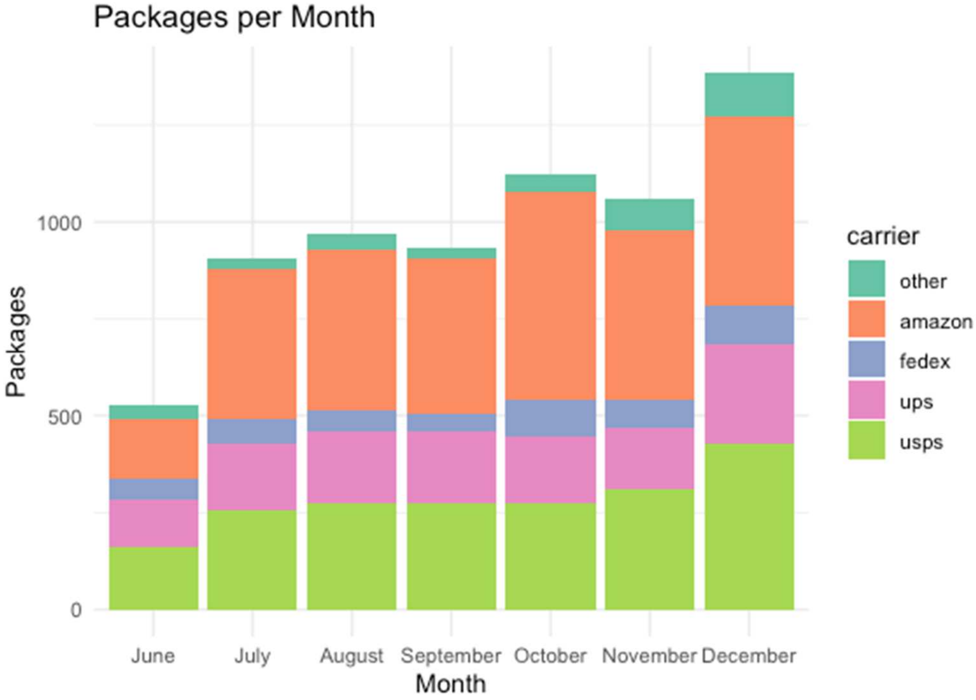


Figure 9: Packages per Month, including distribution of packages by carrier



While deliveries climbed, the occupancy rate rose and fell more regularly throughout the study, peaking in mid-December. In June, the average occupancy was around 20%, compared to more than 40% at its December peak (as seen in Figure 11 and Figure 12). The increased occupancy was mostly due to increased deliveries, but also in part to customers leaving packages in the locker for longer periods. In June, carriers delivered 23.9 packages per day. In December, they delivered 46.1 per day, a 92.8% increase. The average pickup time also rose by 19.1%, from 4.7 hours in June to 5.6 hours. The percentage of the locker occupied at the end of the day remained largely stable throughout the week with only 2% to 4% variation between different weekdays.

Generally, deliveries peaked in the morning and were confined to business hours, while pickups occurred throughout the day until around 8 p.m. The COVID-19 pandemic might have shifted some pickups to earlier in the day. Although the entire study took place during the pandemic, preventing a before and after comparision, presumably more residents were working from home and were nearby when their package was delivered. As seen in Fig. 10, the daily pattern of pickups and deliveries remained stable across all months studied.

Figure 10: Deliveries and Pickups by hour of the day across different months

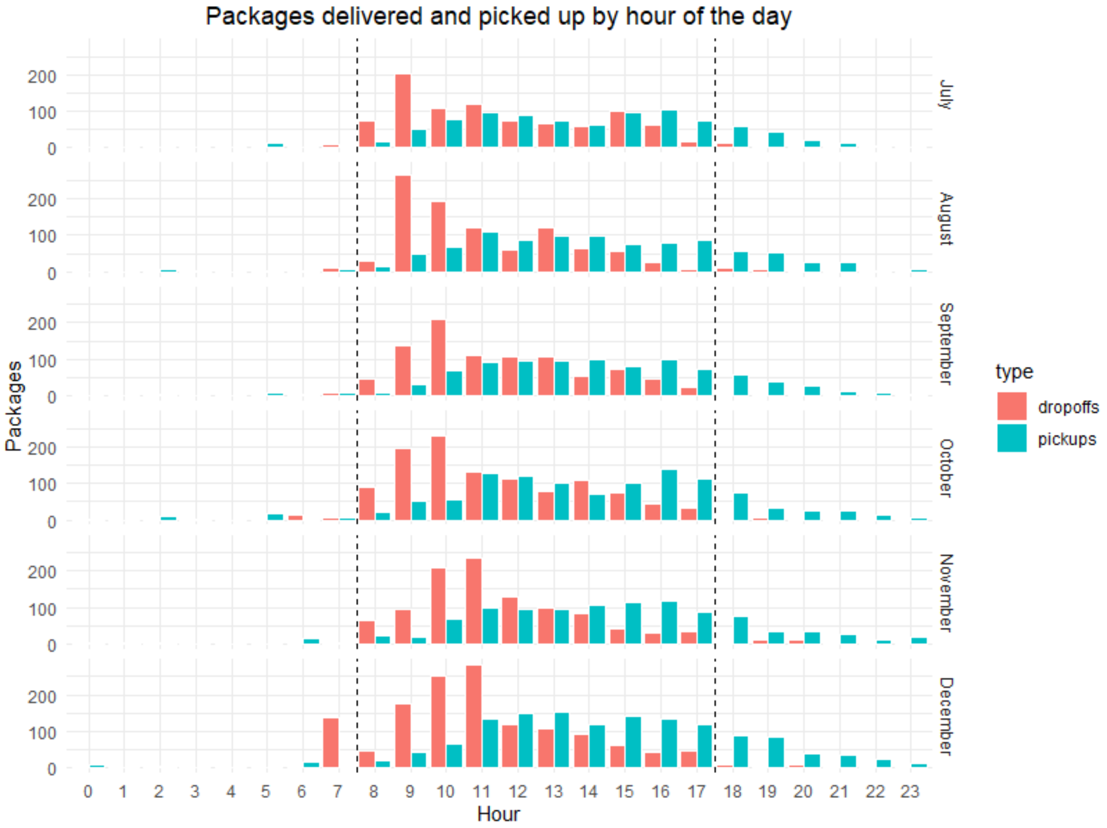


Figure 11: End-of-Day Locker Occupancy Time Series Decomposition

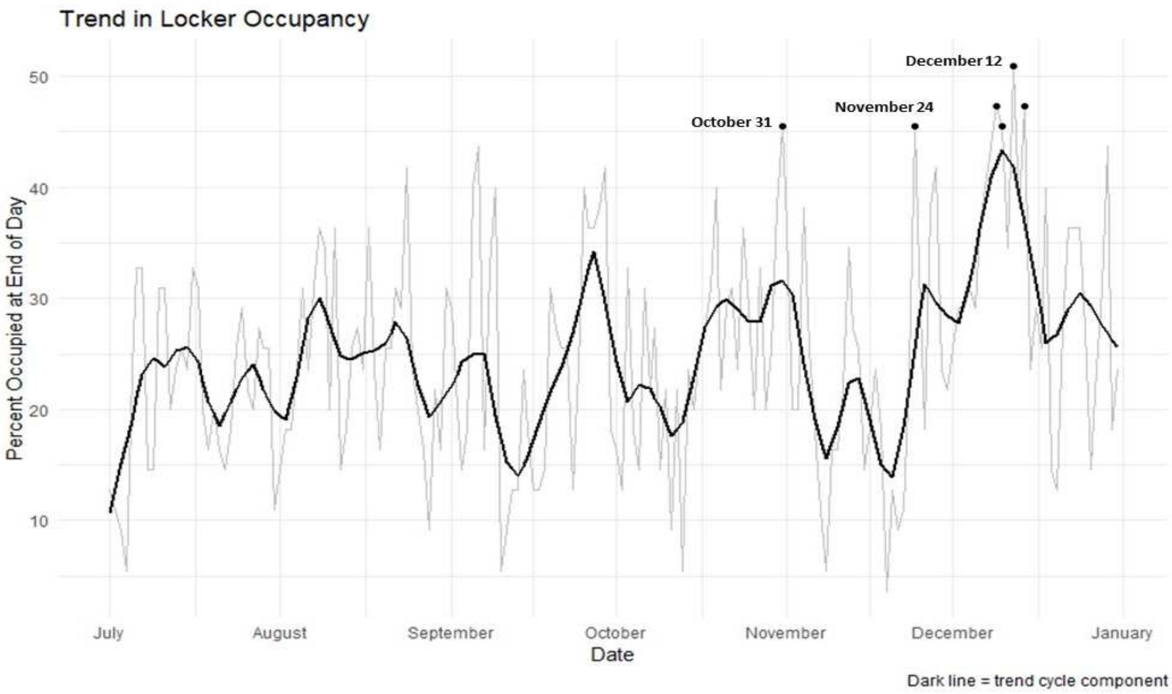
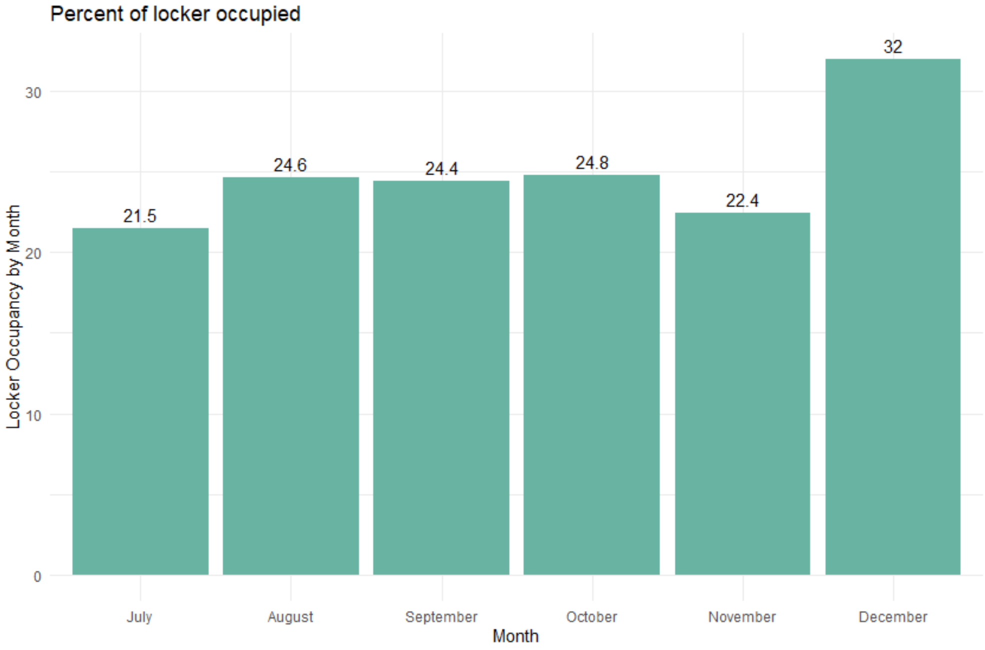


Figure 12: Average Occupancy by Month



4.4.2 Delivery Trends by Carrier

One goal of the common carrier locker is to concentrate deliveries that were previously made door-to-door. However, most deliveries still contain 1 or 2 packages for a single user. Excluding December, Amazon delivered an average of 3.2 packages per delivery spread across an average of 4.3 deliveries per day. The average number of packages per delivery, per customer, was 1. By contrast, USPS deliveries an average of 5.14 packages per delivery, and makes only 1.8 deliveries per day on average. These results could indicate that Amazon customers received multiple shipments over the course of one day, and that Amazon distributes its volume across more deliveries compared to USPS and some other carriers.

The locker data also reveal the variations in carriers' delivery schedules and volume for this residential building, as shown in Table 8. FedEx makes the highest number of deliveries at 8 am, while for Amazon and DHL, the peak delivery hour occurs in the afternoon (12pm and 1pm respectively). A few major carriers account for the vast majority of the delivery volume. Amazon makes the highest percentage of deliveries by far, at 40%, while USPS delivers 28.6% of packages, and UPS, 20%. On average consumers receive one package per delivery, although sometimes several packages for different consumers are dropped off at once.

Table 8: Package Delivery Metrics by Carrier – averaged over 7 months from June through December

Carrier	**Mean time in locker before pickup (decimal hours)**	**Pkgs delivered to date**	**Peak Delivery Hour / pkg per week**	**Mean packages per delivery**	**Mean packages per delivery per customer**	**Mean deliveries per day**
Amazon	5.42	2817 (40.9%)	1 pm (13.4 pkg)	3.13	1.06	4.5
DHL	2.2	30 (.44%)	12 pm (.37 pkg)	1.05	1	1
FedEx	5.27	486 (7.1%)	8 am (7.1 pkg)	2.5	1.06	1.18
UPS	5.30	1257 (18.2%)	10 am (9.6 pkg)	4.43	1.05	1.72

USPS	5.18	1973 (28.6%)	9 am (19.7 pkg)	5.48	1.05	1.96
Overall	**5.35**	**6,894**	**9 am (37.6)**	**3.52**	**1.05**	**8.58**

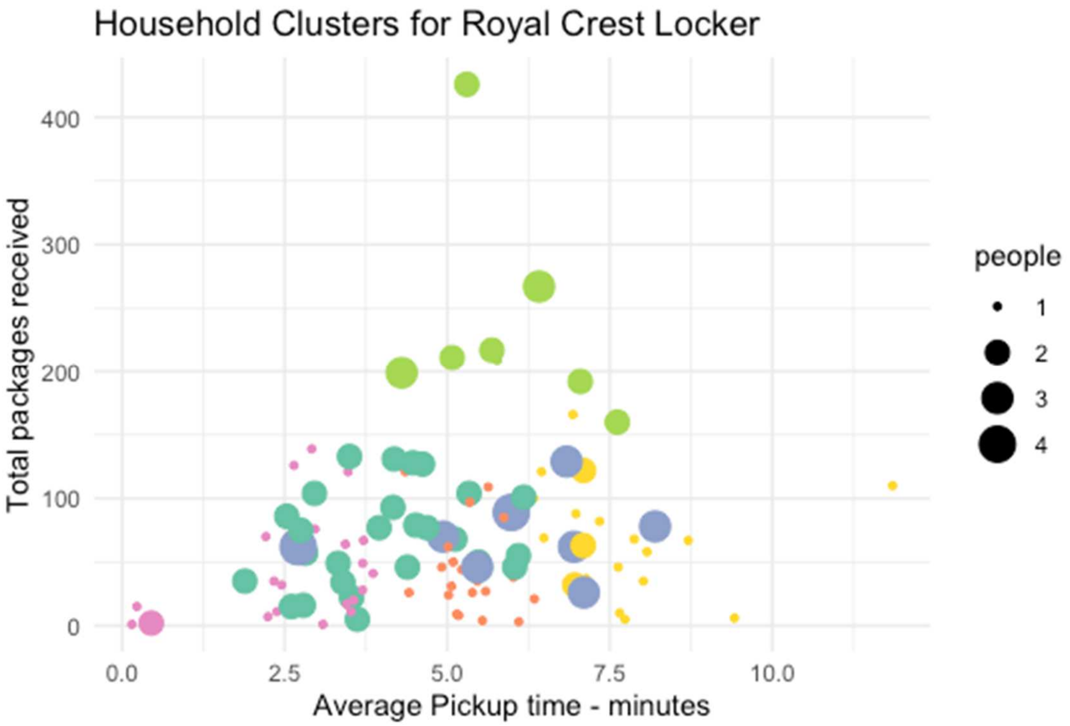
4.4.3 User Behavior

Clustering households: Most households consisted of one or two occupants, although the top quartile of households contained more than three people registered on the Parcel Pending system. It appears that single people were more likely than families to regularly receive e-commerce deliveries, but the most frequent users were 2- to 3-person households. Based on the results of the K-means clustering, I classified users into the following six categories. These are detailed in Figure 13 and the corresponding table.

1. **"Lower volume couples":** These apartments contained around two occupants but ordered at volumes lower than those of the single-account households.
2. **"Core Users:"** This group of single users ordered a moderate number of packages and hovered near the average pickup time, with one occupant per apartment.
3. **"Late-adopter Families:"** These larger households (three people on average) ordered similar total volumes as households with only 1 to 2 people on average. They might receive one package per person every few weeks—very limited e-commerce activity compared with other households in the building. They also took a slightly longer time to pick up orders.
4. **"Quick pick-ups:"** This group had much lower pickup times, one account per apartment, and a moderate package volume. This group contained 3 outliers that had scored near zero on packages and pickup time. These might be errors or accounts used by Parcel Pending to test packages.
5. **"Power Couples:"** These two-person households ordered three to four times more packages per user than the other groups. They were clearly separated from the rest of the households by their heavy e-commerce usage. They picked up packages in a moderate amount of time.

6. **“Slow singles:”** These mostly one-occupant households ordered more packages than any group except the power couples but were characterized by long pickup times.

Figure 13: K-means clustering results for Royal Crest Households



Cluster ID	People	Packages	Avg. Pickup time	Total Pkg per person	Households in cluster
1	2	69.73	4.04	34.87	26
2	1	43.3	5.34	43.3	20
3	3.25	70.25	6.02	21.84	8
4	1.04	44.91	2.66	44.87	23
5	2.12	235.12	5.9	120.92	8
6	1.15	69.35	7.6	63.92	20

Identifying Behavior Patterns through Factor Analysis: The remaining analysis of user behavior centers around 4 underlying facets: Frequency of online orders, size preferences, volume of orders, and pickup time. These were derived using factor analysis from 8 metrics I calculated from the Parcel Pending data. Together, these 4 factors alone explained 71.8% of the variation among the 8 variables:

- Frequency (39% of Variation)
- Size Preferences (12.6% of Variation)
- Volume (11.6% of Variation)
- Pickup Time (8.5% of Variation)

Most of the variation in user behavior is explained by the frequency with which they get deliveries, expressed in the average number of deliveries per day, total number of deliveries, and the share of all days surveyed in which they received a delivery. A smaller amount of variation was due to the size and volume of deliveries, or demand for multiple packages in a single delivery. Differences in the pickup time accounted for the smallest amount of variation, suggesting users do not vary much in their pickup habits. Table 9 shows all of the variables describing users, sorted by which loaded most significantly on each factor. The next chapters detail each of the four factors described above.

Table 9: Summary of Factor Analysis Statistics on Consumer Behavior

Category	Statistic	Mean	St. Dev	Min	25th %ile	75th %ile	Max
Size Preferences	Large Ratio	10%	10%	0%	10%	20%	60%
	Medium Ratio	40%	10%	0%	30%	50%	80%
	Small Ratio	50%	20%	0%	40%	60%	100%
Volume	Most packages in one Day	2.5	1.1	1	2	3	7
	Packages per Delivery	1	.1	1	1	1.1	1.2
Frequency	Days with a delivery	20%	10%	1%	10%	20%	60%
	Number of Deliveries	37.6	30.9	1	16.5	50.5	154

	Packages per day	.2	.2	.01	.1	.3	1
Time	Mean time to pickup (minutes)	298.9	134	9	198.3	390.8	748.5

Frequency: The average user received 37.6 deliveries in a 182-day period from June through November, receiving at least one delivery on about 20% of days. Most users received one delivery per day, and some occasionally received 2. However, the average share of the studied days in which customers received at least one delivery was only 20% (Fig. 14). This suggests that some customers often receive multiple deliveries, each with a single package, on the same day. The most frequent user averaged 1.6 deliveries per day, receiving a delivery on 60% of the days surveyed.

Figure 14: Share of Days with at Least one Delivery

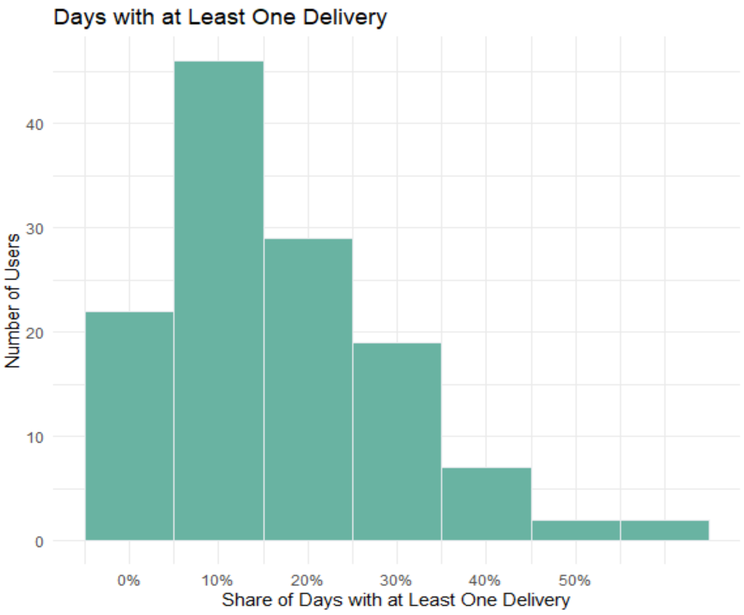
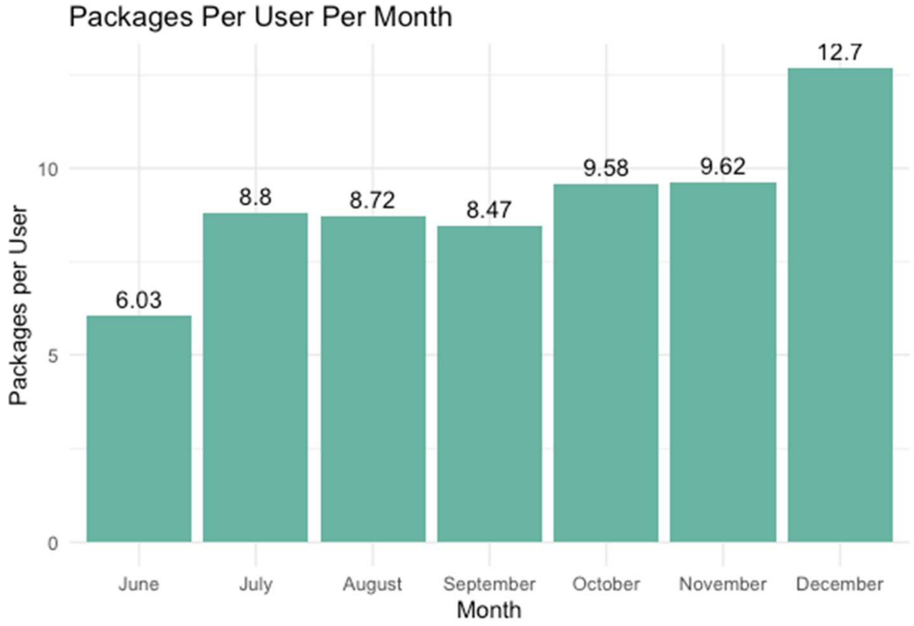
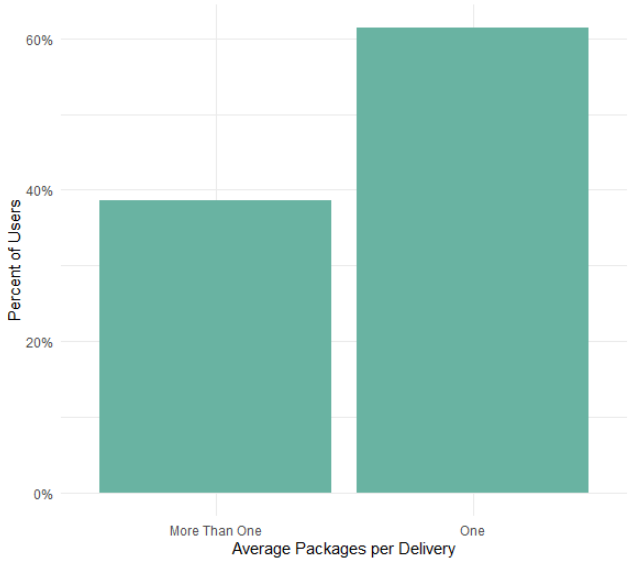


Figure 15: Packages per user per month



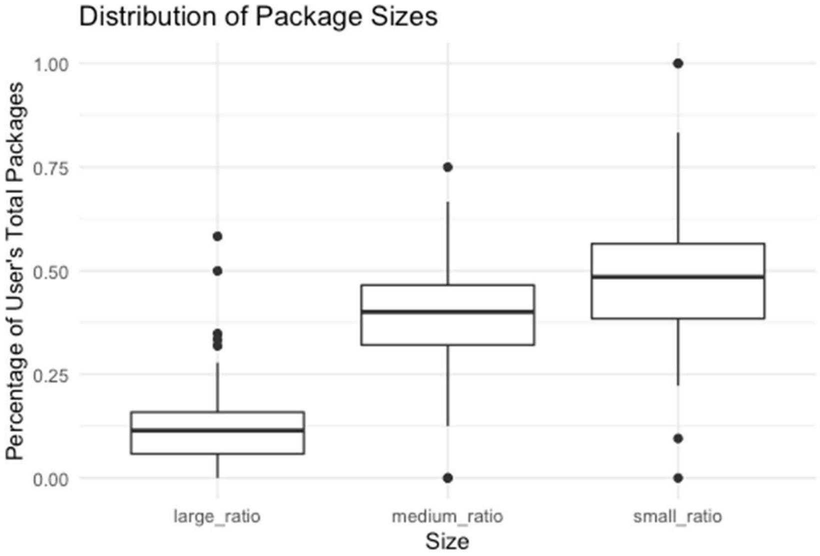
Volume: The average user receives only one package per delivery, as seen in Fig. 17.This number varied little between users, with a maximum of 1.2 packages per delivery. This might indicate that most customers are not receiving consolidated online orders, instead getting each package delivered separately. The maximum number of packages any single user received in one day was 7. The average user received a maximum of only 2.5 packages in a single day.

Figure 16: Average packages per delivery



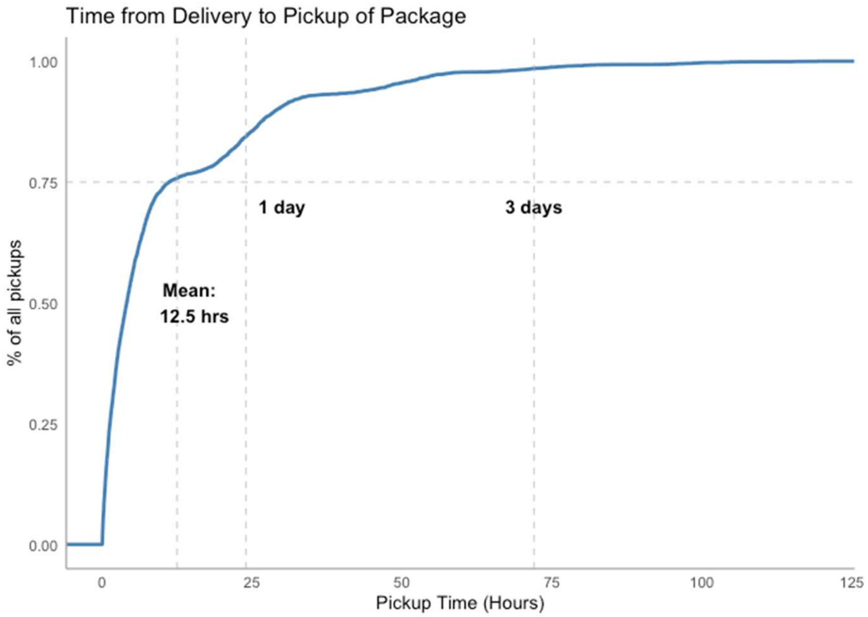
Size Preferences: The average user ordered mostly small packages, followed by medium, shown in Figure 17. Large packages were ordered infrequently. The median user ordered 10% large packages, 40% medium, and 50% small parcels. Overall, the deliveries consisted of 13% large, 38% medium, and 47% small packages. By comparison, the locker made 14.5% of box sizes available to large packages, 34.5% to small, and 51% to medium. This gap suggests that more space could be reserved for small packages to optimize the locker.

Figure 17: Distribution of Package Sizes for all Users



Pickup Time: Users picked up packages throughout the day until late evening. The median time to pickup was 4.2 hours, as seen in Fig. X, but the mean was 12.5 hours, reflecting a right-skewed distribution. 84% of pickups happened within 24 hours of delivery. Nearly all (99%) of orders were picked up within 1 week of delivery. Customers took longer to pick up orders on the weekends and during the Fall and Winter seasons.

Figure 18: Distribution of Average Pickup Times for All Users



4.4.4 Right-sizing the Locker Through Simulation

Discrete Event Simulation (Sensitivity Analysis): After the simulation described on Page 20 was run, the sensitivity of two outputs (occupancy and turnover) to changes in three input parameters was measured. Increases in the number of residents were modeled by increasing the packages per delivery. Changes in delivery frequency were implemented by adjusting the interarrival times. The results are shown in Fig. 20 and Fig. 21.The slope of each line represents the relative sensitivity of the output to the parameter, holding the other variables constant. It measures the change in the objective function given a corresponding change in one parameter.

Based on this analysis, delivery consolidation and time limits on pickups could be effective strategies for managing lockers and online shopping demand. Increasing the frequency of deliveries (decreasing time between arrivals) had a greater marginal effect on occupancy than increasing the number of packages per delivery. Compared to a corresponding change in packages per delivery, a 20% change in delivery frequency caused more packages to pile up, reducing turnover. Changing the pickup time limit affected occupancy at the nearly same rate as adding more packages per delivery. This indicates that controlling the time packages can remain in the locker proves critical to the system’s performance.

Figure 19: Sensitivity of Occupancy to simulation parameters

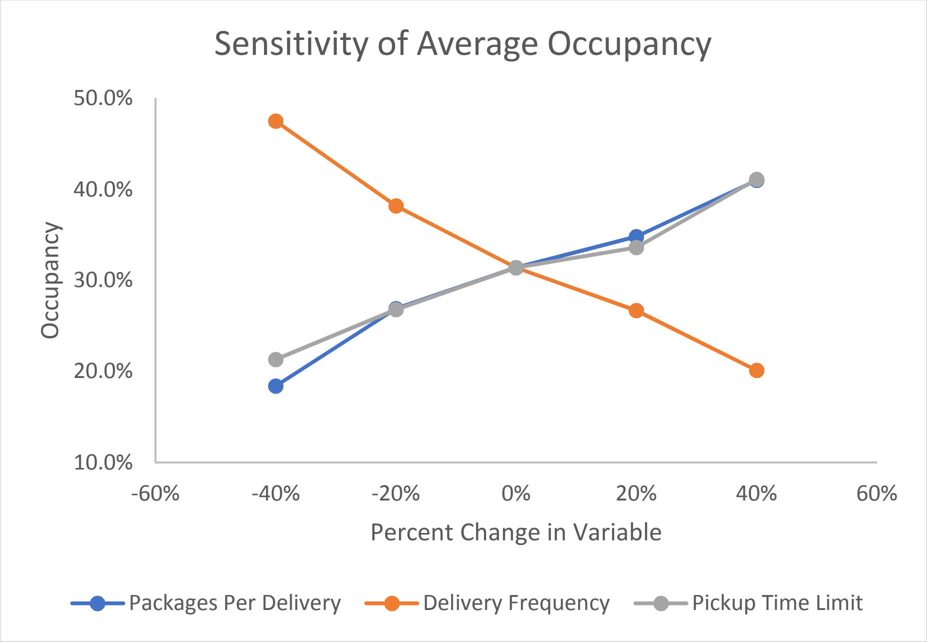
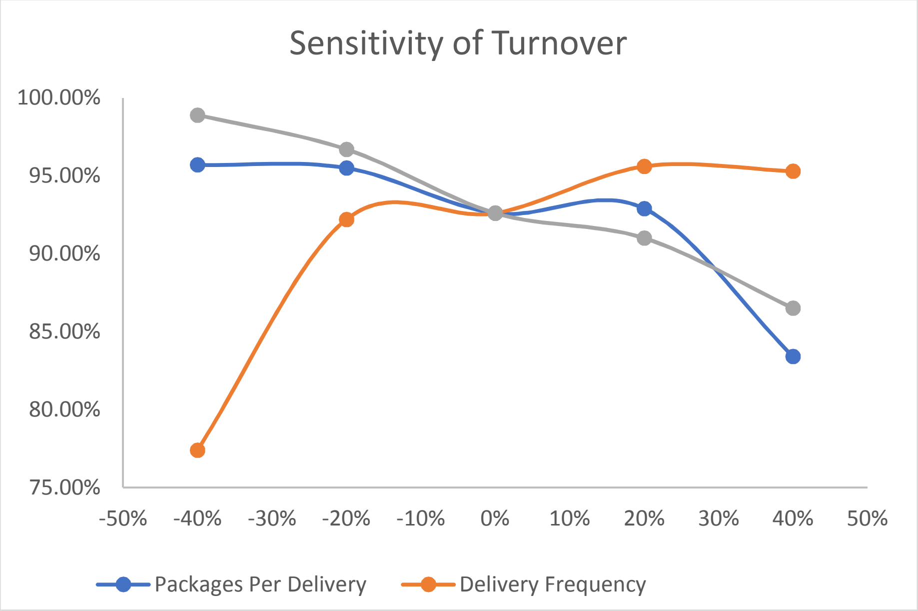
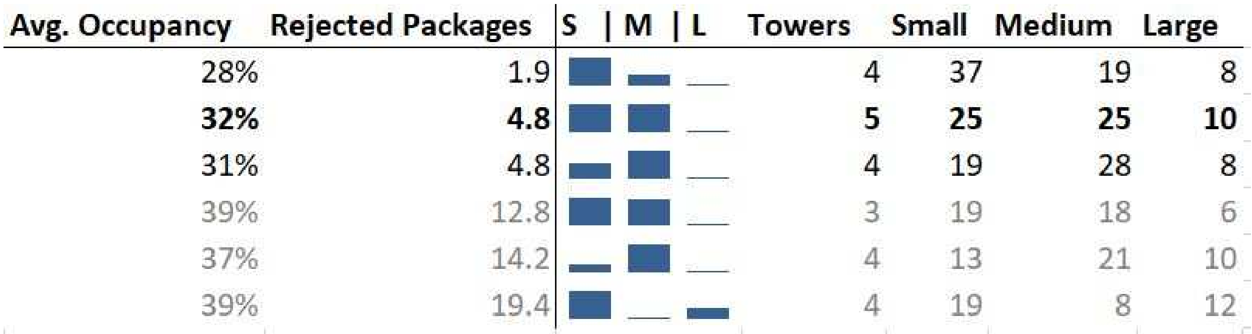


Figure 20: Sensitivity of Turnover to Simulation Parameters



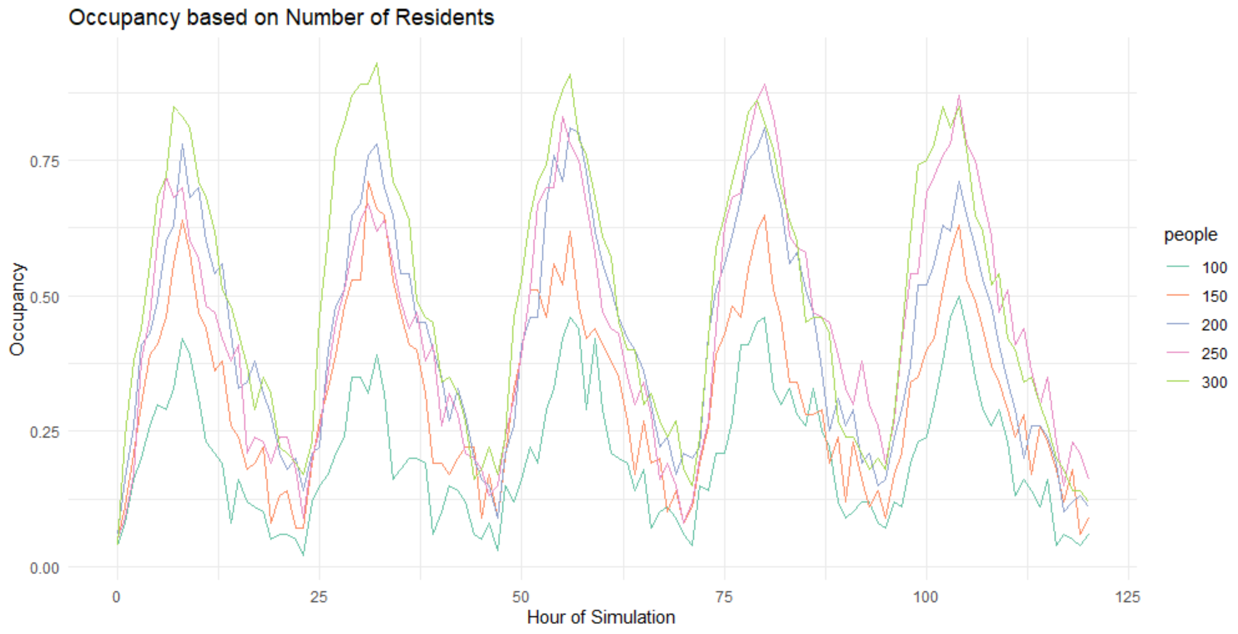
Discrete Event Simulation (Configuration Testing): Several box configurations similar to those at Royal Crest were tested, along with the configuration currently in use. The current configuration (the third row in Table 10) performed well, with about the same occupancy score as a slightly larger 5-tower locker. As seen in Table 10, the lockers with more than 5 rejected packages were too small on the whole. Another combination allocated too much space to one size category, leaving the others empty for long periods and resulting in lower average occupancy. Only four and five-tower lockers with a more even distribution of box sizes kept the number of rejected packages below the constraint.

Table 10: Optimal Configuration for the Royal Crest Locker



Avg. Occupancy	Rejected Packages	S | M | L	Towers	Small	Medium	Large
28%	1.9	█ ▂ ▁	4	37	19	8
32%	**4.8**	█ █ ▁	**5**	**25**	**25**	**10**
31%	4.8	▃ █ ▁	4	19	28	8
39%	12.8	█ █ ▁	3	19	18	6
37%	14.2	▂ █ ▁	4	13	21	10
39%	19.4	█ ▁ ▂	4	19	8	12

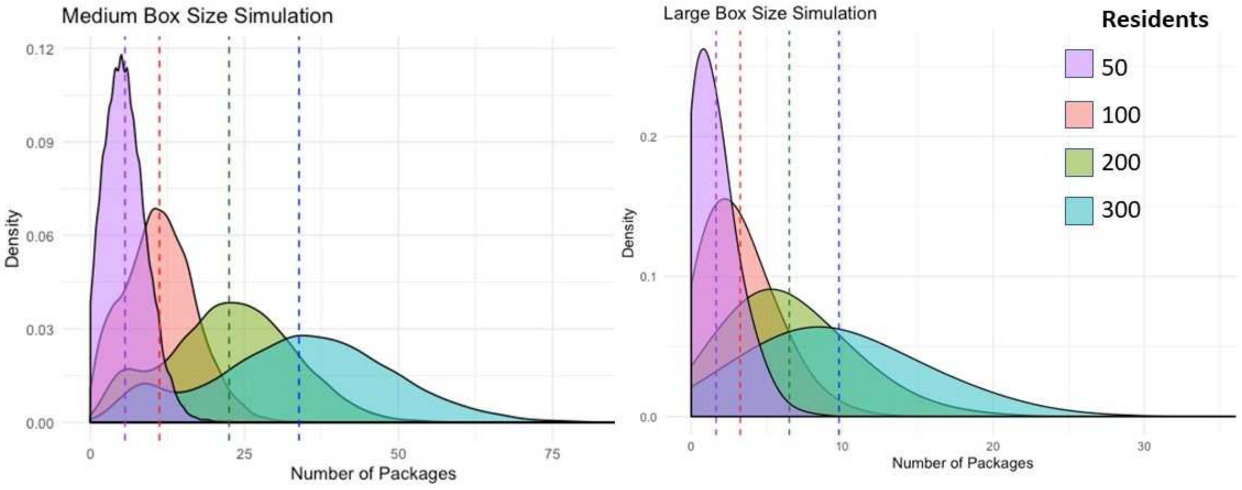
Figure 21: Locker Occupancy by number of residents



Finally, Figure 21 plots the percentage of the locker that was occupied throughout all 5 days for simulations ranging from 100 to 500 building residents. The average occupancy increases with the number of residents. The greatest change occurs from 100 to 200. Because the rate of deliveries did not vary across simulation runs, the daily patterns are roughly the same, with occupancy peaking during high-traffic hours in the day and dropping at night as residents pick up their packages. The locker does not approach more than 85% occupancy until 250-300 people, suggesting the Royal Crest locker can accommodate some additional demand during the Fall season.

Monte Carlo Simulation: The simulations generated probability distributions for the number of packages expected on a typical day from September to November for different population sizes of users. As the number of users increased, the variability in the expected number of packages decreased, as shown by the coefficients of variation in Table 11. With 50 people, the mean of all simulations was 5.96 small packages, 5.66 medium, and 1.65 large. With 300 users, the expected values rose to 35.85, 33.86, and 9.79. Figure 22 shows the distributions of all 10,000 runs of each simulation for populations of 50, 100, 200, and 300.

Figure 22: Monte Carlo Simulation for number of packages delivered



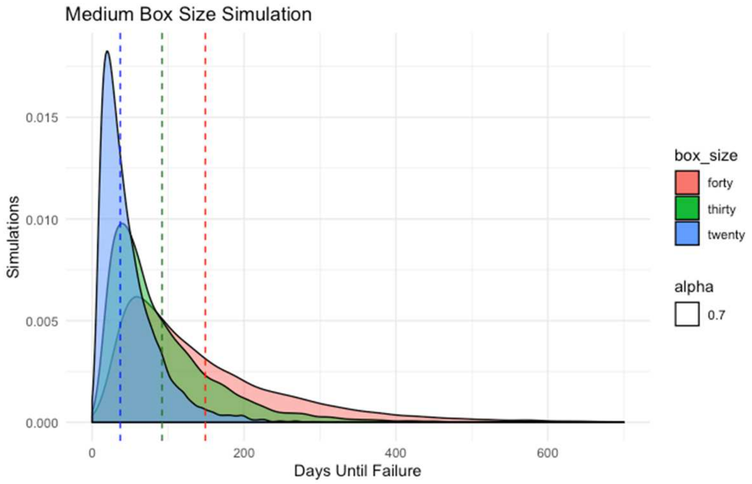
These probability distributions can aid in planning for locker size and box configuration, assuming users come from a similar population as the Belltown residents. The number of boxes will ultimately depend on the decision rule a manager chooses to apply. For example, a more conservative manager might choose to plan for the 90th percentile of the probability distribution, while a more risky, but cost-effective, approach could be to design for the mean. Table 11 contains values for the average and specified percentile ranges of expected deliveries, given populations of 50 to 300 people.

Table 11: Monte Carlo Simulation Results

Small Packages					
Number of People	**Mean**	**Max**	**50% CI**	**90% CI**	**Coefficient of Variation**
50	5.97	26	3 to 8	1 to 12	.57
100	11.81	41	8 to 15	3 to 22	.488
200	23.96	69	17 to 31	7 to 42	.431
300	35.85	113	26 to 45	12 to 61	.41
Medium Packages					
Number of People	**Mean**	**Max**	**50% CI**	**90% CI**	**Coeff of Variation**
50	5.66	28	3 to 8	1 to 12	.597
100	11.2	38	7 to 15	2 to 21	.511
200	22.53	61	15 to 30	5 to 39	.454
300	33.86	92	24 to 44	8 to 58	.436
Large Packages					
Number of People	**Mean**	**Max**	**50% CI**	**90% CI**	**Coeff of Variation**
50	1.65	13	0 to 2	0 to 5	.93
100	3.252	18	1 to 5	0 to 8	.76
200	6.52	27	3 to 9	0 to 14	.634
300	9.79	36	6 to 14	1 to 20	.584

Failure Time Simulation: Another method for choosing the optimal box configuration could be the failure rates for different box sizes. If delivery patterns are known for a specific population, managers could choose an acceptable failure rate and choose the number of boxes that, in simulations, result in a rate closest to that number. An example simulation for different numbers of medium boxes at the Royal Crest locker is shown in Figure 23 (the actual number of such boxes is 28).

Figure 23: Failure Time Simulation Results



5 Discussion / Conclusions

As residential areas see increases in deliveries and congestion, common carrier lockers can reduce time spent inside buildings and at on-street parking spaces. The analysis of the Royal Crest common carrier locker through on-street observations, automated data, and simulation demonstrates a quantifiable effect on time inside and dwell times. Few noticeable changes occurred to parking congestion or curb productivity. However, the study was small and concentrated on a single building.

While one past study has observed some reductions in time spent in the building after lockers were implemented [8], none have demonstrated causal effect. This study found that the locker caused a statistically significant drop in time spent delivering packages inside a residential building, adjusting for the type of vehicle and peak delivery hours. The Gamma generalized linear model suggests that the effect may also be significant at the 95% confidence level even when controlling for volume of goods carried in and out.

This decrease in time spent indoors did not translate to a statistically significant drop in dwell times. However, the sign for the treatment effect was negative, suggesting that the locker did cause some reduction in dwell times for this sample. Several factors could explain this inconsistency. For one, many vehicles in this study area made multiple deliveries from a single stop, so drivers could have been delivering to nearby buildings on the same route. Vehicles sometimes park for an hour or more, so saving a few minutes inside one building might not significantly reduce the overall dwell time. This result suggests that if planners seek to free curbspace in congested urban areas, it may not be enough to install a single locker to speed up deliveries within one building. Realizing the sustainability gains of parcel lockers in dense areas might require a more systemic approach to placing lockers in several major buildings, as well as public spaces.

The locker did not have any significant effect on the average productivity of the curbspace outside Royal Crest, when compared the corresponding change at a similar control building. Productivity was also higher for passenger loading zones at every building in both Summer and Winter. This is likely due to the short dwell times of cars. Future research should examine the effects of building type on curb productivity and explore the potential of light-duty vehicles such as cargo bikes to increase productivity.

Another major limitation to note is that this research was carried out during the COVID-19 pandemic. During this crisis, residential areas saw dramatic spikes in package deliveries, to the point at which major carriers such as UPS refused orders from retailers [40]. This does not affect the difference-in-difference design, as both data collections were carried out during the pandemic. However, it limits the external validity of this study for making statements about individual consumer behavior. Results such as the number of package deliveries per week, or average packages received per consumer cannot be generalized to normal economic situations. The pandemic also forced many middle- to high-income earners to work from home, which could have resulted in shorter times from delivery to pickup. Traffic congestion also dropped in most U.S. cities, 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 after the public health crisis.

Nevertheless, this study yielded insights into consumer behavior with respect to home delivery. Most customers appear to receive single packages rather than consolidated deliveries, although they sometimes receive multiple deliveries in a single day. Customers primarily order small and medium packages. Deliveries for this residential building were highly peaked around 10 a.m., although some carriers, such as Amazon delivered throughout the day. Deliveries remain consistent throughout the week but drop sharply on the weekends. The monthly delivery schedule intensifies gradually from summer to winter, with peaks around major holidays.

The clustering of consumers revealed that single and two-person households more actively use the locker, picking up more packages with less delay compared to households of three or more people. One cluster of single-person households picked up orders in an average of 2 to 3 hours. Planners might seek to locate future lockers in areas with a large population of single-person households or couples to drive demand.

The success of common parcel lockers also depends on customizing the configuration to handle expected volume while remaining useful throughout the day. The simulation model developed in this thesis provides a framework for building managers or other decision-makers to evaluate their locker options, knowing only the number of potential users. The Monte Carlo method provides a means of estimating package delivery rates based on residential populations of different sizes. The sensitivity analysis improves understanding of the underlying processes of deliveries to the locker, specifically where congestion might occur and what policies could most effectively manage this public resource. Notably, decreasing the average time that consumers wait to pick up packages appears to have the same effect as proportional reductions in the average number of packages delivered or increases in the frequency of deliveries.

Given the results of this study, how can planners more efficiently design transportation and delivery infrastructure? For one, the data examined in this study show that e-commerce deliveries consist of small, repeated deliveries. In general, lockers with many smaller boxes would likely work better than those with a few larger boxes. In addition, the e-commerce delivery cycle appears highly peaked. Particular months or hours of the day see unusually high delivery volume. One of the most effective policy solutions would be to enforce shorter time limits during busy periods for customers picking up their parcels, encouraging frequent turnover. Reducing the average time packages spend in the locker had a greater effect on turnover than the other variables and achieved similar changes in occupancy compared to reducing the number of packages per delivery. Time limits can be easily adjusted and communicated electronically to customers. Delivery consolidation, or bundling separate packages into one shipment, also appears to be a promising strategy for managing demand.

Design solutions should prioritize flexibility and modularity. For example, modular systems of boxes could be easily attached or detached from a locker to dynamically adjust the capacity. On the street, emerging curb management technologies such as sensors and dynamic message signs could be used to make additional curbspace available on blockfaces adjacent to lockers during busy months. This study showed that PLZs can be just as productive, if not more so, than CVLZs. Therefore, planners might consider allowing PLZs to be used for goods loading, at least during peak delivery periods.

Future research is needed to demonstrate causal effects of common carrier lockers using larger sample sizes and data collected during different seasons, in areas with different land-use. Comparing the frequency and type of deliveries to lockers in residential and commercial buildings, or between public outdoor and private indoor locations can help determine the optimal location. Further research could also expand on the potential sustainability benefits of lockers by aiming to measure the reduction in emissions due to reduced dwell times and failed deliveries. On the simulation side, further research could attempt to optimize the locker configuration without knowing a set of preexisting combinations to test. More complex simulations could also take into account interactions between changes in the arrival rate of delivery and the number of packages caused by an increase in residents.

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