The Location Choice of Parcel Lockers

An empirical investigation of expansion and cannibalization in the Hungarian last-mile delivery market

by

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Submitted to

Central European University

Department of Economics and Business

In partial fulfilment of the requirements for the degree of

Master of Arts in Economics

Supervisor: Professor Gábor Békés

Budapest, Hungary

2022

Abstract

This thesis analyses the location choice of firms in the context of last-mile delivery. I use transaction level data from a major Hungarian parcel carrier to establish results on the effect of a broad expansion of parcel locker stations on the distribution of transactions. I exploit a quasi-experimental design when inferring the effect of a newly placed locker on nearby, initial lockers and also estimate the effect of the expansion on the aggregate number of users and transactions. I estimate two-way fixed effect equations and models by Sun and Abraham (2021) and de Chaisemartin and D'Haultfœuille (2020) which account for treatment effect heterogeneity and staggered treatment timing. This thesis contributes to the literature in two ways. First, I show that although there is a significant cannibalization effect between initial and new lockers in both the number of users and transactions, there is also a moderate but significant positive effect on the aggregate number of transactions. This mechanism is not measured in previous studies of automated parcel locker networks. Second, I show that there is no substantial difference between estimates by the textbook two-way fixed effect model and models that account for treatment effect heterogeneity and staggered treatment timing in this setup.

Keywords: *location choice*, *last-mile delivery*, *parcel lockers*, *difference-in-differences*

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1 Introduction

Firms' strategy on location choice is a fundamental question of economic geography. In this thesis, I study the importance of location choice in the context of last-mile delivery. I use data from a major Hungarian parcel carrier that experienced a big expansion wave in its last-mile delivery network of automated parcel locker stations. There are two questions that rise considering the potential effect of an expansion in the locker station network: (1) What is the effect of a new locker on the transactions and users experienced by nearby initial lockers? (2) Is there an aggregate effect on transactions because of the expansion?. Since its foundation, the company expanded its locker station network slowly, but in 2021, the operator doubled the number of parcel lockers available for customers. I investigate this intervention in my analysis and use it to estimate the effect of how a placement of a new locker affect the number of transactions in the ones near to the new lockers and the aggregate effect of the expansion of the network. The dataset I use covers the period between January 2021 and February 2022, and contains all transactions experienced by the operator.

To estimate the effect of the placement of a new locker on the existing ones nearby, I exploit a quasi-experimental event study design. I take the initial set of lockers and create a subset of treated lockers that experienced a new locker placement in the 2 km distance near to them. New lockers have been set up quite evenly during the year, but I consider an initial locker treated only if it was treated between May, 2021 and September 2021. I create the control set of lockers from the remaining lockers by choosing one control for each treated unit in a way to satisfy the parallel trend assumption. To estimate the aggregate effect of the growth in the number of parcel lockers, I aggregate the number of transactions to the level of administrative districts. I only leave the districts in this sample, that had at least one parcel locker in the first observed period (intensive margin).

First, I estimate a two-way fixed effect equation for local and aggregate effects, however, the coefficient estimates by TWFE are biased in the presence of staggered treatment timing and treatment effect heterogeneity (Goodman-Bacon 2021). In this case, treatment timing is staggered by design and treatment heterogeneity is present since there are huge differences in the distance of initial and new lockers within treated and control groups. Hence, I use estimators by Sun and Abraham (2021) and de Chaisemartin and D'Haultfœuille (2020) that correct the biases of the textbook TWFE.

Findings suggest that the effect of the placement of a new locker is significantly negative on other nearby lockers. Coefficient estimates show a 12-15% decrease in the number of transactions and users experienced by initial lockers. The effect is quite persistent in time. Aggregate results suggests that there is a 2-3% increase in the number of transactions and users per district, once there is a new locker placement in a district. These results suggest that there is a huge cannibalization between within firm lockers that are placed in a close distance, however, district level aggregated results show that expansion could help attract new users.

2 Literature Review

In this section, first, I review the literature of firm location choice. Although I analyse the expansion of parcel locker stations of a delivery firm, this problem relates to the broader literature about retail and fast food chain expansion. Then, I introduce the last-mile delivery problem and how parcel lockers help in resolving issues related to last-mile delivery. I present the main objectives of firms that operate an automated parcel locker network, and show the key decision points that influence the growth and sustainability of such networks. My main goal in this section is to provide context and potential mechanisms for the local and aggregate effect of the expansion wave in the last-mile delivery network.

2.1 Location choice

One of the fundamental questions of economic geography is the agglomeration of economic activity in a small number of places. According to Fujita and Thisse (1996), the main reasons why economic activity of firms and households tend to form clusters are: *"(1) externalities under perfect competition; (2) increasing returns under monopolistic competition; and (3) spatial competition under strategic interaction"* (Fujita and Thisse 1996, p. 339). My focus in this section is to present how market and firm characteristics influence firms' strategy on location choice.

The first widespread formalization of location choice was introduced by Hotelling (1929). Hotelling's model considers a simplified framework with inelastic demand, constant transport cost and consumers evenly distributed in a linear market. Consumers choose stores based on the price and the transportation cost. In equilibrium with two firms, both will locate their store in the middle of the market and choose the same price (Hotelling (1929); Brown (1989)). When more firms enter the market, there is a tendency for clustering (Huang and Levinson 2008), which is also an important point when considering the market for last-mile delivery. Irmen and Thisse (1998) showed that the predictions of the classic model does not hold when firms compete in a multi-characteristic space. Instead, firms choose to maximize differentiation in the dominant characteristic and to minimize differentiation in the others. When introducing uncertainty about consumers' preferences and market sizes, Harter (1997) found that firms do differentiate in positioning because they gamble on finding markets with less fierce competition.

The location choice of parcel lockers relates largely to the location choice problem of the retail industry (Thomadsen (2007); Shen and Xiao (2014); Ho and Ishii (2011)). Thomadsen (2007) considers optimal retail store positioning by firms with asymmetric competitive strength. The author analyzed the retail location of the two large fast food chains, Burger King and McDonald's retail location choices in the US, where Burger King is considered to be the weaker competitor. The study found that Burger King avoids location in the optimal market location, even when entering first to avoid competition with McDonald's. On the other hand, McDonald's only differentiate itself if the market is large enough, so both firms could monopolize the market, while on a small market, to hinder Burger King acquiring a geographic advantage with a subset of customers, McDonald's would like to match on locations. These findings also relate to Tyagi (2000), who considers product positioning among firms with symmetric demand but asymmetric costs, and found that firms differentiate themselves from companies that have a cost advantage over them.

Market learning and demand expansion could also provide an explanation for clustering when entering new geographic markets. Shen and Xiao (2014) studied McDonald's and KFC entries in China and analyzed how the presence of a rival affects each firm's strategies and found that it has a net positive effect on a chain's expansion decision. They found two reasons for the existence of the positive effect: (1) there is a demand expansion effect, because the presence of a rival may enhance local customer's taste which generates potential demand for new products in the industry; (2) there is a market learning effect, since the expansion of the rival may signal the size and growth of the market for other entrants. Yang (2020) used fast food chain data from Canada to show that when entering new geographic markets, firms may face uncertainty about the profitability of such markets, however, this uncertainty diminishes over time, and a presence of an incumbent can inform the entrants about the market viability.

Another important aspect of location choice is cannibalization, which means competition between stores of the same firm within a geographical market (Igami and Yang 2016). Firms in the retail sector but also on the last-mile delivery market should know the net impact of opening and closing facilities. According to Pancras, Sriram and Kumar (2012), firms should infer each store's incremental sales and compare it to its effect on other stores belonging to the same operator, competing for the same set of customers. The authors analysed data for a fast food chain in a large U.S. city and found that, on average, 86.7% of sales generated by a store is incremental and the remaining would be picked up by other nearby stores belonging to the chain in case of the store's closure. When analysing the effect of a new store opening on the sales of other stores nearby, they found that the average cannibalization effect for stores located within 10 miles (∼16 km) of the new store ranged from 0.85% to 1.61%, while considering stores located between 10–20 miles (∼16-32 km) they found no cannibalization effect. When analyzing cannibalization in the Canadian fast food industry, Igami and Yang (2016) found that stores within the same chain compete more intensely than with shops from other chains. However, they found that there is a trade-off between preemption motives because of threats of rivals' entry and cannibalization within chains, which shapes the entry decisions of multi-store firms.

2.2 Parcel lockers – a solution to the last-mile delivery problem

The last-mile delivery includes "all logistics activities related to the delivery of shipments to private customer households in urban areas" (Boysen, Fedtke and Schwerdfeger 2021, p. 2) There is a relatively high cost related to the last mile delivery, originating from three main factors. First, van Duin et al. (2016) found that successful first time home delivery is only 75%, while Song et al. (2009) found that in cases in which no delivery time or arrangement has been made with the customer in advance, successful first time home delivery can decrease to 40%. The second reason for high cost is the lack of economies of scale, as most of the time a delivery involves only one package per stop. Third, according to Deutsch and Golany (2018), finding the exact home address of customers in large apartment blocks in cities or in rural areas where roads may not have proper signs also contributes to the high cost of last mile delivery.

Alternative delivery concepts that allow for unattended delivery of customer self-services, fixed and reliable pickup points, are promising alternatives at a lower cost. One promising alternative delivery concepts is a system of pick-up stations, which allow customers to choose the time they acquire their parcel. Rohmer and Gendron (2020) divide pick-up stations into two general categories: 1.) customer pick-up points and 2.) automated parcel lockers. Customer pickup points refer to collection points integrated into local shops, gas stations that are operated by staff assistance during usual business hours. On the other hand, automated lockers work without assistance, can be accessed through mobile applications often in a 24/7 schedule, usually located in busy public areas such as shopping malls, transport hubs or large office buildings. The cost of initial investment is high for automated lockers compared to customer pick-up points, however, they provide more flexibility for customers in longer operating times. In this thesis I analyse data from a major Hungarian parcel carrier which operates solely automated lockers.

Pick-up stations increase delivery efficiency and reduce associated operating costs and carbon emission by bundling customer demand and decreasing the number of failed deliveries (Rohmer and Gendron 2020). Kämäräinen, Saranen and Holmström (2001) showed that using parcel lockers in the last-mile delivery resulted in a 42% cost reduction using delivery data from suburban areas in Helsinki. Punakivi, Yrjölä and Holmström (2001) used data from a Finnish retail company and showed that indirect delivery services reduce the cost of last mile delivery up to 60% compared to direct delivery with a two-hour delivery time window.

Indirect delivery services are more flexible in delivery timing, increase vehicle usage efficiency, and hugely decrease failed deliveries, however, they also pose challenges for the operators. The design and operation of such delivery network requires high levels of efficiency, coordination and planning. Rohmer and Gendron (2020) identified three important steps of decisions for planning and operating such networks: 1.) network design and facility location, 2.) vehicle routing, 3.) locker assignment and scheduling. Because I analyse the location choice of parcel locker operators, my focus is on the first point, network design.

Locker station network designers has two major decision points. Operators should decide on the 1.) number of locker stations, which determines the size of the network 2.) and on the location of parcel lockers. A third, but less critical aspect is that locker stations are usually modular, therefore providers have to decide on the amount, size and other configuration (eg. temperature, maximum weight) on the modules in a locker station (Faugere and Montreuil 2017).

While choosing the number of locker stations, operators have to take into account their user base, the existing infrastructure which include competitor service providers' network, and the predicted demand in terms of amount and parcel types. Choosing the optimal number of stations is also a dynamic decision problem in which providers should consider potential growth in demand and the growth in competitor's network, as space for lockers is limited, especially in those areas that generate high flow of traffic or areas that are in central urban position (eg. malls, traffic hubs etc.). The number of locker stations is an important decision in the process, since it carries a high amount of fixed cost, for example rent or central operating unit.

In the context of parcel lockers, Deutsch and Golany (2018) developed a quantitative method to determine their optimal number, locations, and sizes for an automated parcel locker network. The firm's objective in their problem formulation is to maximize profit which is determined by total revenue minus the fixed and operational cost of the delivery network, while taking into account the loss potential of customers who are not willing to travel for the service. The authors write the problem as an Uncapacitated Facility Location Problem (Verter 2011) and apply the solution to an industrial-sized network.

Several studies showed that in the case of last-mile delivery the most important characteristics is location (Iwan, Kijewska and Lemke (2016); de Oliveira et al. (2017); Kedia, Kusumastuti and Nicholson (2017)). Lemke, Iwan and Korczak (2016) studied the assessment of parcel locker usage in Poland using data from the state postal service company and found that 15% of service users would use lockers more often if their location are improved. This finding relates to the theoretical models of location choice, where clustering with competitors and cannibalization within firm's stores are important aspects of firm's location choice. Glaeser, Fisher and Su (2019) showed that similar to the traditional retail industry, cannibalization between within firm locations exist in the context of last-mile delivery. The authors analysed data from an online retailer that uses trucks parked at specific locations on specific days to allow customers to collect their orders. Their set up is different from mine because the retailer's problem is to determine not only the place but the time of a pickup as trucks are mobile while in my case parcel locker stations are fixed. The authors found a 13–18% cannibalization effect for nearby lockers, which serves as a reference point for cannibalization in the context of last-mile delivery. Note, that Glaeser, Fisher and Su (2019) did not estimate aggregate effect in a growing network environment, which would compensate cannibalization.

3 The Hungarian Parcel Locker Delivery Market

In my thesis, I analyse the expansion of Foxpost, a leading Hungarian parcel carrier, was established in 2014 by three Hungarian entrepreneurs. The company specializes in parcel locker delivery methods, and currently owns the largest parcel locker network in Hungary, incorporating 410 lockers by the end of 2021. This results in a coverage where 70% of the Hungarian population is able to find a Foxpost parcel within a 7 minute drive (Ditróy 2021). The company operates solely with automated parcel lockers: customers receive an email about the arrival of a parcel to a previously chosen locker station, and can access their parcel by entering a unique ID to the central unit of the station. The lockers hold a parcel for up to 3 days. Apart from automated parcel locker delivery, Foxpost offers home delivery with a 2 hour delivery window and an option for second delivery or another delivery address; however, in this thesis I only analyze the market of automated parcel lockers. Foxpost offers services to individuals who want to send packages to other individuals (C2C) and businesses that operate online and require last-mile delivery solutions to distribute products (B2C).

The Hungarian postal service market has more than 80 active companies as of 2021 (EMIS 2022). The largest company on the market is Magyar Posta Zrt., the Hungarian national postal service company. Other large players are subsidiaries of major international last-mile delivery companies like GLS, DHL or DPD, while most of the smaller companies are owned by Hungarian entrepreneurs. These companies usually offer home delivery or delivery to customer pick-up points, while Foxpost's main value proposition is its automated parcel locker network. Therefore, I differentiated the market for other types of last-mile delivery, and focus solely on the market for automated parcel lockers.

The only other company that operates automated parcel lockers is Magyar Posta Zrt. Magyar Posta Zrt. offers a wide range of services including mail and parcel delivery to home addresses, automated parcel lockers or post stations. Others services include electronic check payments and government bond distribution. While Foxpost offers more than 400 automated parcel locker stations, Magyar Posta Zrt. only operates 51 in 2022 (posta.hu 2022). What differentiates the two companies in the observed period on the market for automated parcel lockers is that Foxpost doubled the number of available lockers in its network while Magyar Posta Zrt. had no expansion.

It is also important to differentiate between the B2C and C2C deliveries in the market of automated parcel lockers. By 2022, only Foxpost and Magyar Posta Zrt. offers services to C2C transactions, while the market for B2C transactions in automated parcel lockers experienced an entry of two new competitor in the Hungarian market (alza.hu (2020); Zsiborás (2021)). These companies are leading online retail companies that offer a wide range of product in their portfolio. Their automated parcel locker networks are built to serve as a last-mile delivery option exclusively to the customers of these companies. This is a unique setting, where there are huge differences in the development of these markets, hence cannibalization and aggregate effects might differ substantially in B2C and C2C transactions.

4 Data

I use data from Foxpost, a major Hungarian parcel carrier. The dataset contains all transactions experienced by Foxpost between January 2021 and February 2022. In 2021, the company started a big expansion wave in its lockers, in less than 12 months, it doubled the number of lockers available in the network. This expansion wave is important for my analysis, since I use variation in the distance of initial lockers to new lockers to measure cannibalization, therefore I differentiate in my descriptive statistics between initial and newly placed lockers.

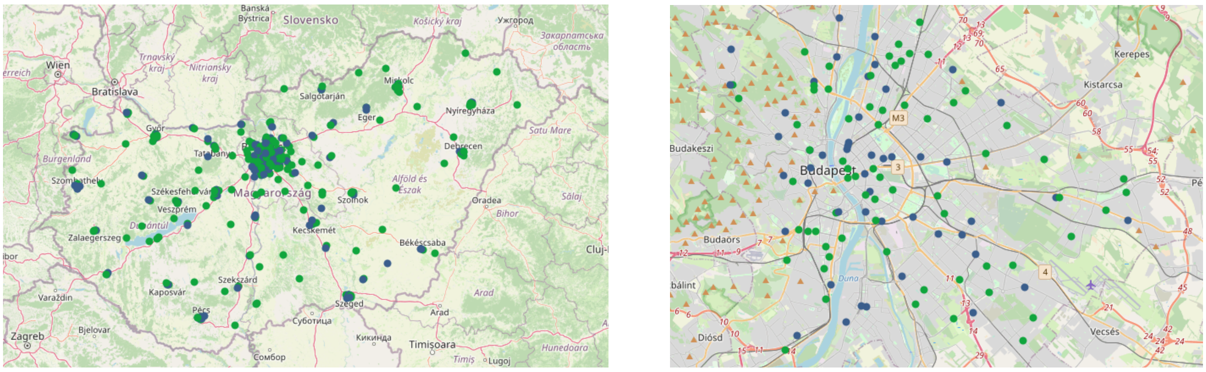
Foxpost has two types of transactions: companies can use the service to deliver products purchased by customers which are called B2C transactions; and self-employed or ordinary people can also use the service to send packages which are called C2C transactions. For B2C transactions only the destination parcel locker data is available while for C2C transactions both source and destination locker is known.

For each locker, I have information on the exact location and the size of the parcel locker. Each parcel locker has several boxes that could accept packages in several sizes. The size of a box ranges from XS to XL[1]. There is a huge inequality in the distribution of the lockers in a capital–country partition. Figure 1a contains all lockers operated in the country, while Figure 1b displays the lockers in Budapest. Blue colored points represents the initial set of lockers, those that were present before the roll-out in 2021 and green colored points represent new lockers, that were placed in 2021.

[1]Table A1 contains details on the sizes of each box.

Figure 1: Initial (blue) and new lockers (green)

(a) All lockers **(b)** Budapest



In Table 1 I present monthly aggregate statistics for parcel lockers. I aggregated the transaction level database to a panel database where the units are parcel lockers and a time period covers one month. There are 3142 observation in this aggregated database, which shows the number month-locker observations. There are 427 unique parcel lockers, 60% of these was put into operation during the observed time period (see Table 1, last row).

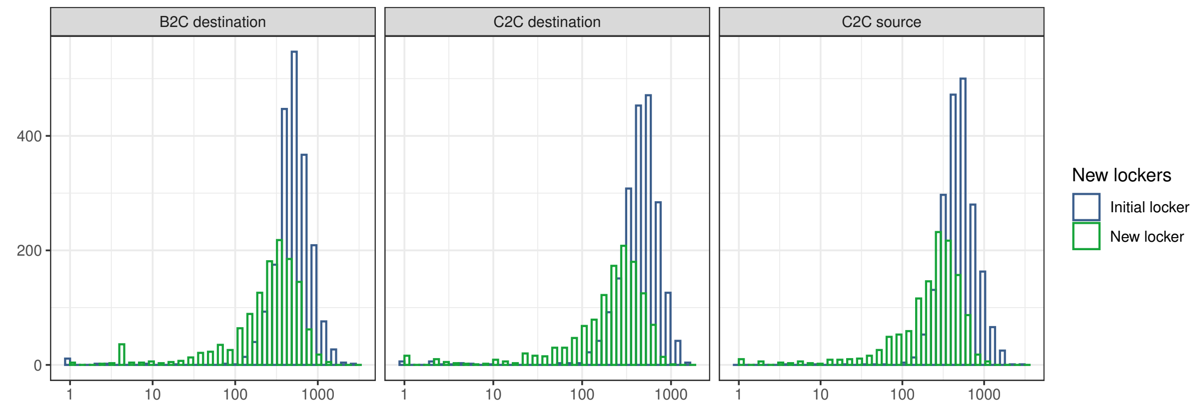
The number of users and the number of transactions is divided to three categories: B2C customer, C2C customers and C2C senders. B2C customers use parcel lockers the most often resulting on average 466 B2C transaction by an average 397 unique user for a locker every month. C2C use is a bit moderate, an average 277 users use the lockers as a customer and 214 as a sender in a transaction. However, the average number of monthly transactions coming from C2C senders (445) is higher than average transactions by C2C customers (404), which seems logical since a C2C user is likely to be a self-employed or actively practicing retail compared to an average customer.

Table 1: Descriptive statistics of monthly aggregates on the parcel lockers

	Monthly count	Mean	Std.	25%	50%	75%
Number of B2C customer	3412	397.12	257.67	226.00	374.0	524.00
Number of C2C customer	3412	276.79	178.51	147.00	259.0	384.00
Number of C2C sender	3412	213.85	140.50	120.00	196.0	285.00
B2C transactions	3412	466.59	304.90	264.00	437.5	614.00
C2C destination locker	3412	404.81	260.06	219.75	385.0	563.00
C2C source locker	3412	444.58	309.23	242.00	403.0	582.25
Locker size	3412	144.56	84.08	106.75	119.0	186.00
New locker (0-1)	427	0.62	0.49	0.00	1.0	1.00

The average locker size shows the number of packages a parcel locker could accept. The average number of sum transactions (B2C + C2C) is more than 1300 a month and the average locker size is around 200 which means that each box is used on average 7 times a month. Since the operator varies the number of boxes in parcel lockers, I did not aggregate the locker size to the level of locker, hence the number of observations. The distribution of the number of monthly transactions follows a log. normal distribution (Figure 2). In each subplot I split the observations based on whether they belonged to a locker that existed in the initial period of the database or was put into place during the year. It seems that the new lockers are far from reaching the performance of initial lockers.

Figure 2: Distribution of the number of transactions per transaction types



In order to analyse the aggregate effect of the increase of lockers in the number of transaction in the network, I aggregated the performance of the lockers to administrative districts.

Hungary has 197 administrative districts (”járás” in Hungarian), 174 in the country and 23 in the capital. The current geospatial distribution of districts was set in 2013 to create a more efficient, cost-effective and customer-oriented territorial administration (CITE). Descriptive statistics on the monthly district aggregations are displayed in Table 2. Patterns in the average number of transactions and users are the same as in the case of lockers. Statistics on the number of lockers per district is also displayed here (last row), but note that here I included each district that had a locker at any time of the observed period.

Table 2: Descriptive statistics on district aggregations

	Monthly count	Mean	Std.	25%	50%	75%
Number of B2C customer	1417	941.60	1031.93	171.0	607.0	1407.0
Number of C2C customer	1417	652.91	648.37	165.0	455.0	954.0
Number of C2C sender	1417	474.27	503.36	80.0	295.0	730.0
B2C transactions	1417	1118.94	1241.41	199.0	713.0	1653.0
C2C destination locker	1417	971.19	964.01	239.0	684.0	1426.0
C2C source locker	1417	1054.73	1137.97	162.0	647.0	1615.0
Number of lockers	1417	2.32	2.29	1.0	2.0	3.0

The distribution of monthly number of B2C transactions[2] is also log. normal (Figure 3a). I differentiated between districts based on whether they had at least one locker in the first observed period since I want to compare the ”cannibalization” effect of a new locker to aggregate effects. The distribution is log-normal with a mean around 1700 for those districts, that had a locker since the first period I observe. The distribution of log. monthly transactions for those districts that are new in the network are displayed by green. Obviously these districts are much less utilized, with mean number of transactions around 130 per month.

[2]Distribution for C2C transactions are displayed on Figure A1

Figure 3: Distribution of monthly B2C transactions **(a)** and the number of lockers **(b)** per district

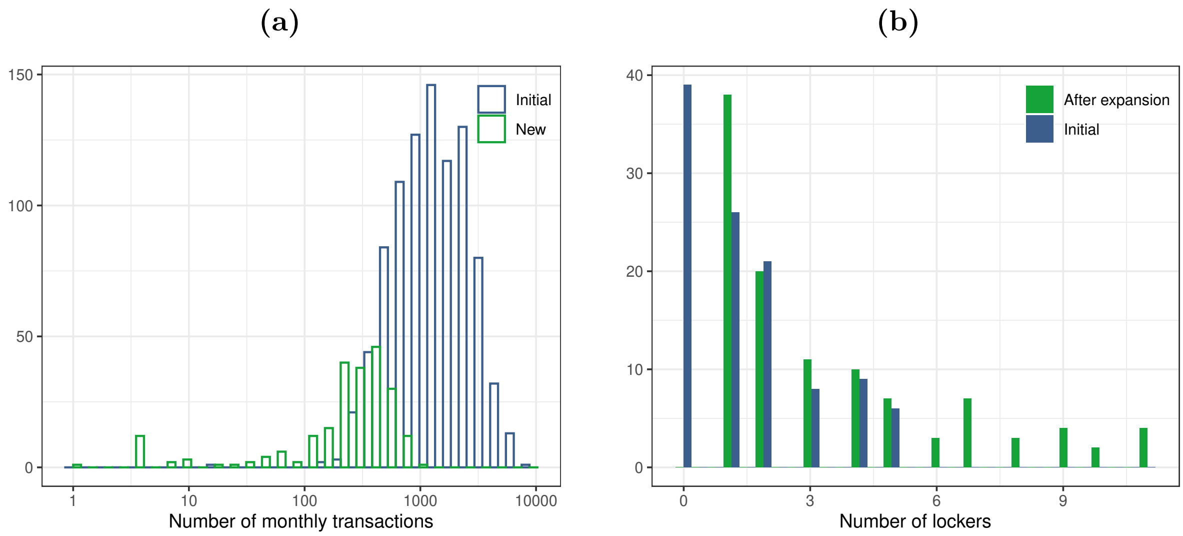


Figure 3b displays the number of lockers per district at the initial (blue) period and the last observed period (green), after the roll-out of the new lockers. There are 65 districts, that still has no lockers – not displayed here. Out of 39 districts that had no lockers before, 35 received one and 4 received two lockers. While in the initial period the maximum number of lockers per district is 5, after the roll-out its 11.

5 Empirical strategy

In this section, I explain the relevance of my quasi-experimental design and discuss the definition of treatment and control groups. Then, I write the equations that I use to estimate the local effect of a new locker placement to initial lockers, and aggregate effects of the expansion with a two-way fixed effect estimator. Finally, I discuss alternative estimators that solve problems with two-way fixed effect related to staggered treatment timing and potential treatment effect heterogeneity.

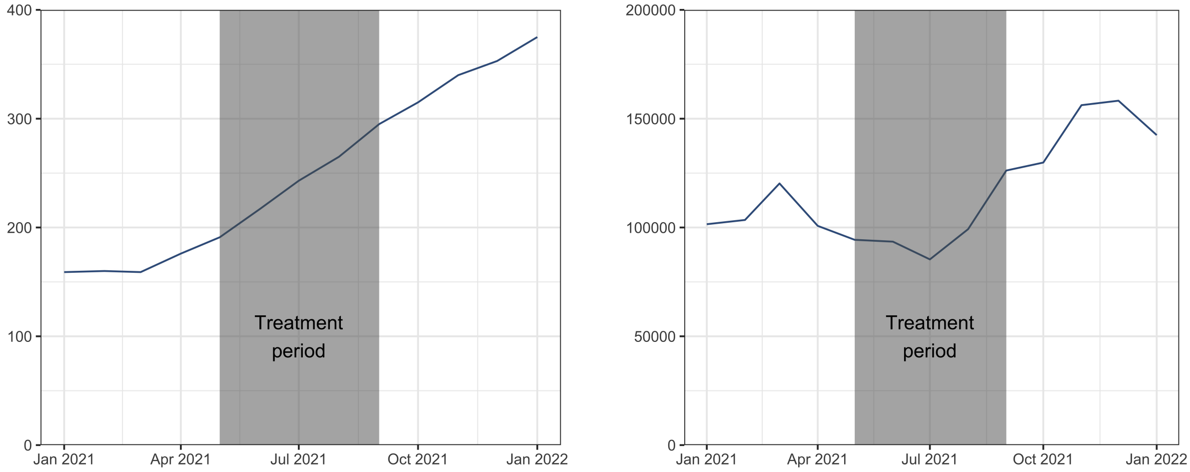
5.1 Quasi-experimental design

To estimate the effect of a new locker placement on the number of transactions and the number of users experienced to already existing lockers I exploited a quasi-experimental design. In 2021, the operator doubled the number of lockers available for customers. Before this expansion, there was only a slow progress in the roll-out of new lockers, therefore one can interpret the big expansion wave as an intervention. Figure 4 displays the increase in the number of lockers and also the amount of transactions experienced by the company. By the end of the year, the number of transactions also increased, following the increased number of lockers.

I defined my initial locker set as the lockers that experienced transactions in the first period. This sample contains 159 lockers altogether. I considered a locker treated when a new locker is placed in a 2 km distance range near to it. Once a locker got treatment, it remains treated for all later periods. The introduction of the new lockers started in March 2021 and once the process started, the progress was quite consistent (Figure 4a). I had to narrow the period from which I consider lockers to be treated, otherwise I would compare lockers that got treated in April 2021 and October 2021 which is not a good comparison because there is a strong seasonality in the utilization of the network. Therefore, I chose lockers that got treated between May 2021 and September 2021 (including) – this period is displayed in gray on Figure 4.

Figure 4: Growth in the number of available lockers and the number of transactions

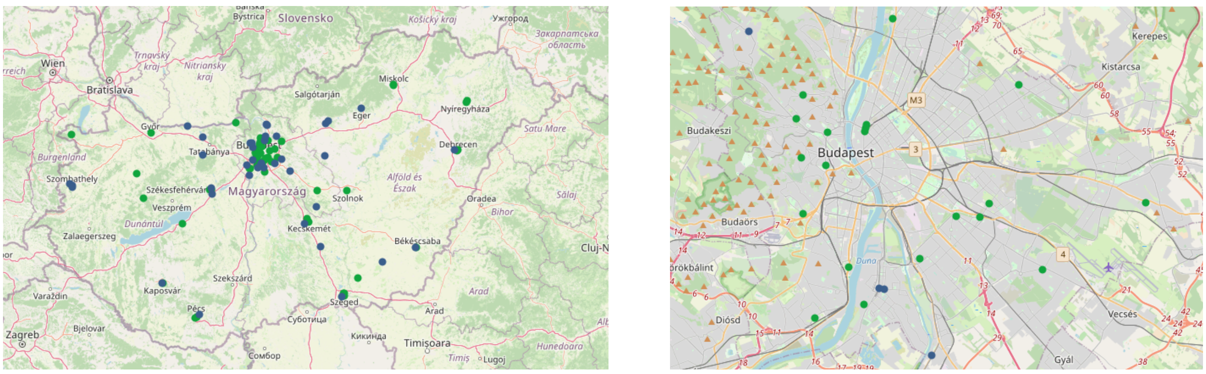
(a) Number of lockers **(b)** Number of transactions



I chose the control lockers from the untreated sample for each cutoff specification, where potential control lockers experienced no new locker near in the cutoff distance. For each treatment locker, I chose one control locker where the average number of transactions experienced in the one-month period before treatment were the closest to the treatment locker (parallel trend assumption). This allows for a potential control locker to be chosen for more than one time as a control.

Figure 5: Spatial distribution of treated (green) and control (blue) lockers

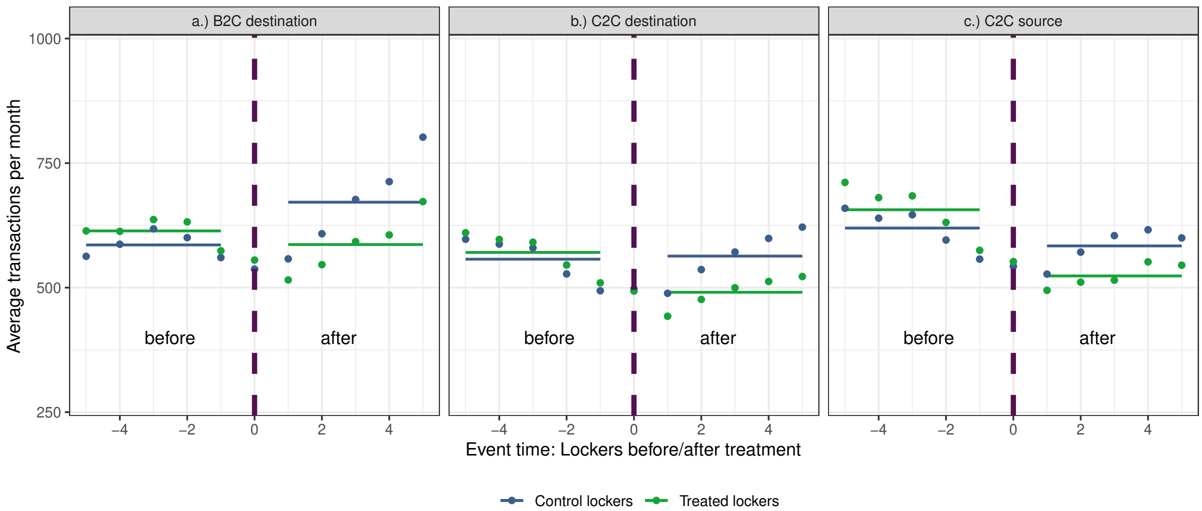
(a) All lockers **(b)** Budapest



The spatial distribution of treated and control lockers (Figure 5) seems good since both treated (green) and control (blue) lockers exist in Budapest and in the country, although in Budapest, treated lockers dominate control ones. This is what one should expect as population density is highly correlated with the number of lockers per areas.

To visualize the potential effect of the treatment, I plotted the average monthly number of transactions before and after a parcel locker received treatment (Figure 6) . Horizontal lines represent the average number of transactions in the pre- and post-treatment periods by treatment and control group. There is a parallel trend in the pre-trend period between treated and control lockers. There is a downward trend before treatment and an upward trend after the treatment. This is due to the fact that the May 2021 – September 2021 period also experienced a U shaped trend in all the transactions received by the operator (Figure 4b) which can be counted for seasonal effects. There is a visible negative effect for all three types of transactions. Note that in the pre-treatment period the control average is below the treatment average, while this is quite the opposite in the post-treatment period.

Figure 6: Average monthly transactions before and after treatment



5.2 Estimation

I use the difference-in-differences methodology which is one of the oldest and most widely used quasi-experimental design to estimate the causal effect of a treatment on an outcome. In the canonical setup there are two observed periods, one before and one after treatment.

There are two independent groups from which one receives treatment and the other does not. It is assumed that in the absence of treatment, the average outcomes for treated and comparison groups would have followed parallel paths over time. The DiD estimator compares the outcomes of the treated group before and after a treatment (difference one) in a treatment versus control group (difference two), which results in the average treatment effect in the treated group.

$$ATT = (\overline{Y}^{post}_{treated} - \overline{Y}^{pre}_{treated}) - (\overline{Y}^{post}_{control} - \overline{Y}^{pre}_{control})$$

If there are more than two periods and more than two groups that receive treatment in different periods, the same idea evolves to compare groups experiencing different evolutions of their exposure to treatment over time (de Chaisemartin and D'Haultfœuille 2020). In practice, this idea is implemented by estimating regressions that control for group and time fixed effects, which is called the two-way fixed effect estimator (TWFE). In my case, the roll-out of new lockers happened for several months starting from March 2021, hence, I estimated the following two-way fixed effect equation

$$M_{it} = \alpha_i + \delta_t + \beta_1 TREATMENT_{it} + \beta_2 log(LOCKER\_SIZE)_{it} + \epsilon_{it} \tag{1}$$

where M_{it} is either the number of transactions or the number of users experienced in locker i in month t, α_i and δ_t are locker and month fixed effects, $TREATMENT_{it}$ is a dummy variable indicating that there has been a new locker placement near locker i in month t; $LOCKER\_SIZE_{it}$ is the capacity of a locker, which varies in time for lockers as the operator changes the number of boxes for some lockers in the observed period; and ϵ_{it} is the error term. Note that once a locker has been treated, the $TREATMENT$ dummy remains 1 for later periods.

To estimate the dynamic treatment effect of a new locker placement, I estimated the following equation

$$M_{it} = \alpha_i + \delta_t + \sum_{l=-5}^{5} \mu_l \mathbf{1}\{t - E_i = l\} + \beta_2 log(LOCKER\_SIZE)_{it} + \epsilon_{it} \quad (2)$$

in which E_i is the time when locker i initially receives the binary absorbing treatment, and the coefficients μ_l are associated with indicators for being l periods relative to the treatment; α_i and δ_t are locker and month fixed effects and M_{it} is either the number of transactions or the number of users experienced in locker i in month t. Here, lockers are categorized into different cohorts based on their initial treatment timing. I estimated μ_l-s for 5 months before treatment to check for the parallel trend assumption and for 5 months after treatment to estimate the dynamic treatment effect. Since I am interested in whether the treatment generated an effect in the treatment group relative to the control, I exclude the period before treatment for each cohort.

I estimated the equations above for six different dependent variables: (1) number of B2C customers per locker; (2) the number of B2C transactions per locker i; (3) number of times locker i was used by a C2C customer and; (4) used as a destination in a C2C transaction; (5) the number of users and; (6) times as locker i was used as a source in a C2C transaction. I estimated the equations using OLS and Poisson models. For the OLS models, I took the natural logarithm of the dependent variable M_{ij}. Standard errors are clustered at the level of treatment, *locker_id*.

To investigate the aggregated effects of increasing the number of lockers in the network I estimated the following equation

$$log(M_{it}) = \gamma_i + \delta_t + \beta NLOCKERS_{it} + \epsilon_{it} \quad (3)$$

where M_{it} is the number of transactions or the number of users experienced in district i in month t, γ_i and δ_t are district and month fixed effects. $NLOCKERS_{it}$ is the number of lockers in district i in month t and ϵ_{it} is the error term. The coefficient of interest is β, which allows me to estimate the effect of increasing the number of lockers to the number of transactions from the within districts variation in the number of lockers. I estimated the equation with OLS and Poisson models. Standard errors are clustered at the level of districts.

5.3 Alternative estimators

Several recent papers raised issues about interpreting the coefficient of a TWFE regressions as causal effect in this setup (Borusyak, Jaravel and Spiess (2021); Sun and Abraham (2021); de Chaisemartin and D'Haultfœuille (2020); Goodman-Bacon (2021); Athey and Imbens (2022)). The issues can be originated from the following three cases (Roth et al. 2022): (*i*) considering potential violations of parallel trends; (*ii*) multiple periods and staggered treatment timing; and (*iii*) dynamics of treatment heterogeneity. I choose my control groups to satisfy the parallel trend assumptions, however, both staggered treatment timing and treatment heterogeneity is an issue when estimating the effect of a new parcel locker on the utilization of initial lockers and also in the case of district level aggregate effects.

Since the roll-out of new lockers was introduced in multiple periods (Figure 4a), I have to address case of the staggered treatment timing. Goodman-Bacon (2021) showed that the static parameter of a DiD model estimated with TWFE can be decomposed into average causal effects and bias terms under differential timing and an unadjusted TWFE estimation of this parameter will be biased. Therefore, even under the assumption of homogeneous treatment effect the use of alternative methods are relevant.

Treatment heterogeneity is the most important issue that persists in the case of parcel lockers. To decide which initial locker was treated and which one was not, I considered whether a new locker was placed into a certain distance to the initial locker. This required me to choose a cutoff value, however, in the treated sample, there will be different distances between the initial and the new locker, hence there is potential for heterogeneous treatment effect[3]. In case of heterogenous treatment effects, de Chaisemartin and D'Haultfœuille (2020) showed that the standard TWFE estimates weighted sums of the average treatment effects (ATE) in each group and period, with weights that may be

[3]See Figure A2 for the distance to the nearest new locker in the control and treated groups

negative. Due to the negative weights, the standard TWFE coefficient may for instance be negative while all the group ATE-s are positive. The authors proposed an alternative estimator that solves this issue and can be used with discrete or continuous treatment variable while other recent methods only work with binary treatment. Therefore, I use de Chaisemartin and D'Haultfœuille (2020) to estimate equation 3, where the variable of interest is discrete.

Callaway and Sant'Anna (2021) investigated the difference-in-differences setup under both heterogeneous treatment effects and differential timing, therefore it would be appropriate to use their method to estimate equation 1. They key idea of their paper is to identify group-time average treatment effects that are a unique ATT for a cohort of units treated at the same point in time and then develop methods to aggregate these group-time estimates. However, I want to estimate not only the aggregate but the dynamic treatment effects. Sun and Abraham (2021) showed that the TWFE estimator using leads and lags of the treatment could also be biased when there is variation in treatment timing across units and treatment heterogeneity. They showed that the coefficient on a given lead or lag can be contaminated by effects from other periods, and apparent pre-trends can arise solely from treatment effects heterogeneity. They proposed an alternative estimator that is free of contamination, which I use to estimate equation 2. Sun and Abraham (2021) also developed a method to aggregate the dynamic coefficients to one static coefficient, which I use to estimate equation 1.

6 Results

Two-way fixed effect estimation results of equation 1 are displayed in Table 3. The OLS results suggest that there is a significant 12-15% decrease both in the number of transactions and in the number of users. I estimated that placing a new locker in a 2 km distance to an existing one results in a 13.3% decrease on average, in the number of B2C transactions over the whole post treatment period compared to its mean within the cross-sectional initial locker as well as its mean across lockers in the actual month.

Robustness test with Poisson models suggests the same, which is a slightly higher decrease in the number of transactions after treatment in Table A2. The same effect is in place not only for the number of transactions but for the number of users. The two variable highly correlated, but it is still interesting to look at this to check whether a difference exists between intensive margin and extensive margin. Results from the Sun and Abraham (2021) estimator (displayed in Table 4) are very close to the TWFE results. There are only slight differences in the point estimates.

Table 3: Event study: TWFE estimated by OLS

Model:	B2C customer (1)	B2C destination (2)	C2C customer (3)	C2C destination (4)	C2C sender (5)	C2C source (6)
Variables						
treatment	-0.131***	-0.133***	-0.122***	-0.120***	-0.145***	-0.159***
	(0.032)	(0.033)	(0.029)	(0.032)	(0.025)	(0.035)
log(locker_size)	0.023	0.031	0.037	0.044	0.026	0.062
	(0.055)	(0.058)	(0.067)	(0.073)	(0.045)	(0.063)
N locker_id	160	160	160	160	160	160
N controls	30	30	30	30	30	30
N treated	57	57	57	57	57	57
Fixed-effects						
locker_id	Yes	Yes	Yes	Yes	Yes	Yes
month	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	1,204	1,204	1,204	1,204	1,203	1,203
R^2	0.880	0.875	0.862	0.847	0.889	0.850
Within R^2	0.061	0.059	0.043	0.037	0.083	0.066

Clustered (locker_id) standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, .: 0.1*

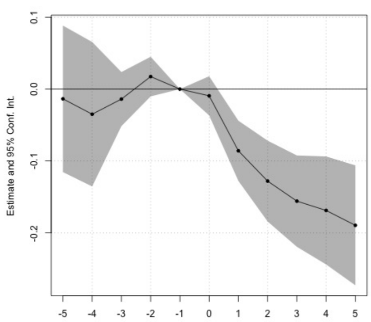
Table 4: Event study (Sun and Abraham 2021) estimated by OLS

Model:	B2C customer (1)	B2C destination (2)	C2C customer (3)	C2C destination (4)	C2C sender (5)	C2C source (6)
Variables						
ATT	-0.129***	-0.132***	-0.135***	-0.133***	-0.155***	-0.163***
	(0.026)	(0.026)	(0.024)	(0.026)	(0.024)	(0.034)
log(locker_size)	0.013	0.020	0.010	0.018	0.007	0.042
	(0.053)	(0.056)	(0.062)	(0.068)	(0.043)	(0.059)
N locker_id	160	160	160	160	160	160
N controls	30	30	30	30	30	30
N treated	57	57	57	57	57	57
Fixed-effects						
locker_id	Yes	Yes	Yes	Yes	Yes	Yes
month	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	1,204	1,204	1,204	1,204	1,203	1,203
R^2	0.888	0.883	0.874	0.858	0.898	0.861
Within R^2	0.122	0.119	0.123	0.111	0.156	0.137

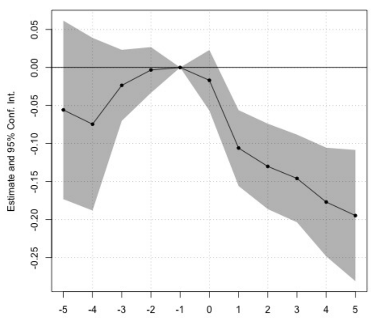
Clustered (locker_id) standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, .: 0.1*

Figure 7: Dynamic treatment effect: TWFE estimated by OLS

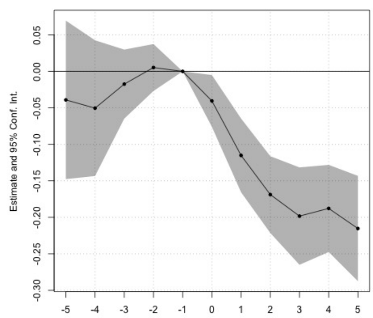
(a) B2C destinations



(b) C2C destinations



(c) C2C sources

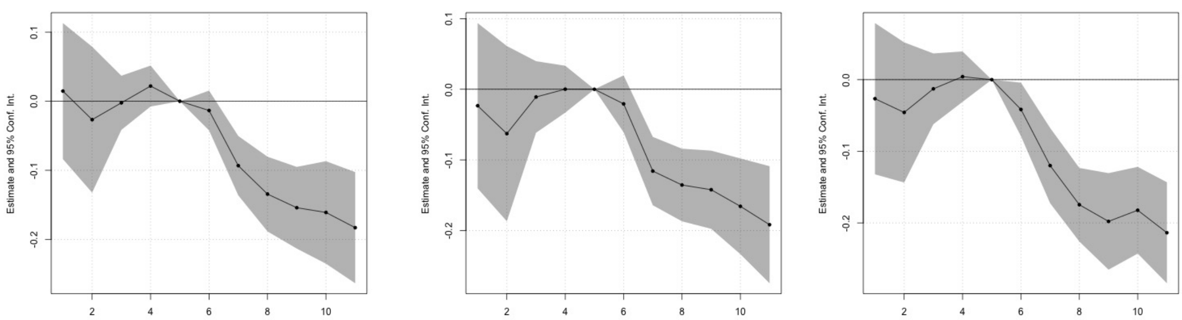


The TWFE estimates of equation 2 suggest that the negative effects persist, and increase slightly over time for B2C and C2C transactions (See Figure 7). There is no significant difference in the lag coefficient estimates in 2 to 4 months before the intervention which shows that the parallel trend assumption indeed holds. There is a sharp drop in the number of transactions right after intervention and this negative effect persists and increase over time. Note that the coefficient estimates are less precise further off the baseline.

I found no substantial differences between the TWFE estimates (Figure 7) and the estimates using Sun and Abraham (2021) (Figure 8). This results is interesting because it suggests that despite in a settings where there is a serious potential for heterogeneous treatment effect, the results are substantially the same for methods that take this heterogeneity into account. It could happen that the treatment effect is homogeneous for groups of lockers and time periods, and that the effect is not sensitive to choosing the treatment distance[4], therefore the bias described in Sun and Abraham (2021) for the TWFE estimator is small. Note that here I only display results with the number of transactions as dependent variable, but using the number of users as dependent variable leads to the same result for both TWFE and Sun and Abraham (2021).

Figure 8: Dynamic treatment effect: Sun and Abraham (2021) estimated by OLS

(a) B2C destinations **(b)** C2C destinations **(c)** C2C sources



The aggregate results from the estimates of equation 3 with OLS (displayed in Table 5) suggest that there is a positive effect of placing a locker to a district on the number of transactions experienced in that district. OLS point estimates are around 5–6% for all types of transactions, but they are significant only at a 10% level for the C2C transactions.

The results are moderate when looking at the estimates by de Chaisemartin and D'Haultfœuille (2020) in Table 6. The de Chaisemartin and D'Haultfœuille (2020) estimator works in the

[4]See Table A3 for TWFE and Sun and Abraham (2021) estimates with 1.5 km as treatment distance as a robustness check. There is no substantive difference between coefficient estimates for the different methods.

Table 5: District level aggregation TWFE estimates by OLS

Model:	B2C customer (1)	B2C destination (2)	C2C customer (3)	C2C destination (4)	C2C sender (5)	C2C source (6)
Variables						
Number of lockers	0.055*	0.057*	0.058$^{\cdot}$	0.065$^{\cdot}$	0.049$^{\cdot}$	0.055$^{\cdot}$
	(0.027)	(0.028)	(0.032)	(0.035)	(0.025)	(0.029)
N areas	109	109	109	109	109	109
Fixed-effects						
district	Yes	Yes	Yes	Yes	Yes	Yes
month	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	910	910	910	910	910	910
R^2	0.952	0.950	0.922	0.911	0.961	0.944
Within R^2	0.078	0.079	0.066	0.073	0.076	0.065

Clustered (district) standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, .: 0.1*

following way for discrete treatment variables: For each pair of consecutive time periods $t-1$ and t and for each value of the treatment d it compares the outcome evolution among the switchers, the groups whose treatment changes from d to some other value between $t-1$ and t, to the same evolution among control groups whose treatment is equal to d both in $t-1$ and t. Then the estimator averages across all pairs of consecutive time periods and across all values of the treatment. There is a significant 2.3 % increase in the B2C transactions and users, 2.2-2.6% in C2C customers and only 1.3-1.5% for C2C senders. These estimates are much smaller than the point estimates by the TWFE estimator therefore, it could be that the negative weights for the group ATE-s that account for the bias of TWFE estimators are present in this setup. It is also interesting, that the de Chaisemartin and D'Haultfœuille (2020) estimates are far more precise than the ones with the two-way fixed effect estimator. The 95% confidence interval of the de Chaisemartin and D'Haultfœuille (2020) point estimates fall entirely into the 95% confidence interval of the TWFE estimates. Poisson regression estimates of the TWFE equation (Table A4) are closer to the results by the de Chaisemartin and D'Haultfœuille (2020) estimator.

It is interesting that not only there is a positive effect on the number of transactions but on the number of users too. This shows that increasing the number of lockers not only increases the number of transactions (it could be that already existing users start to use the service more often), but it helps to attract new users, which, of course is an important objective of the operator.

Table 6: District level aggregation estimates by de Chaisemartin and D'Haultfœuille (2020)

Model:	B2C customer (1)	B2C destination (2)	C2C customer (3)	C2C destination (4)	C2C sender (5)	C2C source (6)
Variables						
Number of lockers	0.023***	0.024***	0.022***	0.026**	0.015***	0.013*
	(0.006)	(0.006)	(0.006)	(0.012)	(0.004)	(0.007)
N areas	109	109	109	109	109	109
Fixed-effects						
district	Yes	Yes	Yes	Yes	Yes	Yes
month	Yes	Yes	Yes	Yes	Yes	Yes

Clustered (district) standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, .: 0.1*

7 Conclusion

This thesis examined the importance of the location choice of parcel lockers in a last mile delivery network. I used a transaction level database from a major Hungarian parcel which doubled the number of parcel lockers available for customers between January 2021 and February 2022. I exploited a quasi-experimental, event study design to infer on the effect of new locker placements to existing lockers. I defined the treated subset of lockers that experienced a new locker placement in the 2 km distance near to them while I considered other lockers as potential control lockers and chose one control locker for each treated control to satisfy the parallel trend assumption. To estimate the aggregate effect of the growth in the number of parcel lockers, I aggregated the number of transactions and the number of users to the level of administrative districts.

I complemented the textbook two-way fixed effect estimator with recent estimators introduced by Sun and Abraham (2021) and de Chaisemartin and D'Haultfœuille (2020) that account for the staggered nature of treatment in time and treatment effect heterogeneity. Both problems should be treated carefully in this setup. The roll-out of new lockers by design introduced in multiple periods, hence the treatment timing is staggered. Also, there is a huge potential for treatment heterogeneity since treated lockers are chosen whether there is a new locker placement in a 2 km radius, however, the exact distance could also influence the size of the effect and it could happen that there are more than one new locker placements which I did not take into account.

The main limitation of this thesis is that I did not measure competition. The use of quasi-experimental design is important to estimate causal effect, however, even in this setup a potential confounding effect of competitors expansion should be considered. Since the B2C market experienced a huge expansion in parcel lockers, it could happen that there was a new locker placement within a treatment distance near to an initial locker of Foxpost by a competitor service provider in the same month as Foxpost placed a new locker. This confounding effect is not present in the C2C market, since the only competitor, Magyar Posta Zrt. did not implement changes in its locker station network. Further research could exploit the potential of using data from competitor parcel carriers to investigate clustering and cannibalization among competitor services. Also, acquiring data for a longer period would help in the interpretation and validity of the local effect's persistence and the aggregate effect's magnitude.

I found a strong cannibalizing effect of placing new lockers near existing ones, I estimated a 13% decrease in both the number of transactions and the number of customers for B2C and C2C transactions as destination and a 15-16% decrease in the number of senders for C2C transactions. Since there is no strong difference between the point estimates of the effect on the B2C and C2C markets, the potential unobserved confounding effect of competitors in the B2C market is less likely. These results are close to the ones by (Glaeser, Fisher and Su 2019), who studied retail last-mile delivery using mobile trucks as reception points. I found that despite cannibalization, there is a significant positive aggregate effect of the expansion in the network. I estimated a 2-3% increase in the number of transactions and the number of users as a result of each new locker placed in an administrative district, which suggests that network growth could help attract new users.

Previous studies found strong differences in the sign and magnitude of coefficient estimates by TWFE and estimators that account for staggered treatment timing and potential treatment effect heterogeneity. An interesting contribution of this thesis is that coefficient estimates of the two-way fixed effect model differ only slightly from estimates by Sun and Abraham (2021) when estimating local cannibalization. In case of the aggregate results, point estimates by de Chaisemartin and D'Haultfœuille (2020) are a third the size and more precise compared to the TWFE estimates.

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Appendix

Table A1: Locker size categories and corresponding volumes. Source: (Foxpost 2022)

Size category	Volume	Max. weight
	4,5 cm x 36 cm x 53 cm	
XS	8,5 cm x 19 cm x 61 cm	5 kg
	5 cm x 33 cm x 53 cm	
S	11,5 cm x 36 cm x 61 cm	15 kg
M	19,5 cm x 36 cm x 61 cm	25 kg
L	37,5 cm x 36 cm x 61 cm	25 kg
XL	60 cm x 36 cm x 61 cm	25 kg

Figure A1: Distribution of the number of C2C transactions in district aggregation

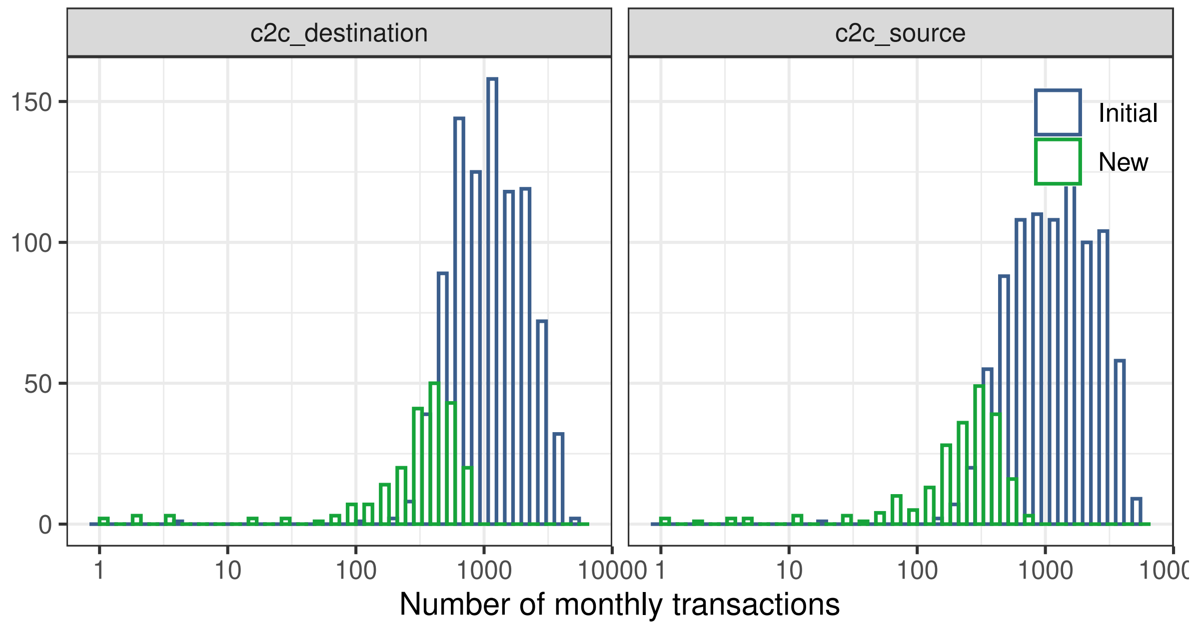
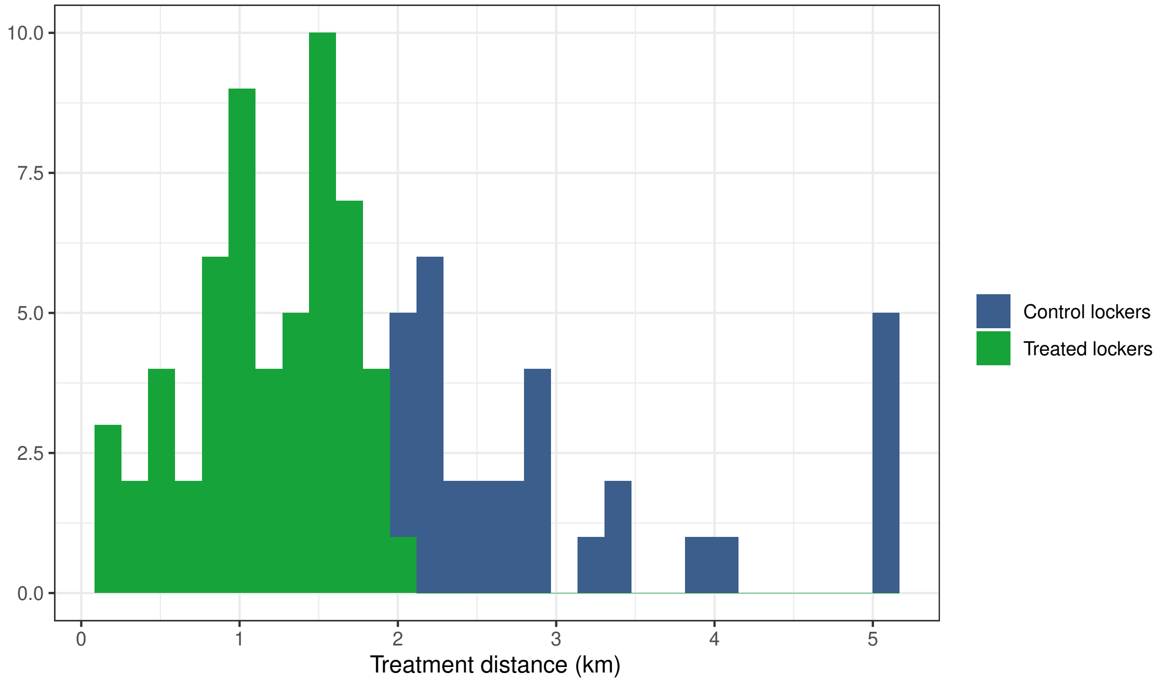


Figure A2: Initial lockers' distance to the nearest new lockers



Note: Maximum distance is capped to 5km.

Table A2: Robustness test estimated by Poisson models

(a) TWFE

Model:	B2C customer (1)	B2C destination (2)	C2C customer (3)	C2C destination (4)	C2C sender (5)	C2C source (6)
Variables						
treatment	-0.152***	-0.158***	-0.150***	-0.152***	-0.159***	-0.188***
	(0.032)	(0.033)	(0.027)	(0.030)	(0.026)	(0.039)
locker_size	0.0002	0.0002	0.0001	0.0001	0.0003$^{\cdot}$	0.0003
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
N locker_id	160	160	160	160	160	160
N controls	30	30	30	30	30	30
N treated	57	57	57	57	57	57
Fixed-effects						
locker_id	Yes	Yes	Yes	Yes	Yes	Yes
month	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	1,209	1,209	1,209	1,209	1,209	1,209
Squared Correlation	0.904	0.900	0.903	0.900	0.894	0.883
Pseudo R^2	0.809	0.820	0.785	0.813	0.731	0.789
BIC	19,669.9	22,470.2	17,318.7	22,296.0	17,122.0	30,207.9

Clustered (locker_id) standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, .: 0.1*

(b) Sun and Abraham (2021)

Model:	B2C customer (1)	B2C destination (2)	C2C customer (3)	C2C destination (4)	C2C sender (5)	C2C source (6)
Variables						
ATT	-0.132***	-0.136***	-0.140***	-0.136***	-0.150***	-0.163***
	(0.027)	(0.027)	(0.023)	(0.026)	(0.024)	(0.037)
locker_size	0.0002	0.0002	6×10^{-5}	0.0001	0.0003	0.0003
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
N locker_id	160	160	160	160	160	160
N controls	30	30	30	30	30	30
N treated	57	57	57	57	57	57
Fixed-effects						
locker_id	Yes	Yes	Yes	Yes	Yes	Yes
month	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	1,209	1,209	1,209	1,209	1,209	1,209
Squared Correlation	0.909	0.906	0.909	0.905	0.901	0.890
Pseudo R^2	0.814	0.825	0.791	0.818	0.736	0.796
BIC	19,546.0	22,216.4	17,207.3	22,003.5	17,141.8	29,617.9

Clustered (locker_id) standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, .: 0.1*

Table A3: Robustness test estimated with 1.5 km treatment distance

(a) TWFE

Model:	B2C customer (1)	B2C destination (2)	C2C customer (3)	C2C destination (4)	C2C sender (5)	C2C source (6)
Variables						
treatment	-0.124**	-0.128**	-0.104**	-0.102*	-0.129***	-0.166***
	(0.038)	(0.039)	(0.037)	(0.040)	(0.029)	(0.038)
log(locker_size)	0.019	0.026	0.032	0.040	0.030	0.070
	(0.073)	(0.077)	(0.088)	(0.096)	(0.059)	(0.079)
N locker_id	160	160	160	160	160	160
N controls	28	28	28	28	28	28
N treated	40	40	40	40	40	40
Fixed-effects						
locker_id	Yes	Yes	Yes	Yes	Yes	Yes
month	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	843	843	843	843	842	842
R^2	0.847	0.845	0.819	0.806	0.854	0.820
Within R^2	0.047	0.046	0.026	0.022	0.057	0.063

Clustered (locker_id) standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, .: 0.1*

(b) Sun and Abraham (2021)

Model:	B2C customer (1)	B2C destination (2)	C2C customer (3)	C2C destination (4)	C2C sender (5)	C2C source (6)
Variables						
ATT	-0.123***	-0.128***	-0.110***	-0.108**	-0.142***	-0.172***
	(0.034)	(0.034)	(0.032)	(0.034)	(0.028)	(0.035)
log(locker_size)	0.021	0.028	0.015	0.022	0.012	0.050
	(0.071)	(0.075)	(0.083)	(0.091)	(0.055)	(0.072)
N locker_id	160	160	160	160	160	160
N controls	28	28	28	28	28	28
N treated	40	40	40	40	40	40
Fixed-effects						
locker_id	Yes	Yes	Yes	Yes	Yes	Yes
month	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	843	843	843	843	842	842
R^2	0.857	0.855	0.832	0.819	0.864	0.835
Within R^2	0.108	0.107	0.098	0.083	0.121	0.138

Clustered (locker_id) standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, .: 0.1*

Table A4: District level aggregation estimates by Poisson

Model:	B2C customer (1)	B2C destination (2)	C2C customer (3)	C2C destination (4)	C2C sender (5)	C2C source (6)
Variables						
Number of lockers	0.031***	0.032***	0.025**	0.029**	0.027**	0.028*
	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.011)
N areas	109	109	109	109	109	109
Fixed-effects						
district	Yes	Yes	Yes	Yes	Yes	Yes
month	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	910	910	910	910	910	910
Squared Correlation	0.983	0.982	0.983	0.981	0.981	0.975
Pseudo R^2	0.967	0.969	0.955	0.959	0.954	0.961
BIC	20,299.9	23,416.3	15,773.5	20,879.9	13,858.4	26,424.4

Clustered (district) standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, .: 0.1*