How Markets Clear Without Prices? Service Time in Online Grocery*

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July 30, 2021

Abstract

We study how online grocers respond to local competition and demand conditions when prices are uniformly set at the national level. Based on data collected twice a week from 180 Israeli localities over 3.5 years, we show that online grocers set identical prices in all markets where they operate. In contrast, service time is shorter in more competitive markets, on low-demand/low-cost weekdays and for deliveries offered by high-priced grocers. Next, we exploit regional and temporal variation in entry decisions to examine incumbents' response to entry. We find that incumbents facing entry reduce service only on low-demand weekdays. The reduction in service time begins before entry, is greater in monopolistic markets and when entrants pose a larger threat. Service time falls also in markets that did not experience entry, yet served by a fulfillment center serving markets facing entry. Our findings underscore the importance of supply-side considerations when analyzing firms' response to changes in demand and competition, particularly when prices are unresponsive.

JEL: D83; L81; L66

Keywords: Supermarkets; service time; newsvendor problem; uniform pricing; entry

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1 Introduction

Standard economic models show that prices balance demand and supply, ensure efficient resource allocation and facilitate market clearing. Prices are also at the core of monetary policy, marketing strategy and competition analysis, and have implications for income inequality and market dynamics. Yet, growing evidence shows that multi-store firms tend to set similar prices in very different environments (e.g., Cavallo et al. (2014), Adams and Williams (2019), Hitsch et al. (2019), DellaVigna and Gentzkow (2019)). Recent studies also find that multi-store firms do not change prices when local demand and competition conditions drastically change (Arcidiacono et al. (2020), Gagnon and López-Salido (2020), Goldin et al. (Forthcoming)). These findings motivate our research questions: How firms strategically respond to changes in demand and competition without using prices? How operational capabilities affect these strategic choices by firms?

We address these questions by investigating how firms use service time to cope with changes in local demand and competition conditions. Service time has long been recognized valuable for consumers and firms, and its prominence grew further with the rise of e-commerce and respective changes in customers' time preferences. The online grocery market is particularly suited to study the link between service time, demand and competition. First, consumers in this market observe service time before they buy, and service time affects their decision where to buy.[1] Second, demand for online grocery service is characterized by peak (pre-weekend) and off-peak (beginning of the week) demand periods. This within-week demand seasonality provides a unique opportunity to examine how online grocers adjust service time in a given market, facing the same rivals, yet in different demand conditions. Third, online grocery markets have been growing rapidly in recent years and online retailers have been expanding into new local markets.[2] Our analysis exploits variation in retailers' entry decisions to offer a causal interpretation of the impact of competition on service time offered by the incumbent. Fourth, investments to improve service times are often made at the local level. Accordingly, variation in service time can be attributed to decisions at the local level. Finally, as we later show, Israeli online grocers set identical prices in markets characterized with very different competition conditions.[3] This price uniformity is important given the research questions we address.

Our findings suggest that firms strategically use service time in response to changes in demand

[1]Survey evidence shows that nearly half of online grocery shoppers consider speed an important factor. Two-thirds of respondents would consider switching vendor if delivery time offered by their normal retailer is not within a two-day window. See, www.statista.com/statistics/630351/factors-when-buying-food-online-in-the-united-kingdom-uk/, and getfabric.com/2019-grocery-report/. We use data from a shopping platform to show that online consumers are more likely to switch to rival grocer on long service time days.

[2]For instance, the online grocery market in the U.S. more than doubled between 2016 and 2018 (www.businessinsider.com/online-grocery-report.). In the UK, the online grocery channel is the fastest growing purchase channel (www.statista.com/topics/3144/online-grocery-shopping-in-the-united-kingdom/). This trend is likely to further increase due to COVID-19.

[3]Cavallo (2017) using data from 10 countries also shows that online retailers set similar prices across locations.

and competition. Our estimates suggest that incumbents online grocers improve service time by up to 20% when facing entry by a rival online grocer. This improvement occurs shortly before entry take place, suggesting that strategic or competitive considerations are driving it. At the same time, we also show that the magnitude of the incumbent's response to entry significantly falls when the costs of providing timely service are high. In particular, on high-demand/high utilization days we do not find evidence that incumbents facing entry improve service time. Thus, both competitive and operational considerations determine how retailers use service time to address changing competition and demand conditions.

To motivate our empirical analysis, in section 2 we build on the canonical newsvendor problem model (Arrow et al. (1951)) to derive testable predictions. In this model, a retailer chooses her capacity before knowing the actual demand level. The capacity choice highlights a classic trade off between the cost of setting too high capacity if demand turns out to be low, and the opportunity cost incurred when realized demand is low relative to the chosen capacity. The opportunity cost can be decomposed into the sum of a retailer's lost margin from a missed order today and the losses incurred if these customers continue to buy at rivals also in the future. We modify this trade off to our setting – assuming a larger capacity translates into shorter service time – and derive the following testable predictions. First, as capacity costs increase online grocers offer longer service time. Second, online grocers who set higher prices offer shorter service time. Third, online grocers set shorter service time in more competitive environments. Finally, the effect of competition on service time is expected to be greater when capacity costs are low, in concentrated markets and when entrants pose a larger threat to incumbents.

We test these predictions using rich data which we describe in section 3. Our main data include service time data collected by a web crawler between August 2016 and December 2019 from 180 distinct markets/addresses across Israel. For each market/address, the crawler records the available service time, measured as the elapsed time between order time and promised delivery time, offered by the five online grocers that were active in Israel throughout. The number of retailers that offers service to each address is our measure of competition in a given market. The crawler was active twice a week, at midnight on Wednesday and on Saturday, which represent high (pre-weekend) and low (weekend) demand conditions, respectively. Panel A of Figure 1 displays the relationship between service time and competition. The figure shows the average service time offered by each of the five retailers across markets characterized by different competition levels. The figure shows a clear pattern of a downward sloping service time curve for each of the retailers. The larger the number of rivals in a market the shorter the service time offered. We supplement the crawler data with two additional data sources. First, we collect detailed bi-weekly comprehensive price data for all online retailers active in the 180 local markets. We use the price data to show that online grocers set identical prices across markets, and that prices on high demand weekdays are not higher than on low-demand weekdays. Panel B of Figure 1 presents the price of a basket of the same 52 popular products sold by the five online grocers. As can be seen, the online grocers set identical prices in all markets that they serve, irrespective of the number of rivals they face. Second, we use longitudinal customer-level data from an online grocery platform that enables customers to shop and switch across online retailers. We use the online platform data to illustrate that demand for online grocery is three times larger on Wednesdays than on Saturdays, to present substitution patterns across online retailers, and to show that customers are more likely to switch to rival grocers on days when service time is long.

Short service time is potentially driven by factors other than local competition. In particular, more online grocers offer service in dense urban areas, where they can potentially exploit economic of density and achieve shorter service time. Thus, we may erroneously attribute shorter service time to competition, where in fact other reasons drive this relationship. To address this concern, in section 4 we take advantage of the panel structure of our data to estimate the effect of entry on the incumbent's service time. The regression analysis exploits the expansion of online retailers into new local markets. The changes in market structure during the time period that we study are substantial. For instance, in the first month in our sample (August 2016), 79 local markets out of the 180 markets that we track were served by one online retailer. In December 2019, the last month in our sample, only 47 markets were local monopolies. Moreover, since we record service time on both high and low demand weekdays, we can examine how the incumbent's service time changed before and after a rival enters the same market but in very different demand conditions.

Our estimation results show a significant drop in service time on low-demand weekdays. This drop begins shortly before entry takes place and is considerably greater in pre-entry monopolistic markets. It is also greater when we focus on entry by aggressive rivals - those who pose a larger competitive threat to the incumbent. Our estimates suggest that in monopolistic markets and on low-demand days service times fell by about 15 percent in the two months before entry, and continued at this level after entry. That service time falls before entry suggests that incumbents try to accommodate entry by improving consumers' goodwill. Importantly, on high-demand weekdays we do not observe a change in service time. Our next analysis sheds light on the link between competition and the production technology of service time. In particular, we examine the relationship between service time improvements in a local market that faces entry and service time in adjacent markets which do not experience entry, though served by the same fulfillment center as the market that experiences entry. Our findings suggest that entry in one market triggers improvements in service time also in adjacent markets. This improvement in service time also materializes before actual entry in the adjacent market takes place and only on low-demand weekdays. Finally, the effect is greater when we focus on entry by the more aggressive entrants, and is smaller in magnitude compared to the main effect.[4]

This paper contributes to several strands of the literature. First, to our knowledge, this is the first study that empirically examines the link between service time, demand and competition. Our findings show that firms strategically use service time to respond to demand and competition conditions in a given market. We also show that cost considerations or utilization of capacity are critical when evaluating how firms use service time. The scarcity of empirical research on service time is probably due to lack of data at the market level. In the absence of service time, existing studies sometime use the distance between sellers and buyers in ebay (Einav et al. (2014), Hortaçsu et al. (2009) and Amazon (Houde et al. (2017, 2021)) as a proxy for transaction cost and service time. In contrast to the dearth of empirical evidence, there exists a large theoretical literature in economics and operations examining how service times, capacity concerns and competition interact (e.g., Luski (1976), De Vany and Saving (1977, 1983), Allon and Federgruen (2007, 2008, 2009), Kalai et al. (1992), and Cachon and Harker (2002)). Second, our paper adds to the literature on price-settings and particularly to the recent debate regarding the prevalence and implications of uniform pricing (e.g., DellaVigna and Gentzkow (2019), Hitsch et al. (2019), Cavallo et al. (2014), Adams and Williams (2019), Ater and Rigbi (2020)).[5] Butters et al. (2020) show that national chains respond to local excise taxes and may deviate from uniform pricing when these taxes exist. More generally, their findings imply that solving the puzzle of uniform prices requires understanding how national firms respond to local changes in demand and competition. Our study addresses this gap by showing how national firms that set identical prices across markets, use service time to cope with changes in demand and competition. More broadly, our findings highlight the importance of using non-price attributes and particularly service times in competition analysis. With the rapid growth of e-commerce and online markets, the importance of service time rises, requiring both researchers and competition agencies to take service times into account more seriously. Also related to competition analysis is our finding that capacity constraints play an important role and determine firms' response to entry. Finally, our findings add to the literature on productivity and competition (e.g., Syverson (2004), Syverson (2011)), showing that competition has a significant positive impact on productivity, as measured by service time, though this effect depends on underlying market and cost conditions.

Several empirical papers examine the impact of competition on broadly-defined quality mea-

[4]A potential concern with interpreting our findings is the timing of entry decisions are not random. In section 4.5 we address such concerns and show entry decisions are driven by regional operational considerations and long-term market demographics. We also provide evidence that the entry or exit decisions by physical stores are unlikely driving our results.

[5]Various explanations were proposed for uniform pricing. DellaVigna and Gentzkow (2019) suggest that firms set uniform pricing due to large managerial costs; Hitsch, Hortaçsu, and Lin (2019) claim that lack of data hinders optimal pricing decisions, and Ater and Rigbi (2020) focus on the role of fairness in driving price uniformity.

sures. Olivares and Cachon (2009) examine the relationship between the number of car dealers in the local market and inventory, Berry and Waldfogel (2010) explore the relationship between restaurant quality and market size, and Mazzeo (2003) the relationship between an airline's on-time performance and on-route competition. More recent studies use panel data techniques to examine how incumbents adjust quality in response to entry threats or actual entry. Prince and Simon (2014) show that airlines facing entry or a threat of entry by Southwest Airlines degrade their quality service measured by on-time performance. Orhun et al. (2015) how incumbents respond to entry in the US movie-exhibition industry. They find that an incumbent facing entry does not improve its quality, as measured by popular and recent movies. Probably closest to our study is Matsa (2011) who shows that incumbent supermarkets reduce their stock-out rate after Walmart enters. Like us, Matsa uses the newsvendor model to motivate his work, though he does not observe prices and cannot examine how incumbents respond to entry in different demand conditions. A common feature of previous studies is that they rely on quality measures that are observed ex-post purchase (i.e., a flight's on-time-performance) or only upon arriving at the store (i.e., product availability). Thus, these studies implicitly assume that consumers can compare quality attributes across retailers, and determine where to buy. In contrast, service time is observed at the time of purchase and can be compared across different online retailers.

Finally, few empirical papers examine how waiting times affect purchase decisions. Allon et al. (2011) studies the impact of waiting times in the fast food industry, and Lu et al. (2013) and Png and Reitman (1994) examine how a length of a queue and waiting times affect purchasing decisions in retail stores and gasoline stations, respectively. Other studies use a single firm data to examine how consumer's behavior changes when shopping food online, and how the online grocery channel affects traditional food stores (Pozzi (2012, 2013), Chintagunta et al. (2012), Gil et al. (2020)).

2 Theoretical Framework for Service Time in Online Grocery

In this section we use the newsvendor problem to motivate our empirical analysis and derive testable predictions that we later test in the data. Online grocers face uncertain demand for their services and before demand is realized they make capacity decisions that affect the service time they offer to customers. Capacity-related decisions involve both capital and labor inputs. For instance, online grocers rely on specialized trucks for food delivery, as regulations require food delivery to be conducted under strict temperature standards. They also need to recruit and train workers to collect orders and drivers to distribute these orders. Retailers set the schedule for these workers given expected and realized demand. Notably, many of these decisions are determined at the regional and at the local store level.

The newsvendor problem offers a useful setting to examine a firm optimal capacity choice when facing uncertain demand for its service. If realized demand is above the chosen capacity, the retailer forgoes the opportunity cost of lost sales, incurring what is often referred to as overage costs. Overage costs include both the direct one-time lost margin from customers who do dot purchase, and indirectly also the goodwill costs borne when customers are unable to complete their order. Below, we assume that goodwill costs increase with the number of alternatives that customers face, implying that when a customer buys at a rival once he may choose to continue buying from that rival also later. However, if realized demand is below the chosen capacity level, the retailer is not utilizing its resources and is incurring underage costs. Thus, a retailer that chooses the optimal capacity faces a trade off between overage and underage costs. Below, we assume that the capacity level chosen by a firm also determines the service time offered to customers. We use the newsvendor problem to show how this trade off varies with the price that retailers set, the level of competition and the marginal cost of capacity.

A retailer chooses capacity, K, to serve online grocery orders. This capacity level reflects the maximum number of orders that can be handled in a time period, and is a function of inputs such as the number of delivery trucks and manpower. Let c be the marginal cost associated with installing additional capacity. This marginal costs could be increasing if adding capacity is costly, for instance when the utilization of trucks is high, or decreasing due to potential economies of scale. Demand for service is uncertain, distributed with continuous cdf $F(\cdot)$, where R is a fixed margin earned for each order. Let γ represents the goodwill cost when the retailer cannot offer service to a customer. This goodwill cost increases in the number of alternatives a customer faces. Thus, a retailer decides its optimal capacity, K, in order to maximize its expected profits:

$$Max_K \int_0^K (Rx - cK)dF(x) + \int_K^\infty (RK - \gamma(x-K) - cK)dF(x)$$

The solution to this maximization problem gives a standard characterization of optimal capacity and the inherent trade off between lost opportunity sales and cost of of unused resources:

$$F(K^*) = 1 - \frac{c}{R+\gamma} \tag{1}$$

This trade off underscores the importance of three factors: 1) marginal cost of capacity (c); 2) price (R), and 3) goodwill cost (γ). To apply this trade off in our context, we assume that service time, denoted by s, is negatively related to capacity: increased capacity translates into shorter service time ($\frac{\partial s}{\partial K} \leq 0$).[6] Accordingly, changes in c, R and γ affect service time. First, when marginal capacity costs are high retailers prefer to risk losing unserved customers resulting in low

[6] Positive service time (i.e., orders are not served immediately) is reasonable given that orders are made in different hours, and retailers deliver orders in trucks that contain several orders to the same locality.

capacity and long optimal service time ($\frac{\partial s}{\partial c} > 0$). Second, when prices ($R$) are high, retailers are concerned about not being able to serve customers, and will therefore invest in capacity and offer short service time ($\frac{\partial s}{\partial R} < 0$). Third, when goodwill costs (γ), measured by the number of rivals are high, retailers are concerned about not serving customers, and therefore increase capacity and reduce service time ($\frac{\partial s}{\partial \gamma} < 0$). In Section 3.3 we present evidence consistent with these predictions. To offer a causal interpretation for our findings, below we also derive testable implications that arise from entry.

2.1 The effects of entry on service time

Following entry, an incumbent firm faces a higher risk that customers would switch to the entrant. The optimal capacity trade off captures this impact of entry by a higher value of γ, implying that incumbents offer shorter service time when facing entry ($\frac{\partial s}{\partial \gamma} < 0$). We term this effect the *strategic effect* of entry. As we explain below, the effect of entry on service time might vary with pre-entry competition conditions, capacity cost and the identity of the entrant.

Pre-entry competition level. As more online retailers operate in the market, the marginal effect of an additional entrant on service time offered by the incumbent diminishes. Formally, this prediction is captured by $\frac{\partial^2 s}{\partial \gamma \partial \gamma} > 0$. This prediction is a standard prediction in entry models which focus on prices and empirical evidence (e.g., Bresnahan and Reiss (1991)) supports it. Thus, we expect that service time will be more responsive to entry in concentrated markets than in competitive markets.

Capacity cost. Changes in service time following entry might depend on the incumbent's capacity cost. If marginal capacity costs are high, the incumbent will find it more costly to improve service time when a rival enters. Formally, this is captured by $\frac{\partial^2 s}{\partial \gamma \partial c} > 0$. In the empirical analysis, we assume that the incumbent uses the same capacity in both high and low demand weekdays. Accordingly, on low-demand weekdays it has slack resources and low marginal capacity costs compared to high-demand weekdays when utilization and marginal costs are high.

Entrant type. Changes in service time following entry might depend on the identity of the entrant. If an entrant poses a larger competitive threat for the incumbent, the incumbent's response is more likely to respond. We consider entrants that are more likely to stir incumbent's customers as more aggressive. For instance, when an entrant offers low prices, the incumbent is more concerned about customers switching, making the sensitivity of service time to γ greater. In the empirical analysis, we also use customer level data to determine substitution patterns between customers of the incumbent and entrants to classify entrants as aggressive. We use this distinction to show that the incumbent reduces service time more when more aggressive rivals enter.

Pre and post effect of entry. A second, more nuanced, effect of entry on service time is through its indirect impact on capacity costs. Following entry, the number of orders received by the incumbent falls as at least some customers switch. As a result, the incumbent's marginal cost of capacity, c, might change. The direction of this change depends on the shape of service cost function. If delivery costs are convex, then the fall in the number of orders should result in lower c which in turn lead to faster service time. We refer to this effect as a positive demand effect. If, however, delivery costs are concave, due to economies of scale and density in delivery (e.g., Cachon and Harker (2002)) then the fall in the number of orders could translate into higher c and longer service time by the incumbent. We refer to this latter effect as a negative demand effect. Both the strategic and positive demand effects imply that following entry service time falls. To empirically separate these effects, and identify whether strategic considerations are important we look how service time changes before a new rival enters. Importantly, pre-entry changes in service time cannot be explained by demand changed and hence are driven by strategic considerations. In contrast, post-entry changes in service time could be driven by both demand and strategic effects Thus, an improvement in service time before entry is likely driven by retailers' trying to improve customers' goodwill, presumably to reduce the likelihood of future switching to the entrant.

3 Industry Background, Data and Descriptive Statistics

3.1 The online grocery market in Israel

Online grocery sales in Israel have been growing rapidly in recent years, already before the pandemic. Our analysis focuses on the five traditional supermarket chains that offered online grocery service between 2016 and 2019: Shufersal, Mega, Rami Levy, Victory and Yinot Bitan. The joint market shares of these supermarket chains in the traditional retail food market was 68% in 2014.[7]

Shufersal is the dominant player both in traditional stores and the online segment, operating 283 stores at the beginning of 2016. Industry insiders estimate that the market share of Shufersal is about 70% of the online grocery market.[8] According to its annual financial report, 13.6% of Shufersal's annual sales come from the online channel, up from 4.2% in 2014 and 11.5% in 2017. Already before COVID-19, Shufersal expected that its online channel will capture 20%-25% of its sales in the upcoming years. Shufersal's home deliveries are being distributed from 34 large stores across Israel, where several nearby localities are served by each distribution center. Mega, the second largest chain, suffered substantial losses and entered bankruptcy procedures in early 2016. Consequently, Mega divested many of its stores, falling from 172 stores in January 2015 to 125 stores in the following year, and 99 stores in mid 2019. The three other chains increased

[7] The description of the market relies on chains' financial reports, government agencies and media coverage. Financial reports for publicly traded firms can be found at: https://maya.tase.co.il/en/reports/finance.

[8] See https://www.ynet.co.il/articles/0,7340,L-4907570,00.html.

the number of stores over the time period. Yeinot Bitan, the third largest chain, increased the number of physical stores it operated, going from 72 in Jan 2016 to 88 in Mid 2019 accordingly. In July 2016, the competition authority also cleared the merger between Yeinot Bitan and Mega. Yet, the operations of the two chains, and particularly their online service was kept separate. The two remaining chains, Rami Levy and Victory also witnessed a rapid growth and increased the number of stores they operate. Rami Levy, the second largest chain in terms of overall turnover, is well known for its low price strategy. Rami Levy operated 27 stores in January 2015 and 52 stores in June 2019. Finally, Victory, the fifth largest chain in terms of overall volume has also increased significantly its number of stores, growing from 29 stores to 51 stores. In 2019, 7.2% and 4% of Rami Levy and Victory sales are from the online channel. The respective figures for the non-publicly traded chains, Mega and Yeinot Bitan, are not available but are estimated to be lower than the online sales by the publicly-traded chains.

Each of the five online retailers operates a dedicated website for its online grocery service (e.g., Shufersal.co.il, www.rami-levy.co.il). The supermarket chains rely on their own distribution apparatus to deliver food, though sometimes use external contractors to run the deliveries. Online service also requires the recruitment of manpower (pickers, drivers) and designated delivery trucks. Prices in the online channel are set at the chain-national level and are identical across markets. Delivery fees are also set nationally and are about NIS 30 (about $9), and sometimes cheaper for orders that are above a certain price threshold.

3.2 Data

3.2.1 Crawler data

Our main source is a web crawler that accessed twice a week the websites of each of the five supermarket chains that offer online grocery service. Between August 2016 and December 2019, the crawler recorded service times for each of the chains in 180 different home addresses throughout Israel. Each address corresponds to a different locality and since retailers either offer online service to all addresses in a given locality or not at all, we consider each address as a separate market.[9]

The crawler records information on whether a retailer offers online service to each address. The total number of retailers that offers service to each address is our measure of local competition. To avoid over-identifying instances of entry and exit which are driven by the malfunctioning of the crawler on specific dates, we aggregate the data recorded by the crawler to the monthly level. The crawler records the 6 earliest available home-service time slots offered by each chain for each address. In the empirical analysis, we focus on the time difference between the crawling time which corresponds to the order time and the first available service time. The crawler was active

[9] Tel Aviv is an exception and there we use addresses from the three distinct regions of the city.

twice a week on midnight of Wednesday and Saturday. We chose Wednesday and Saturday as they represent high (pre-weekend) and low (weekend) demand conditions, respectively. Below we show that this is indeed the case.

3.2.2 Online grocery platform data

The second data source that we use is proprietary data from MySupermarket.co.il, an online platform that enables users to shop at each of the 5 online retailers. In particular, users of MySupermarket can compare prices and contemporaneously observe available service times offered by each retailer. Figure A1 and Figure A2 in the online appendix show examples of screens observed by users of mysupermarket free-of-charge service. To complete the purchase, MySupermarket users transfer the list of items that they want to purchase to the website of the particular retailer and complete the transaction there. We use data on all orders performed through MySpermarket during the relevant 3.5 years. The individual customer/order data from MySupermarket cover several hundred thousand orders by nearly 90,000 customers. About 95 percent of these customers live in localities that we track.[10] For each order, we have information on the date and time of the order; the identity of the retailer, the total amount paid, the customer id and the city where the customer lives. The average basket contains 64 items and its price is NIS 550 ($150). Unfortunately, these data do not include information on service time, and due to confidentiality concerns we cannot reveal the exact number of total monthly orders through MySupermarket.

We use MySupermarket data in three ways. First, we show that the number of online grocery orders changes significantly over weekdays. In particular, the number of orders on Wednesdays is about three time larger than on Saturdays. These weekdays correspond to the days in which the crawler records service time. We also show that customers are more likely to switch, i.e. order not from their regular vendor, on days in which demand is high. Third, we use these data document customers' switching patterns across retailers, characterizing entrants as more vs. less aggressive.

3.2.3 Price data

We use detailed data on the prices of 52 popular items sold by each of the online retailers. We use these prices to calculate the average weekly price of this basket at each of the 5 online grocers. The product-store-day price data is available from Pricez.co.il, a price comparison platform. The price data is available following the price transparency regulation that made prices of all products sold by Israeli supermarket chains in both online and traditional stores available online (Ater and Rigbi (2020)). We use the price data in three ways. First, we show that online grocers set identical

[10] Users of mysupermarket.co.il are likely not representative of all online consumers. They are likely less loyal to a particular chain and live in localities where more than one online retailer offers service. Nevertheless, we think that these individuals are particularly helpful for our study because chains are concerned that these individuals will switch once a new rival enters the market.

prices across markets. Second, we show grocers that set high prices tend to offer short service time. Third, we show that online grocers do not raise prices on high-demand weekdays or lower prices on low demand weekdays.

3.2.4 Store and demographic data

We also obtain demographic information on the 180 markets in our sample. This information from the Israeli Central Bureau of Statistics (CBS) includes population size, income per capita, vehicle per capita, socioeconomic index and periphery index for each market for the years 2016, 2017 and 2018.[11] We also obtain data on the location of physical stores operated by the five chains from chains' websites and retailers' annual reports. We use these data to verify that our results are not sensitive to changes in number of open nearby physical stores.

3.3 Descriptive statistics

Our baseline sample is a balance sample of 180 local markets. For each market we construct the monthly average service time for potential orders made on Wednesday and on Saturday between August 2016 and December 2019. Below we present descriptive statistics that support the predictions implied by the service time trade off discussed in section 2. In the next section, we focus on entry decisions and use regression analysis to mitigate concerns about the causal interpretation of the evidence presented below.

3.3.1 Service time, competition and prices

Figure 1 presents separately for each retailer the relationship between competition and service times (panel A) and competition and prices (panel B). Panel A shows a clear pattern of a downward sloping curve of service time, where service time is considerably shorter in markets served by more online retailers. This negative relationship holds for each retailer separately. For instance, Shufersal's mean service time in markets where it is the only online grocer is 44 hours. In markets where Shufersal competes with four online retailers, its mean service time is only 22 hours. Panel B of Figure 1 focuses on the relationship between prices in the online grocery channel and the number of online grocers. The weekly mean price is calculated based on a basket of 52 similar popular items sold by each of the five online retailers. We calculate the basket price in each week for each retailer in all markets served by that retailer. As seen in the figure, each retailer sets identical prices in all the markets it serves, irrespective of the number of competing online retailers. Moreover, different grocers choose different price levels, and we observe a strong negative relationship between service

[11] The Socioeconomic index for each locality is based on demographic and economic variables, such as dependency ratio, average years of schooling employment and income levels. Lower values correspond to lower socio-economic status. The periphery index is based on the distance between each locality and population concentrations and particularly Tel Aviv. The index range from 1 to 10 while 1 is the most peripheral and 10 is the less peripheral.

times and prices. More pricey retailers offer shorter service time. For instance, the chain that sets the lowest prices, Rami Levy, offers the longest service time. In contrast, Shufersal offers short service times and also sets high prices.

Overall, the patterns shown in panels A and B in Figure 1 regarding the relationship between competition and service time, and the relationship between price and service time lend support to the predictions outlined in Section 2.1.

3.3.2 Service time in different demand and cost conditions

To further explore the validity of the service time trade off, we also want to examine how service times vary with the marginal costs of capacity. Since we do not have direct access to these costs, we use the distinction between low and high demand weekdays, assuming that marginal costs are greater on high demand weekdays. This assumption makes sense if in some local markets, the relevant capacity (e.g., trucks) is used on both low and high demand weekdays. Therefore, grocers that operate in these markets have excess capacity and low marginal costs on low demand weekdays, while on high-demand weekdays they face high utilization of capacity and high marginal costs. To support the distinction between low and high demand weekdays, Panel A in Figure 2 presents the percent of orders through MySupermarket in each day of the week. We denote in red the days that the service time crawler recorded data, i.e., Wednesday and Saturday. Since service times are determined based on the back-load of orders and the average service time is longer than 24 hours it makes sense to aggregate the orders over periods longer than 24 hours. Accordingly, panel B shows the cumulative percent of orders in the 48 hours before the time the crawler was active. The pattern shown in panel B shows that the cumulative percent of orders on Wednesdays is about 3 times larger than on Saturdays. Taken together, the Figure supports our claim that the marginal costs of capacity on low demand weekdays are lower than on high demand weekdays.

Panel A in Figure 3 builds on this distinction and presents Shufresal's service times across markets with varying competition and cost conditions. The figure shows that service times on high demand/high cost weekdays are longer than on low demand/low cost weekdays. Furthermore, service times fall in more competitive markets as well as the difference in service times between high and low demand weekdays. For instance, Shufersal's mean service time in markets where it is a monopoly is 52 hours on Wednesdays and 37 hours on Saturdays. In markets with 5 online retailers, the mean service time is 25 hours on Wednesdays and 20 hours on Saturdays.[12]. For completeness, panel B in Figure 3 presents a time series of Shufersal's mean basket price, focusing on the basket price on Sunday and on Thursday in each week. As can be seen in the figure, unlike

[12]In Israel grocery deliveries are unavailable on Friday afternoon and on Saturday. To take this into account, we subtract 30 hours from deliveries scheduled after Saturday. Ignoring this aspect, would only make the differences in service times between low and high demand weekdays (Saturday vs Wednesday) larger.)

service times, Shufersal's prices do not vary with demand conditions over the days of the week. That is, there is no discernible difference between the price of the basket in the beginning (Sundays) and towards the end (Thursdays) of the week.[13] The patterns shown in Figure 3 lend additional support to the predictions laid out in the theoretical framework discussed in Section 2.1.

3.3.3 Switching patterns over days of the week

A main premise of our analysis is that customers value short service time. An implication is that customers who face high service times are more likely to switch to a competitor. To demonstrate this, we use the longitudinal customer-level data from MySupermarket, and consider cases in which customers are not buying at their regular online vendor. Specifically, we define loyal customers of a given chain as customers who used the online grocry platform more than 10 times over the time period, and in more than half of the times ordered from the same retailer. Next, we examine on what days did these customers preferred an alternative retailer. Figure 4 shows the distribution of switching decisions by these loyal customers. As can be seen, shifts to a rival retailer are significantly more common on days where service times are longer, that is towards the end of the week.

3.3.4 Market structure evolution and the incumbent's response to entry

The raw data patterns presented above are consistent with the predictions derived from the service time trade off described in Section 2.1. Nevertheless, we are cautious not to interpret these findings as causal since they do not take into account other factors that may affect service time decisions. In particular, markets where multiple retailers offer online service are different than markets where fewer online grocers operate. If markets with several grocers enable firms to offer shorter service time, say due to economics of density in dense urban areas, then we should not attribute shorter service time to competition. Below, we address this concern by looking how incumbents respond to competition once a new firm enters a local market. Before moving to this analysis, we present descriptive statistics that demonstrate the variation in retailers' entry decisions over time.

Panel A in Figure 5 presents the evolution of market structures in our sample. In August 2016, nearly 80 markets where monopolies and all five online retailers were active only in 11 markets. Over the 3.5 years, competition intensified and in the end of 2019, 48 local markets were served by one retailer and 37 markets were served by five online retailers. Panel B shows the growth patterns for each of the retailers, except Shufersal which was active in all 180 markets throughout the sample period. As can be seen in the Figure, Victory, Yeinot Bitan and Rami Levy experienced a massive growth in the number of markets that they serve, growing from 21, 43 and 44 markets

[13] Similar pricing and service time patterns hold for the other chains.

in August 2016 to 52, 72 and 91 in the end of 2019, respectively. Overall, we observe at least one entry in 130 of these markets.

Table 1 presents demographic information on all 180 markets, including those that did and those which did not experience entry. Specifically, odd columns in Table 1 focus on markets that experienced entry, distinguishing between markets that were pre-entry monopolies (Column 1) pre-entry monopolies and duopolies (Column 3) and all markets. In even columns we show the mean differences and t-tests comparing the characteristics of markets that experienced entry and those which did not experience entry, keeping the same number of online retailers at the beginning of the period. The patterns presented suggest that more online retailers operate in more populated and dense cities, located closer to the center of Israel and with higher socioeconomic status. However, we do not observe clear differences between markets that experienced entry vs. those which did not.

Our empirical analysis focuses on Shufersal's response to entry. Figure 6 shows the mean service time before and after entry in different market structures, while distinguishing between low and high demand weekdays. Consistent with our previous findings, the figure shows that service times are shorter on low-demand weekdays. Also, in both low and high demand weekdays, service times are shorter when more grocers offer service. More importantly, the figure suggests that the decline in service times occurs before entry, and that this reduction is more pronounced on low demand weekdays. Moreover, the reduction in service time, as measured by the slope of the service time, is larger in monopolistic markets than in competitive markets.

4 Empirical Strategy, Estimation and Results

We seek to identify the impact of entry on service times offered by the incumbent. Our estimation i s based on difference-in-differences with variation in treatment timing, and involves two primary exercises. First, we conduct an event-study estimation which enables us to examine how the response by the incumbent varies over time, before and after entry. Second, we run a parametric estimation which allows us to quantify the effect of entry on the incumbent's service time. In both exercises, we focus only on markets that experienced entry at some point during the sample period. Moreover, in both analyses we examine how service time responds to entry in different demand and competition conditions. In Section 4.4.2, we consider how these entry events also affected markets that did not experience entry. Before turning to describing the specific estimation exercises, we discuss the main challenges in evaluating the relationship between competition and service time.

4.1 Empirical challenges

Online retailers often operate in urban areas where a large base of customers live and where they can exploit economies of density, thereby reducing average time between deliveries.[14] Thus, in large dense cities, more online grocers operate and are able to offer short service time. Thus, it would be likely erroneous to attribute shorter service time in these markets solely to competition. To address this concern, we use the panel structure of our data, exploiting geographical and temporal variation in entry decisions to markets facing different demand and competition conditions. The panel structure of our data and the expansion by online retailers into new local markets enable us to control for time-invariant conditions within the same market, and time-variant effects which are fixed across markets.

One potential limitation of exploiting entry to learn about the relationship between competition and service time is that entry affects not only the competition level but also the output provided by the incumbent. As a new firm enters, some customers that used to rely on the incumbent will switch to the entrant. As a result, the incumbent serves fewer customers and this may affect the marginal cost of service time (c in the model presented in Section 2). In addition, entry also raises the risk that a customer would switch to a rival (γ in the model presented in Section 2). To disentangle the two effects of entry on service time, we consider the incumbent's response before and after entry. We consider pre-entry changes in service time as driven by the effect of competition (γ), whereas post-entry changes in service time are the joint effect of competition and output changes.

A third concern is contemporaneous changes in prices and in service time. Theoretically, service levels could vary with prices. For instance, if incumbents set lower prices when a new firm enters, then our estimates on the effect of competition on service levels are potentially confounded with the change in prices. Our setting, where prices are set nationally and are identical across all markets served by a given retailer, enable us to overcome this issue. Fourth, in many settings that involve local markets, evaluating the impact of competition requires defining a geographical local market, and then changes in the level local competition. Related studies need to consider alternative geographical borders, implicitly taking into account customers' tendency to shop outside the local market. In our setting, deliveries by a given retailer to a customer's home address is either offered or not. We are less concerned that customers will order grocery service to an address which is not their home address.

The last challenge is that timing of entry decisions are not random. If the timing of entry

[14] In an interview, explaining the failure of Webvan probably the first online grocery service, its VP said that "The biggest failure of Webvan was delivery density. Mean travel time between delivery stops is the key to success in the home delivery business." See https://www.reuters.com/article/net-us-amazon-webvan/from-the-ashes-of-webvan-amazon-builds-a-grocery-business-idUSBRE95H1CC20130618.

is correlated with unobserved factors that affect the incumbent's service time then our estimates might be biased. We comprehensively address this concern in section 4.3. Here we mention the following. First, like Goolsbee and Syverson (2008) and Matsa (2011) our analysis focuses on the incumbent's response to entry rather than the behavior of the entrant. Second, we show that entry patterns are driven by operational considerations, and retailers prefer to offer new service in regions where they already operate, thereby taking advantage of cost efficiencies (Holmes (2011)). Thus, the incumbent's service time is likely not driving the timing of entry. Finally, our setting allows us to examine the effect of entry on low and high demand periods in the same market. This within market comparison allows to examine pre-entry trends, and presumably rule out concerns that the timing of entry is driven by changes at the market level.

4.2 Nonparametric event-study estimation

Our first empirical exercise is a nonparametric estimation of an Event Study design. In this exercise we seek to estimate the effect of a rival entry on the incumbent's service time before and after entry takes place. In particular, we analyze the coefficients on the log of Shufersal's service time for each month relative to the month of the entry (the event). The primary advantage of this nonparametric event study is that it allows us to visually (and flexibly) assess the pattern of service time relative to the entry month and to identify any anticipation response even before entry takes place. The basic nonparametric event study specification has the following form:

$$Log(delivery\_time)_{it} = \gamma_i + \alpha_t + \sum_{j=\mu}^{6+} \beta_j entry_{it+j} + u_i \tag{2}$$

where the dependent variable, $Log(delivery\_time)_{it}$, is log of the average service time offered by Shufersal in locality i in month t. γ_i and α_t are locality and month-year fixed effects, respectively. Locality fixed effects account for market characteristics that may have affected entry decisions. Month-year fixed effects account for seasonal and other trends at the national level. $entry_{it+j}$ are dummy indicators for months relative to entry. Standard errors are clustered at the locality level to account for within-market correlation in the error term.

The key coefficients of interest are β_j which estimate the change in the dependent variable at a given j relative to its average value in the excluded period, which are months earlier than the μ months before entry. Following Goolsbee and Syverson (2008) we choose the μ months before entry as the excluded period since we expect that the effect of entry on service time may take place even before actual entry. Subscript j is running from μ months before entry to six months after entry, where the dummy for the sixth month is a single dummy for the period six or more months after entry. In our baseline analysis we estimate equation (1) separately for low and high demand weekdays (Saturday and Wednesday, respectively) and for a sub-sample includes only pre-entry monopoly markets and another sub-sample includes only pre-entry monopoly and duopoly markets. To interpret the nonparametric event study coefficients on indicators for months respective to entry in equation (1) as the causal effect of the entry would require the identifying assumption that, conditional on entry during our sample period and the included controls, the timing of the entry is uncorrelated with service time. The nonparametric event study allows us to examine patterns in outcomes in the months leading up to the entry to rule out any pre-trend that can bias our estimates. We discuss this identifying assumption more in details in section 4.5.

4.3 Parametric estimation

We use the parametric event study to quantify the effect of entry on service times, and to test for differences in service times before and after entry takes place. This analysis is particularly important for identifying the forces discussed in Section 2.1 which might drive the observed changes in service times. Our choice of functional form is guided by the patterns seen in the nonparametric event study estimation. The nonparametric event study estimation revels a pre-entry response at least two months before entry. Hence, in the main specification of the parametric event study, we compare the effect in the two months before entry, and the observed response after entry.

In particular, we estimate the following specification:

$$Log(delivery\_time)_{it} = \gamma_i + \alpha_t + \beta_1 pre\_entry_{it} + \beta_2 post\_entry_{it} + u_i \tag{3}$$

where pre_entry_{it} is a dummy for the 1-2 months preceding entry into the local market and $post\_entry_{it}$ is a dummy for the months after entry into the local market. To capture potential changes in the number of online retailers in a market beyond the first entry that we observe (additional entries or exits), we estimate also specifications including dummies for exits and subsequent entries. To capture potential time trend of improving service time (e.g. technological changes) we estimate also specifications including specific fulfillment center linear time trend.[15]

We also use the parametric estimation to examine if the incumbent differently responds to entry by different retailers. Arguably, if certain retailers pose a greater threat on the incumbent, then we could expect a more aggressive response when these retailers enter. We rely on the findings in sections 2.2 and 3.2 to classify the four entrants in our data to two groups of retailers, which we consider aggressive and non-aggressive online retailers.

[15]Shufersal use 34 fulfillment centers to pick and distribute online orders. We matched to each market in our sample the closest fulfillment center by driving distance.

4.4 Results

Figure 7 presents the results of the event-study analysis. The figure graphs the point estimates and the 90 percent confidence intervals for the β_j coefficients in equation (1) where j runs from -6 (six months before entry) to 6 (six months after entry, and j=6 equals one also for more than six months after entry).[16] Estimation results are shown separately for low and high demand weekdays. Sub-figure A reports the results for markets served by one online retailer before entry takes place, sub-figure B focuses on markets served by up to 2 online retailers, and sub-figure C reports the results for all markets.

In pre-entry monopoly markets, we find that service times dropped by about 10 to 20 percent on low demand weekday. This drop in service time materialized already before the rival entered. Looking at the change in service times before and after entry on high demand weekdays, we do find evidence for change in service times. Also, in more competitive markets we do find any evidence for a significant change in service times in response to an entry. In Figure 8 we report the results from a specification that expands the event window to 12 month before entry. The results for this analysis are consistent with our main findings, and further shows that the improvement in service times materialized primarily in the two months preceding the entry.

Table 2 presents the results of the parametric estimation. Columns 1-3 focus on low demand weekdays and columns 4-6 on high demand weekdays. The results in Table 2 are consistent with the event study results. A significant decline of 15 percent in service times is observed before and after entry in markets where only Shufersal operated before entry, and only on low demand days. On the other hand, while the estimates in the high demand weekdays are much smaller and statistically insignificant. Estimates for more competitive markets, both in low and high demand weekdays are small and statistically indistinguishable from zero.

4.4.1 Response by entrant type

We expect a larger decline in service times when a rival that poses a larger threat enters. To test this conjecture, we repeat the analysis focusing on entry decisions by the chains: Rami Levy and Victory.[17] Table 3 reports the results of the parametric estimation only for entries by Rami Levy and Victory. The results show clearly that the incumbent retailer, Shufersal, improves its service time when Rami Levy or Victory enter. The magnitude of the effect is nearly 50% larger than in the the main analysis, and it is negative and significant not only in pre-entry monopoly markets.

[16] To obtain a balance sample period around the 6 months window, we exclude markets in which entry occurred towards the beginning or the end of the sample period.

[17] Rami Levy, sets the lowest prices, and Victory offers the shortest delivery service times. In contrast, Mega, is the most expensive chain and Yenot Bitan offers medium prices and the long service times are non aggressive retailer. In the appendix, we use the consumer data from MySupermarket to show that Rami Levy and Victory are closer substitutes to Shufersal – Shufersal's online customers move to these chains when they choose not to order from Shufersal (36% move to Rami Levy and 32% move to Victory).

Interestingly, also when we restrict attention to Rami Levy and Victory, we do not find that the incumbent improved its service times on high-demand/high-utilization weekdays.

Overall the results in Tables 2 and 3 suggest that increased competition triggers shorter service time more in concentrated markets, and on days in which the incumbent likely have slack resources such as low demand weekdays. These results are consistent with the predictions of the newsvendor problem model developed in section 2.

4.4.2 Supply side externalities

How incumbents improve service times on low demand weekdays? First, the incumbent can expand working hours of existing workers, use trucks that are typically used on the high demand weekdays. Alternatively, the incumbent can shift production factors that are used in adjacent markets, where entry does not take place, and use them to improve service time in markets it expects entry to occur. If incumbents prioritize markets that face entry at the expense of markets which do not, then service times in these adjacent markets will rise once a rival enters in a nearby market.

To shed light on these alternative conjectures, we classified each of the 180 markets in our sample to 34 fulfillment centers that Shufersal uses to pick and distribute online orders. Next, we focus on the 50 markets that did not experience any change during the sample period, and repeat the parametric estimation where the entry dummy variable refers to entry in these markets. In particular, these indicators receive the value of one if entry occurred in another local market that is served by the same fulfillment center. We focus on entry events to monopolistic markets and distinguish between entry by aggressive retailers (Rami Levy and Victory) to entry by any retailer. Table 4 reports the results for this analysis. Interestingly, the results show that Shufersal improves service time not only in markets in which the actual entry takes place but also in adjacent markets. Moreover, consistent with our previous findings, this improvement is observed only on low demand weekday, and it is larger when entry is by an aggressive rival. These results point towards supply-side externalities in the production of short service time. That is, improved service time in one market has spillover effects on markets that are not directly threatened but are served by the same distribution center.

4.5 The timing of entry decisions

In this section, we address the concern that the timing of entry into markets is correlated with unobserved factors that are also associated with the service time offered by the incumbent. In Figure 9 we present the distribution of timing of entry in all markets and into monopolistic markets. As can be seen, the distribution of timing of entry is not concentrated in a particular time period, mitigating concerns about strategic timing of entry. Before addressing other concerns about the timing of entry, we note that all markets included in the analysis in section 4.2 and 4.3 experienced entry during the sample period. Hence, we are not comparing markets that experienced entry with those that did not, but rather consider the implications of different timing of entry into different market. For several reasons we think this concern is unlikely driving our results.

First, our panel structure estimation controls for time-invariant unobserved factors that are associated with online service in the local markets. Market fixed-effects capture factors such as the size of the local population, expected population growth, and retail food alternatives. To the extent that these factors do not significantly change over time then we should be concerned that these factors are driving our estimates. Presumably, population growth patterns do not significantly change in three years, making the assumption plausible. Moreover, short-lived changes in population are also less relevant since entry decisions are likely based on long-term market characteristics of the local market. Likewise, the incumbent's infrastructure was in place at the beginning of the time period we study, and to our knowledge has not changed significantly. Nevertheless, if unobserved time variant factors affect demand for online service and also influence the timing of entry, then our estimates are potentially biased.

Second, our analysis focuses on service time offered by the <u>incumbent</u>. Accordingly, from identification point of view, the concern is that timing of entry is correlated with the incumbent's online capabilities or demand in that market. For instance, a retailer will enter a market in 2017 instead of 2018 because the incumbent's service time capabilities are temporarily damaged. Below, we argue that entry decisions are predominantly driven by the entrant's operational concerns rather than on the incumbent. Moreover, if entrants do time their entry and focus on markets where the incumbent faces stricter capacity constraints, then our estimates are biased downward.

Third, entry decisions are predominantly driven by entrants' operational concerns. Offering online service requires non-trivial investments, such as training workers, converting trucks into food-delivery trucks, modifying physical stores for distribution, and investing in local advertising. These investments depend on a retailer's capabilities and available infrastructure in the respective region. To save costs retailers offer service to several localities in the vicinity of the same distribution center. Figure A3 in the Online Appendix shows the geographical expansion of online service offered by each of the four chains. The figures also present the location of the brick and mortar stores of each of the retailers. The patterns shown in the figure suggest that entry decisions are geographically clustered, and often take place within a relatively short frame from each other. For instance, between 2016 and 2019 Rami Levy expanded its online service primarily towards the north of Israel, whereas Victory towards the south of Israel. Our assumption is that these patterns are not driven by unobserved time-variant factors that affect service time by the incumbent.

Fourth, a related threat to identification is substitution between online and brick-and-mortar stores. The market fixed-effects control for unobserved time-invariant factors at the market level, which include the set of alternate food stores. In some specifications, we also include linear time trends to control at the fulfilment center. Nevertheless, the specifications may not control for changes that occurred during the sample period. For instance, if an entrant opens a brick-and-mortar store before they offer online service and online customers of the incumbent switch to the newly opened store, then our estimates are biased and are driven by the new brick-and-mortar store rather than the new online service. We think this concern is not driving our estimates for two reasons. First, retailers did expand during the time period we cover not at a limited scope compared to the growth in the online channel. More importantly, when we include the dates of the opening of new stores in the estimation, we obtain similar results. In appendix, we report these results and also present more analyses that concern the relationship between opening a new store and the online service. Second, had the opening of a new store nearby affected the demand for the incumbent online service, then we should expect to see a decline in both high and low demand weekdays. The fact that we see a decline only on low-demand weekdays suggests that the opening of the new brick-and-mortar store nearby it not driving our results.

Finally, our analysis compares the response to entry in high and low demand periods. As entry occurs in both high and low demand periods, the comparison between low and high demand periods is not sensitive to concerns about endogenous entry. Moreover, the fact that on high demand weekday and on more competitive markets we do not find any change in service time lends additional support that unobserved time-variant factors are not driving our results.

5 Discussion and Concluding Remarks

With the growth of online markets, service time is becoming increasingly important for consumers, firms and for policy makers that examine these markets. Despite a large theoretical literature on service time and competition, little is known empirically on how firms actually use service time, and how it varies with demand, competition and cost conditions.

We address this gap in the literature by studying the Israeli online grocery market. Using bi-weekly longitudinal data on service time and prices 180 markets, we show that online grocers set shorter service times in more competitive markets and on low-demand weekdays. Furthermore, retailers that set higher prices offer shorter service time. Our main empirical analysis, considers the effect of entry on the incumbent's service time. This analysis takes advantage of the rapid expansion of online retailers into new local markets, and is useful to identify a causal effect of competition on service time. In this analysis, we find that incumbents improve service time shortly before a new rival enters the local market. The effect of on service time is considerably larger in more concentrated markets and on low demand weekdays. Interestingly, on high-demand weekdays, when incumbents likely face capacity constraints we do find that incumbents respond to entry. Moreover, our finding that incumbents improve service time before entry takes place implies that strategic considerations are driving these improvements rather than the indirect effect of reduced demand for the incumbent's service which might only arise after entry takes place. Overall, these results suggest that firms strategically use service time to respond to changes in competition. Yet, firms' cost structure in different demand conditions also determine how retailers respond to competition.

We also highlight the differences between short and long term effects of competition. Our estimation captures the short-term effect of competition on service time, assuming that the choice of capacity is largely fixed and the input decisions are inflexible in the short run. In the long-run, firms are able to increase their capacity, by adding relevant inputs or changing production technology. Indeed, the cross-sectional variation in service time indicate that firms offer shorter service time in both high and low demand weekdays. While these differences might by attributed to intrinsic differences between markets, they are likely also driven by firms strategic decisions. We leave this issue for further research.

Our results speak to the debate about uniform pricing. Growing evidence shows that national chains set similar prices in very different environments and moreover do not change prices as competition and demand conditions change. These findings cast doubt on the relevancy of standard models of competition and of traditional competition analysis, which emphasize the role prices. Our findings can explain how, in a setting where firms set identical prices across markets, retailers use service time to respond to competition and demand conditions, thereby enabling markets to clear.

Perhaps more broadly, the patterns we uncover for service time in different demand and competition conditions offer a mirror image to what standard models of competition predict for prices. In particular, according to a Bertrand with differentiated products model with fixed quality, we expect that prices will be lower in more competitive markets and in low-cost environments. Moreover, in these models entry has a greater impact on prices in monopolistic markets and when incumbents face low marginal costs. Remarkably, we find parallel evidence for service time in markets with fixed prices. Thus, service time is higher in monopolistic markets and on high demand weekdays. Likewise, service time falls following entry in monopolistic markets, when stronger rivals enter and when costs are lower. Thus, one may conclude that in the absence of prices, service times could facilitate market clearing.

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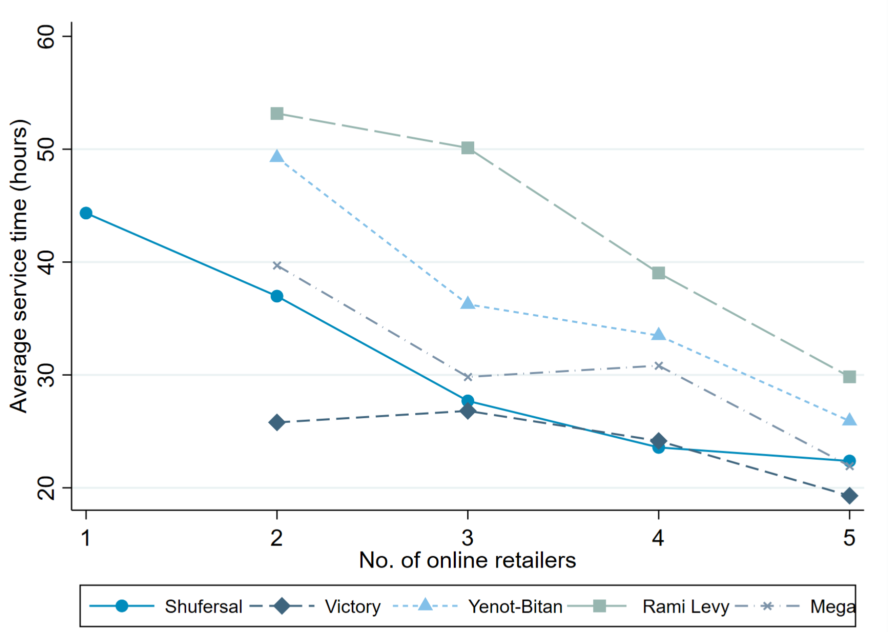
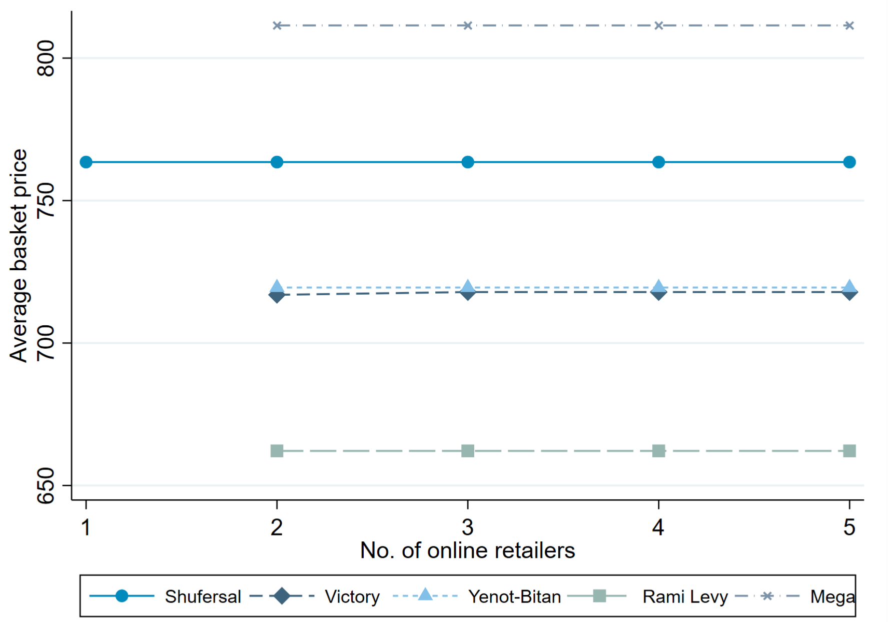
Chad Syverson. What determines productivity? Journal of Economic literature, 49(2):326–65, 2011.

Figure 1: Service time and prices across competition level by retailers

(a) Average service time by number of active online retailers



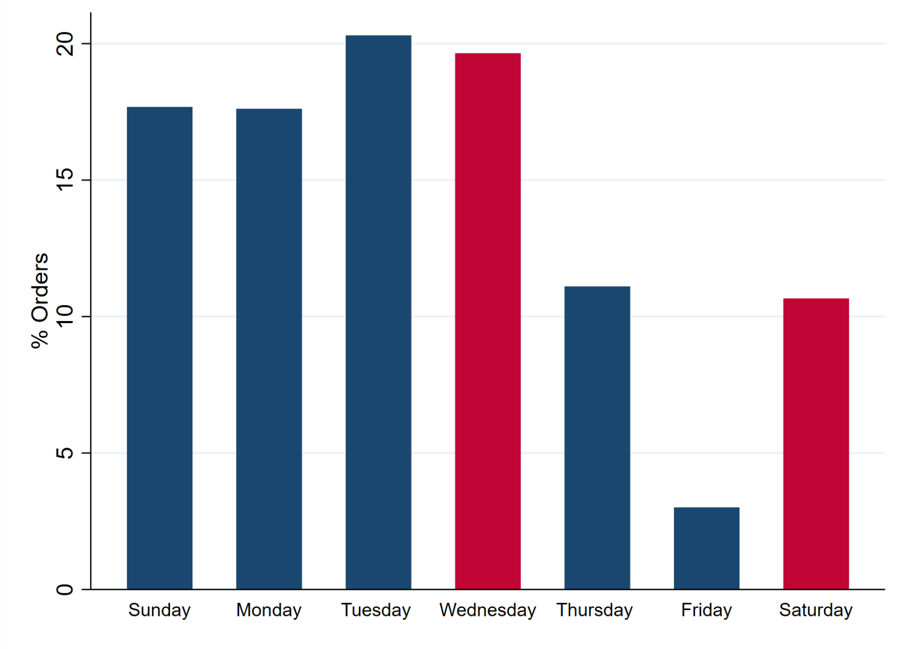
(b) Average basket price by number of active online retailers



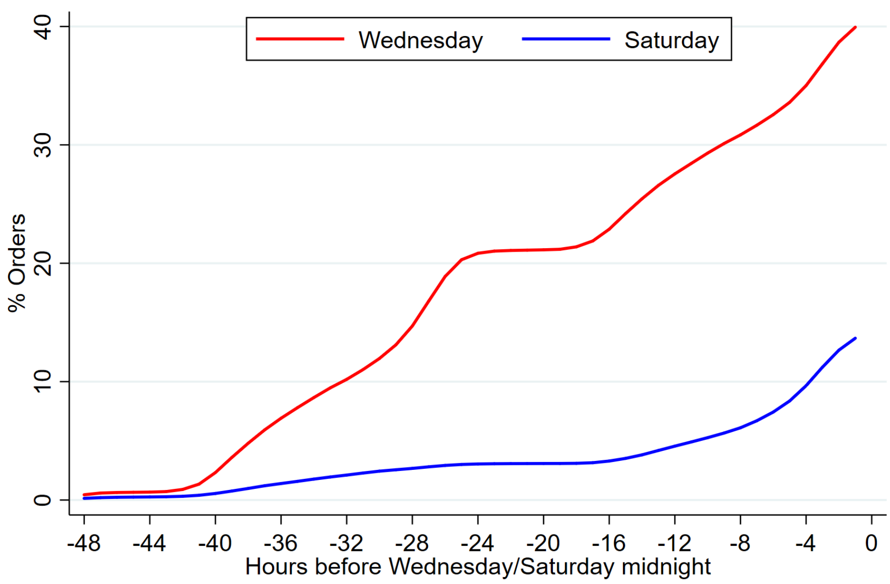
Notes: Figure (a) shows the average service time for each retailer by the number of active online retailers in each market. Figure (b) shows the average monthly basket price for each retailer by the number of active online retailers in each market. Both figures based on monthly data from August 2016 to July 2019.

Figure 2: Demand for online grocery over the week

(a) Percent of orders from MySupermarket by weekday



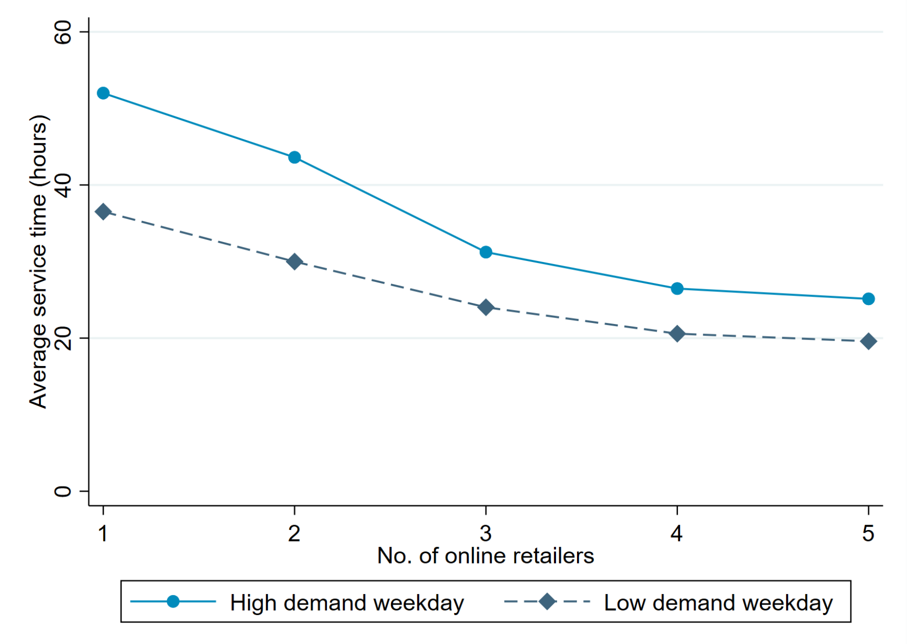
(b) Cumulative percent of orders before crawler time



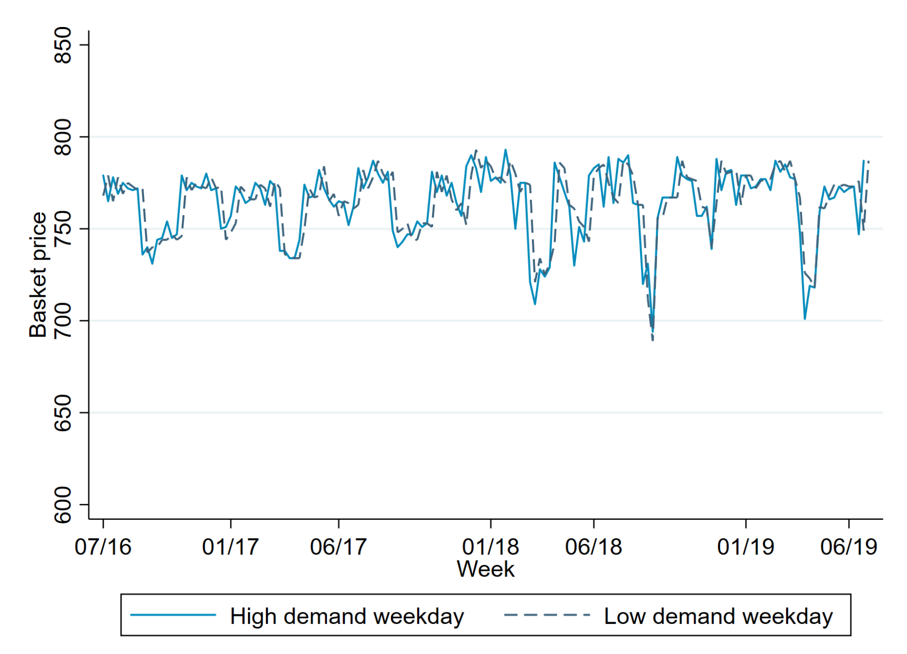
Notes: The figure shows a normalized measure of the number of consumers that order through MySupermarket, an online platform that enables consumers to order online at each of the five online retailers. Figure (a) shows the percent of orders (out of total orders) in each day of the week. Figure (b) shows the cumulative percent of orders over the 48 hours that precede the crawler time (midnight at Saturday and Wednesday).

Figure 3: Service time and prices across competition and demand levels - incumbent only

(a) Average service time by number of active online retailers and demand level

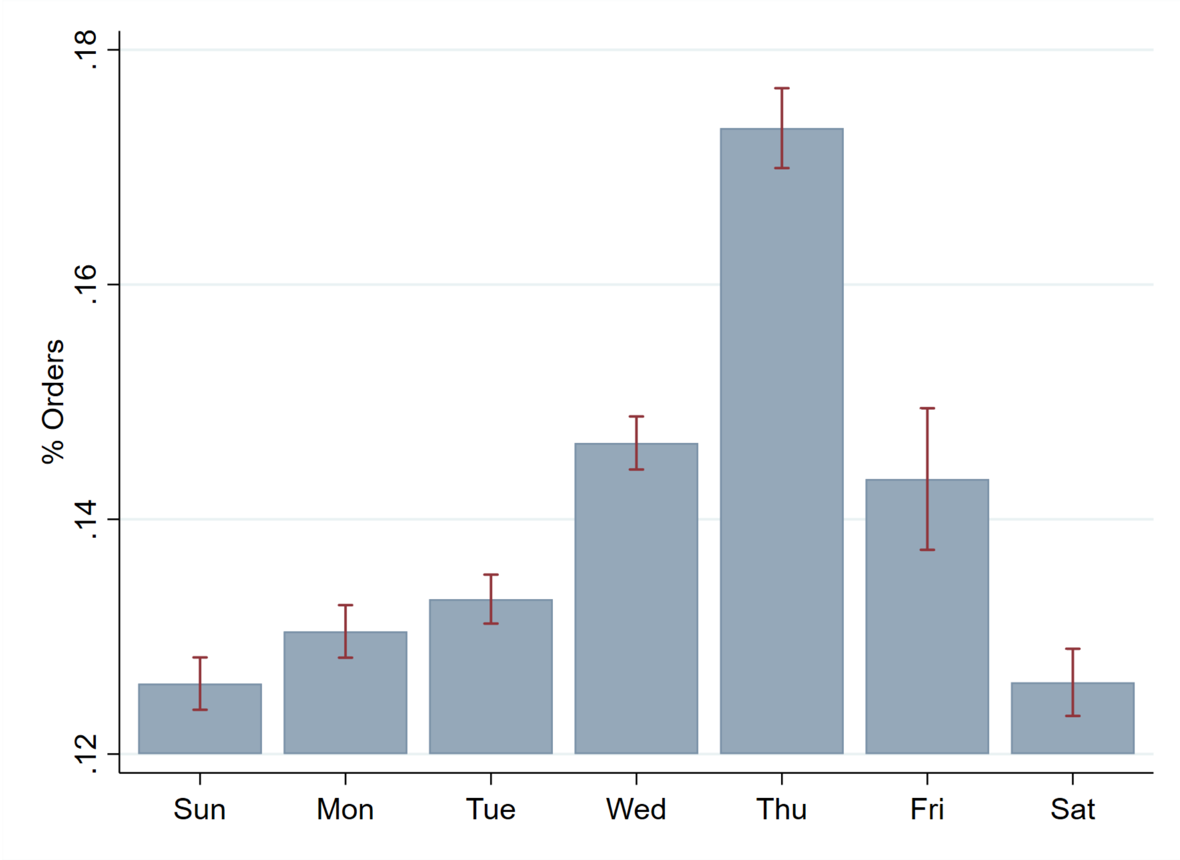


(b) The incumbent's basket price on low and high demand weekdays



Notes: Figure (a) shows the average service time of Shufersal by the number of active online retailers in each market separately for low demandcost weekdays and high demand/high cost weekdays based on monthly data from August 2016 to July 2019. Figure (b) shows the daily basket price of Shufersal online separately for Sundays (following low demand on Saturday) and Thursdays (following high demand on Wednesday) for each week during the sample period from August 2016 to July 2019.

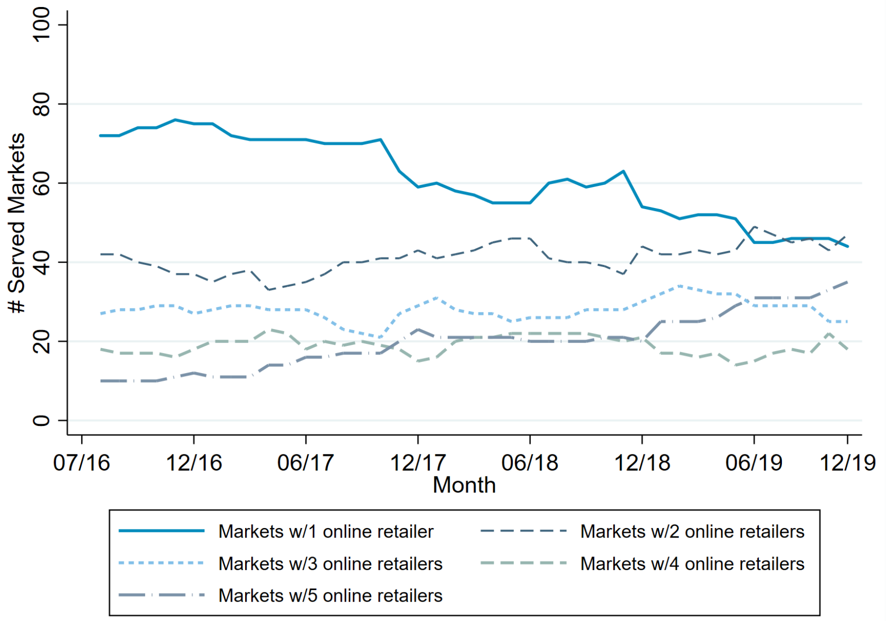
Figure 4: Customers' switching patterns across days



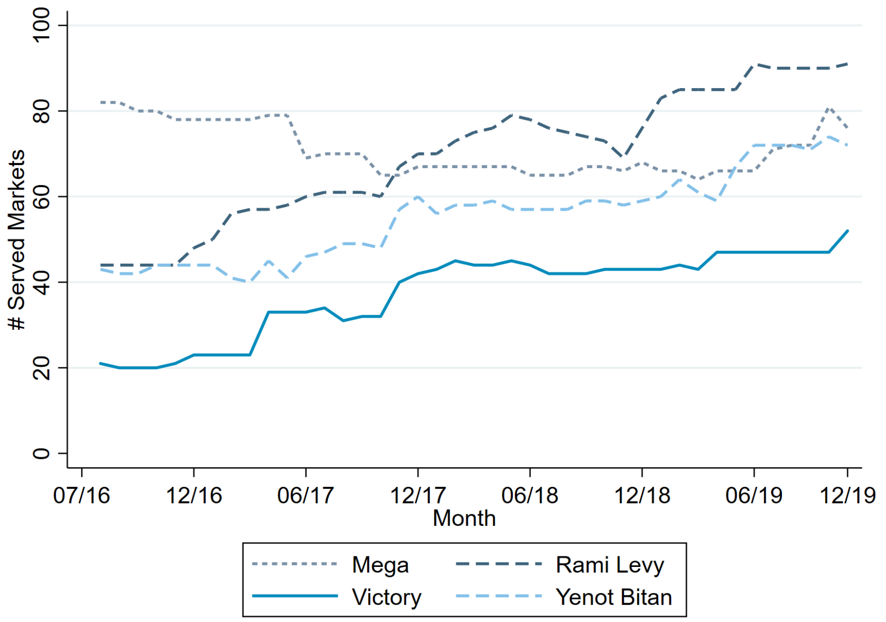
Notes: The figure shows the percentage of loyal customers who choose not to purchase from not their regular retailer by day of the week. A loyal customer used MySupermarket platform more than 10 times and at least 60% of the times bought from the same retailer. There are 9182 loyal customers in the sample, where more than 17% of switches by loyal customers occur on Thursday compared to about 12.5% of switches to a non-regular vendor on Saturday and on Sunday. The figure suggests that customers are more likely to switch retailers on long service time days.

Figure 5: Changes in Market structure and online retailers' expansion

(a) Market structure evolution

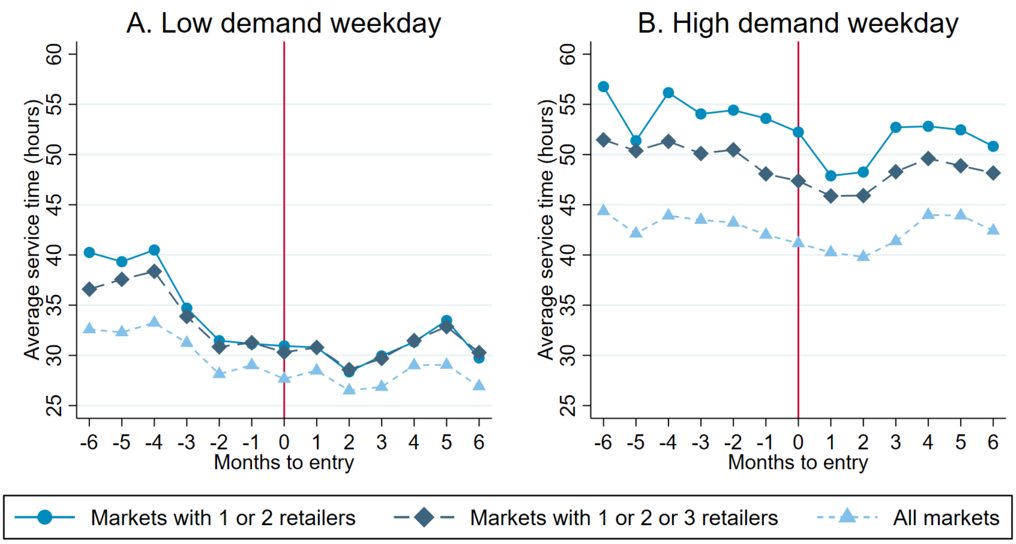


(b) Online retailers' expansion



Notes: Figure (a) shows the evolution of the competition level during the sample period. The figure plots the number of market at each competition level for each month while level of competition is based on the number of active online retailers. Figure (b) displays the number of market served by each of the 4 online retailers over the sample period. We exclude Shufersal from the figure since it operates in all 180 markets throughout the three years.

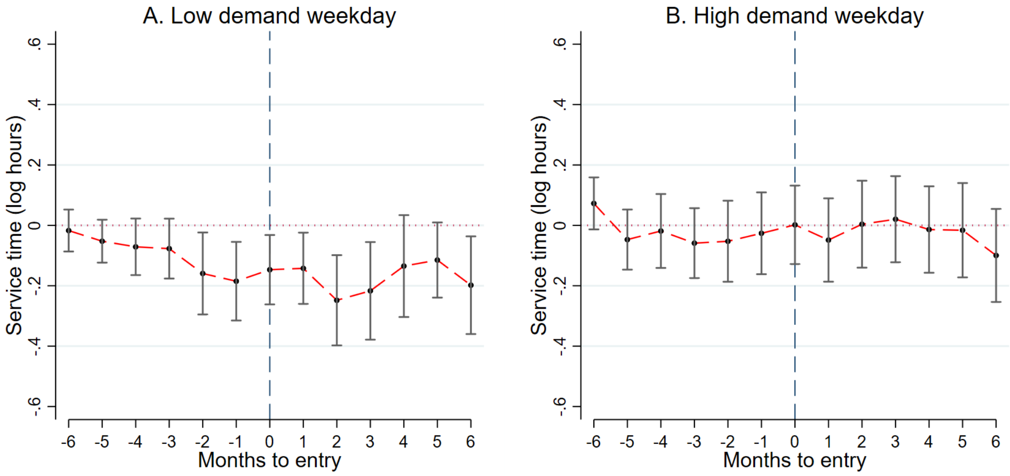
Figure 6: Service time before/after entry by market competition and demand levels



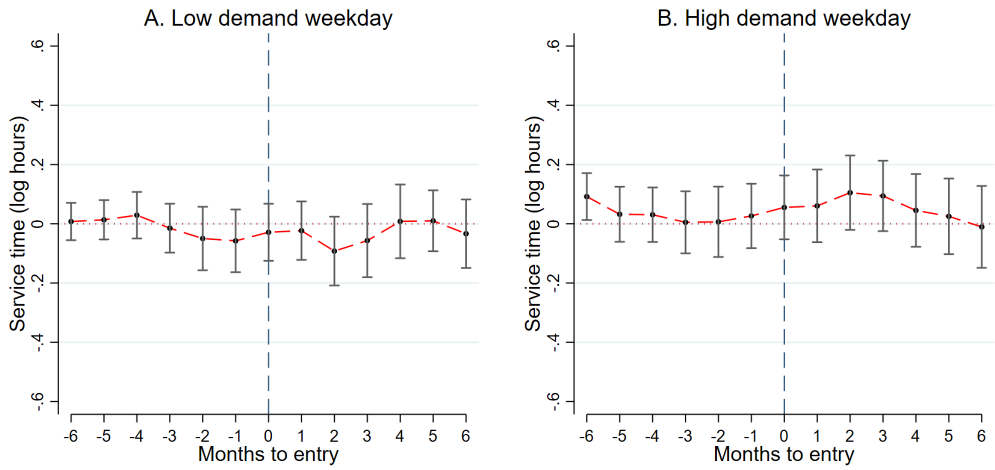
Notes: The figure plots average service times by months before and after entry of a rival during the sample period (August 2016 - July 2019). The figure distinguishes between low (Left) and high (Right) demand weekdays and between markets with different number of active retailers before entry. High demand weekdays and less competitive markets exhibit longer service times. Furthermore, service times fall 2-3 months before entry on low demand weekdays.

Figure 7: The effect of entry on incumbent service time by competition and demand level

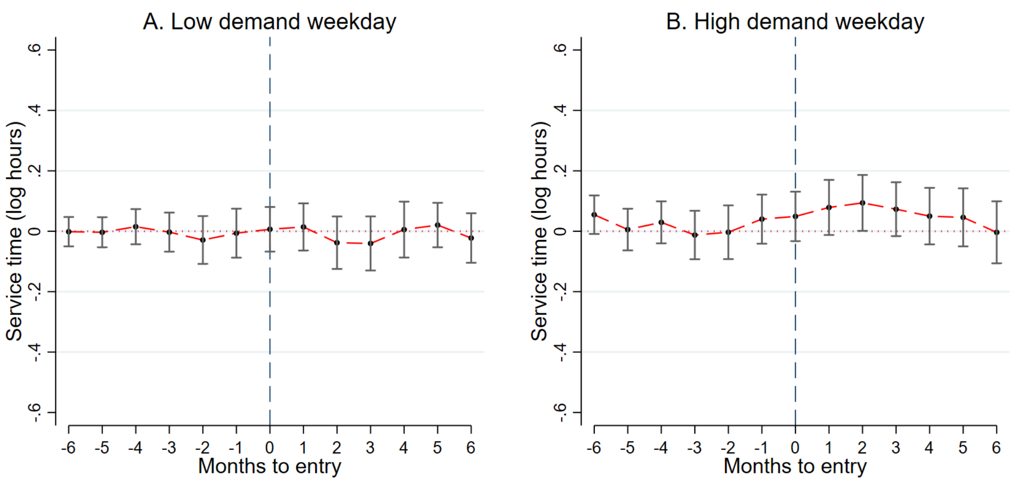
(a) pre-entry monopolistic markets



(b) pre-entry monopolistic / duopolistic markets



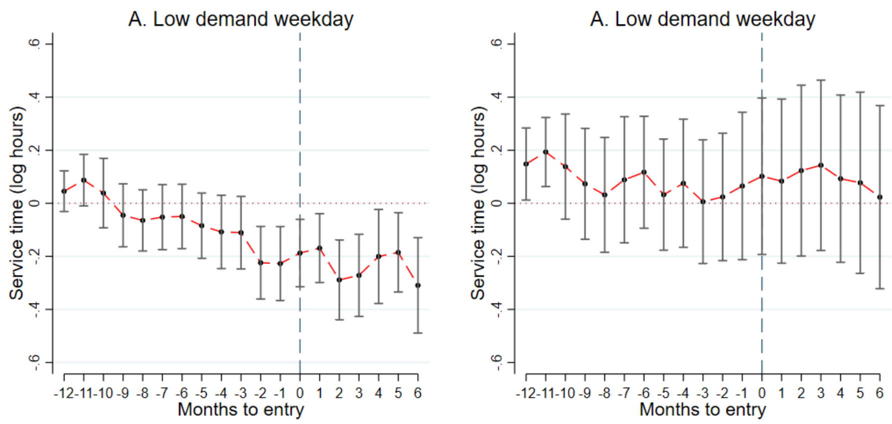
(c) all markets



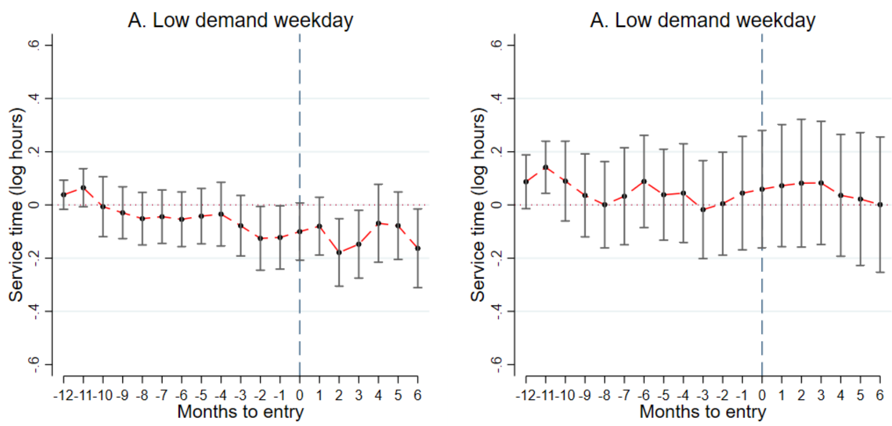
Notes: The figure plots the coefficients β_j for j running from -6 to 6 and their 90 percent confidence intervals from a regression of equation (1) for different sub-samples. Estimated results are separate for low damned weekday and high damned weekday. Panel A includes only pre-entry monopolistic markets, panel B includes only pre-entry monopolistic or duopolistic markets and panel C includes all markets. The depended variable is the log service time of Shufersal in the local market. The regression also includes locality fixed effects and month fixed effects. Standard errors are clustered at the locality level.

Figure 8: The effect of entry on incumbent service time by competition and demand level

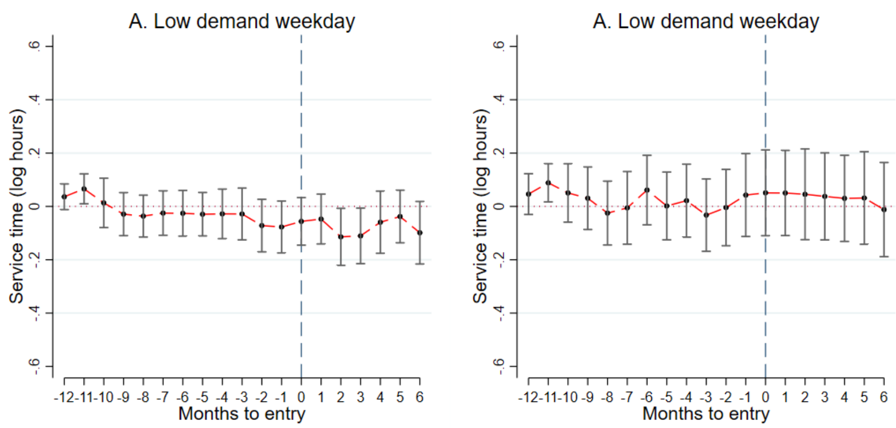
(a) pre-entry monopolistic markets



(b) pre-entry monopolistic / duopolistic markets



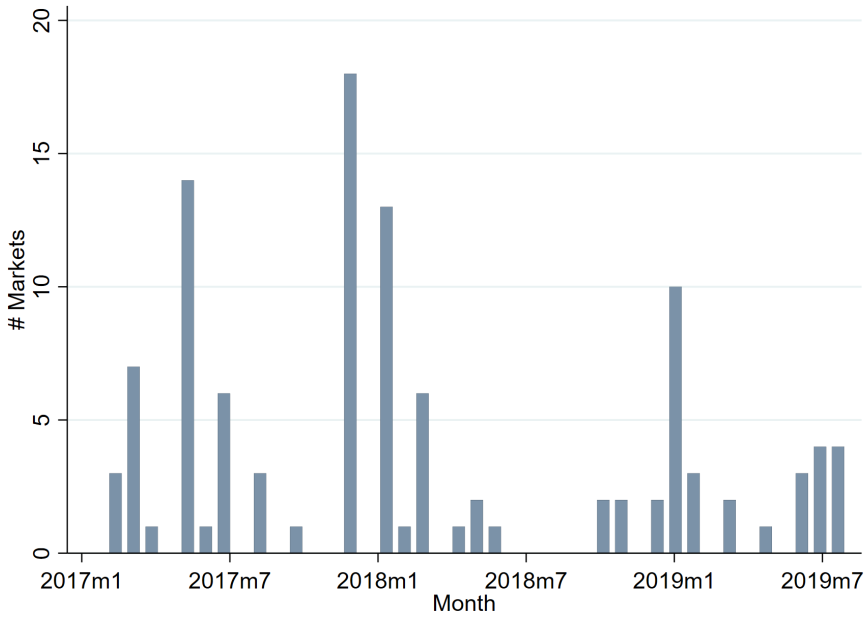
(c) all markets



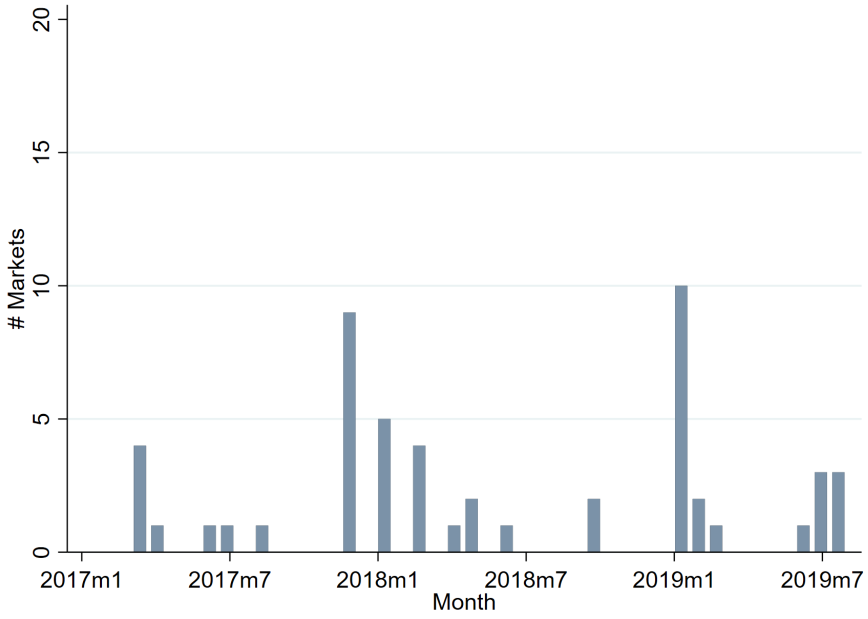
Notes: The figure plots the coefficients β_j for j running from -12 to 6 and their 90 percent confidence intervals from a regression of equation (1) for different sub-samples. Estimated results are separate for low damned weekday and high damned weekday. Panel A includes only pre-entry monopolistic markets, panel B includes only pre-entry monopolistic or duopolistic markets and panel C includes all markets. The depended variable is the log service time of Shufersal in the local market. The regression also includes locality fixed effects and month fixed effects. Standard errors are clustered at the locality level.

Figure 9: The distribution of timing of entry

(a) All markets



(b) Pre-entry monopolistic markets



Notes: Figure (a) shows the number of markets experienced entry in each month during the sample period. Figure (b) shows the number of monopolistic markets experienced entry in each month during the sample period.

Table 1: Markets' demographics characteristics by entry status and competition level

	Markets with 1 or 2 retailers		Markets with 1 or 2 or 3 retailers		All markets	
	Markets with entry	ΔMarkets w/o entry	Markets with entry	ΔMarkets w/o entry	Markets with entry	ΔMarkets w/o entry
	(1)	(2)	(3)	(4)	(5)	(6)
Population (K)	28.83	-2.27	40.78	-12.80	51.60	-9.49
	(20.41)	[4.39]	(96.49)	[16.69]	(95.31)	[14.23]
	(0.583)	[0.107]	(0.464)	[0.080]	(0.391)	[0.056]
Density (population/km)	5,489	-795.1	6,722	-2,229	8,401	-1,384
	(4,130)	[995.1]	(6,959)	[1,398]	(7,304)	[1,255]
Average income per capita	9,901	74.38	10,197	-28.15	10,356	497.9
	(2,043)	[460.6]	(2,240)	[441.5]	(2,295)	[383.7]
Vehicle per capita	0.407	-0.080	0.384	-0.055	0.38	-0.020
Socioeconomic index	6.316	-0.116	6.429	-0.134	6.562	0.278
[1-low to 10-high]	(1.734)	[0.388]	(1.714)	[0.342]	(1.661)	[0.277]
Periphery index	4.474	-0.074	4.879	-0.232	5.477	0.163
[1-v.perif. to 10-not.perf.]	(1.548)	[0.333]	(1.618)	[0.317]	(1.831)	[0.314]
Markets	57	30	91	34	130	50

Notes: The table reports means and standard deviations in parenthesis for local markets' characteristics in markets with entry and the mean differences with standard errors t-test in brackets in markets' characteristic between markets with entry and markets with out entry. Column 1 include markets where only Shufersal was active at the beginning and a rival entered during the sample period. Column 2 includes markets where only Shufersal was active during the whole sample period or Shufersal and one more rival were active during the whole sample period. Column 3 includes the same markets as in column 1 and markets where Shufersal and one more rival were active at the beginning and a rival entered during the sample period. Column 4 includes the same markets as in column 2 and markets where Shufersal and two more rivals were active during the whole sample period. Column 5 includes all markets faced a rival entry during the sample period. Column 6 includes all markets with a constant number of active firms during the whole sample period.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Effect of entry on the incumbent's service time by competition and demand level

	Low demand weekday			High demand weekday		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: pre-entry monopolistic markets						
pre_entry	-0.147**	-0.146**	-0.158**	-0.072	-0.073	-0.102
	(0.061)	(0.061)	(0.060)	(0.082)	(0.082)	(0.078)
post_entry	-0.155**	-0.157**	-0.156**	-0.040	-0.036	-0.021
	(0.063)	(0.062)	(0.060)	(0.069)	(0.068)	(0.072)
Markets	52					
N	2128					
Panel B: pre-entry monopolistic / duopolistic markets						
pre_entry	-0.062	-0.061	-0.069	-0.025	-0.026	-0.053
	(0.047)	(0.047)	(0.046)	(0.059)	(0.059)	(0.053)
post_entry	-0.055	-0.057	-0.052	0.004	0.006	0.009
	(0.043)	(0.043)	(0.041)	(0.055)	(0.055)	(0.054)
Markets	80					
N	3274					
Panel C: all markets						
pre_entry	-0.021	-0.021	-0.040	-0.009	-0.009	-0.039
	(0.036)	(0.036)	(0.035)	(0.044)	(0.045)	(0.041)
post_entry	-0.025	-0.026	-0.036	0.023	0.025	0.003
	(0.032)	(0.032)	(0.030)	(0.044)	(0.043)	(0.042)
Markets	111					
N	4538					
controls for exits and additional entries		X	X		X	X
fulfilment center linear time trend			X			X

Notes: Standard errors in parentheses are clustered at the market level. The table reports the estimated results for equation (2). The depended variable in columns 1-3 is the log service time of Shufersal in the local market on Saturday night. The depended variable in columns 4-6 is the log service time of Shufersal in the local market on Wednesday night. *pre_entry* is an indicator for two or one months before the first rival enter the market. *post_entry* is and indicator for the month when the first rival enter the market and the following months. The sample in Panel A includes only markets where Shufersal were active before the entry. The sample in Panel B includes only markets where Shufersal and one more rival were active before the entry and the sample in Panel C includes all markets. The regression also includes market fixed effects and month fixed effects. Regression in columns 2 and 5 includes dummy variables for exits and subsequent entries and regression in columns 3 and 6 includes also fulfilment center linear time trend.
Standard errors in parentheses are clustered at the market level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 3: Effect of entry by aggressive retailers on service time by competition and demand level

	Low demand weekday			High demand weekday		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: pre-entry monopolistic markets						
pre_entry	-0.171**	-0.170**	-0.199**	-0.057	-0.057	-0.095
	(0.076)	(0.076)	(0.076)	(0.095)	(0.095)	(0.092)
post_entry	-0.199**	-0.202**	-0.205***	-0.058	-0.054	-0.025
	(0.076)	(0.076)	(0.072)	(0.084)	(0.083)	(0.085)
Markets	41					
N	1678					
Panel B: pre-entry monopolistic / duopolistic markets						
pre_entry	-0.088	-0.087	-0.129**	0.0007	0.0002	-0.039
	(0.063)	(0.063)	(0.060)	(0.075)	(0.075)	(0.069)
post_entry	-0.101*	-0.104*	-0.118**	0.004	0.006	0.023
	(0.058)	(0.058)	(0.052)	(0.072)	(0.071)	(0.070)
Markets	58					
N	2374					
Panel C: all markets						
pre_entry	-0.051	-0.051	-0.087*	0.012	0.011	-0.026
	(0.049)	(0.049)	(0.047)	(0.057)	(0.057)	(0.053)
post_entry	-0.068	-0.071	-0.084**	0.014	0.016	0.024
	(0.044)	(0.044)	(0.040)	(0.057)	(0.057)	(0.056)
Markets	77					
N	3150					
controls for exits and additional entries		X	X		X	X
fulfilment center linear time trend			X			X

Notes: Standard errors in parentheses are clustered at the market level. The table reports the estimated results for equation (2). The depended variable in columns 1-3 is the log service time of Shufersal in the local market on Saturday night. The depended variable in columns 4-6 is the log service time of Shufersal in the local market on Wednesday night. *pre_entry* is an indicator for two or one months before the first aggressive rival enter the market. *post_entry* is and indicator for the month when the first aggressive rival enter the market and the following months. The sample in Panel A includes only markets where Shufersal were active before the entry. The sample in Panel B includes only markets where Shufersal and one more rival were active before the entry and the sample in Panel C includes all markets. The regression also includes market fixed effects and month fixed effects. Regression in columns 2 and 5 includes dummy variables for exits and subsequent entries and regression in columns 3 and 6 includes also fulfilment center linear time trend. Standard errors in parentheses are clustered at the market level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

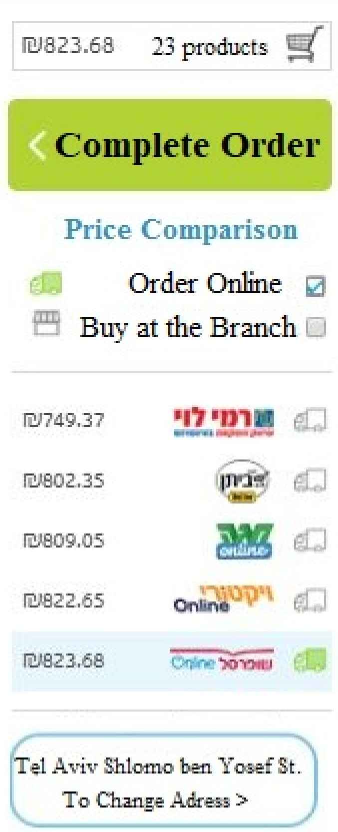
Table 4: The effect of entry to monopolistic markets on incumbent service time in adjacent markets by demand level

	Low demand weekday		High demand weekday	
	Entry by all retailers	Entry by aggressive retailers	Entry by all retailers	Entry by aggressive retailers
	(1)	(2)	(3)	(4)
pre_entry	-0.076	-0.148*	0.083	-0.041
	(0.0536)	(0.077)	(0.070)	(0.089)
post_entry	-0.067	-0.115*	0.088	-0.058
	(0.044)	(0.064)	(0.082)	(0.097)
Markets	50			
N	2044			

Notes: Standard errors in parentheses are clustered at the market level. The table reports the estimated results for equation (2) estimated with a sample include only markets that did not experience any entry or exit during the sample period. The depended variable in columns 1-2 is the log service time of Shufersal in the local market on Saturday night. The depended variable in columns 3-4 is the log service time of Shufersal in the local market on Wednesday night. *pre_entry* is an indicator for two or one months before the first rival enter adjacent market served by the same fulfillment center. *post_entry* is and indicator for the month when the first rival enter adjacent market served by the same fulfillment center and the following months. The entry indicators in columns 2 and 4 refer only to entry to by Rami Levy or Victory. The regression also includes market fixed effects and month fixed effects.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

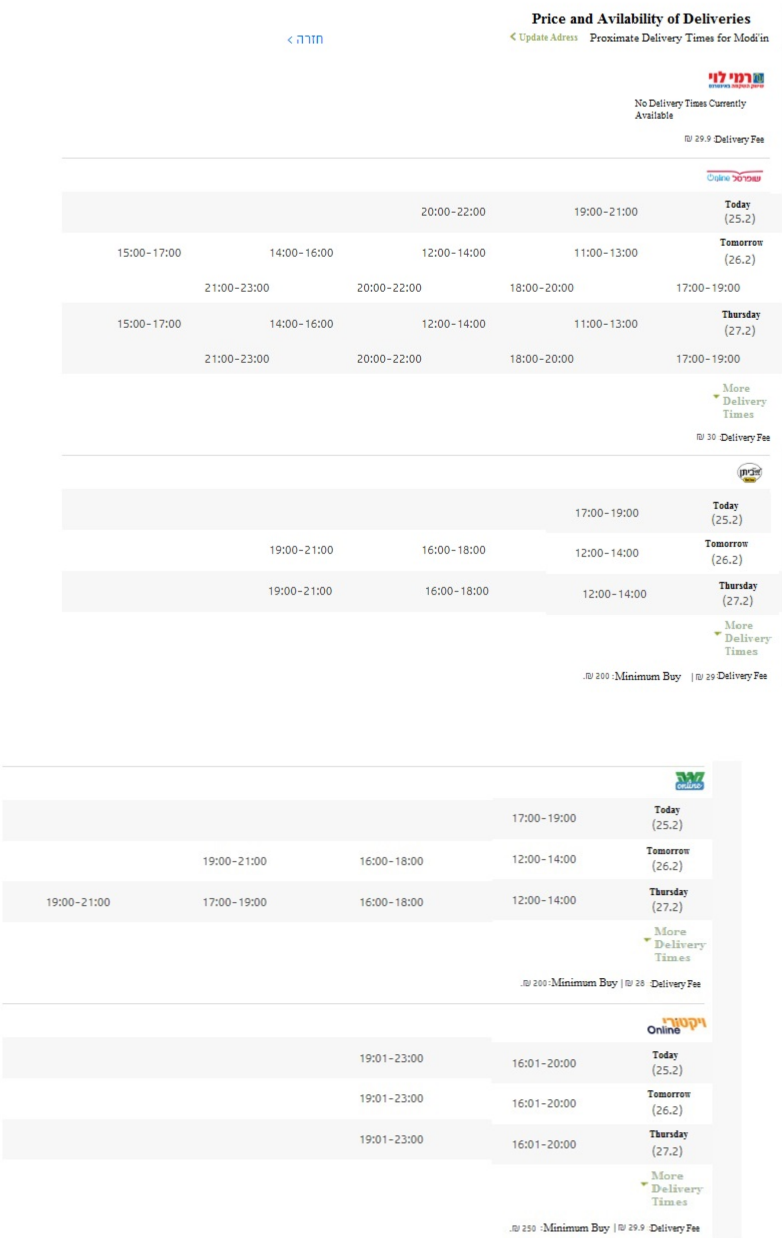
A Appendix

Figure A1: Online shopping platform - basket price



Notes: The figure shows a screenshot from MySupermarket.co.il webpage where consumers observe the respective price by each online retailer and can choose which online retailer they want to order from. Rami Levi, the heavy discount chain offers the cheapest price for this basket (NIS 749.37).

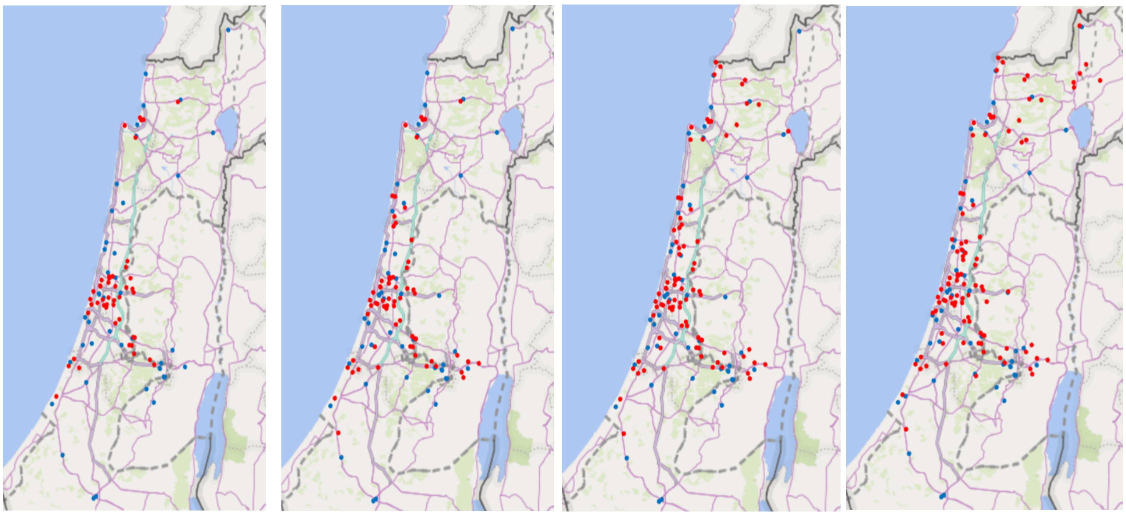
Figure A2: Online shopping platform - service time



Notes: The figure shows a screenshot from MySupermarket.co.il webpage where consumers observe available service times offered by online retailers that offer service to their address.

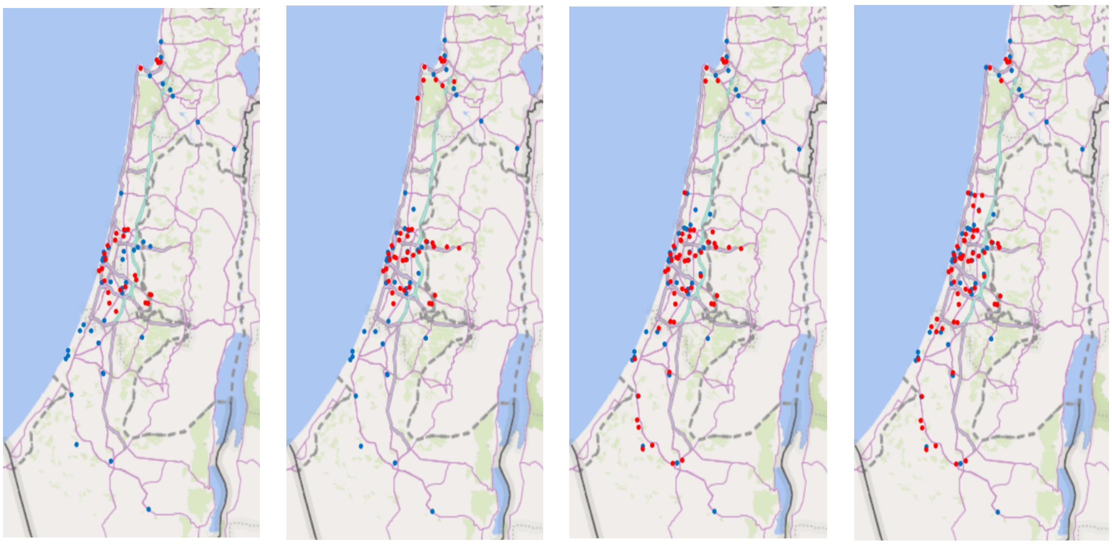
Figure A3: Chains' online service coverage (red) and location of traditional stores (blue)

I. Rami Levy



Aug. 2016 | Jul. 2017 | Jul. 2018 | Jul. 2019

II. Victory

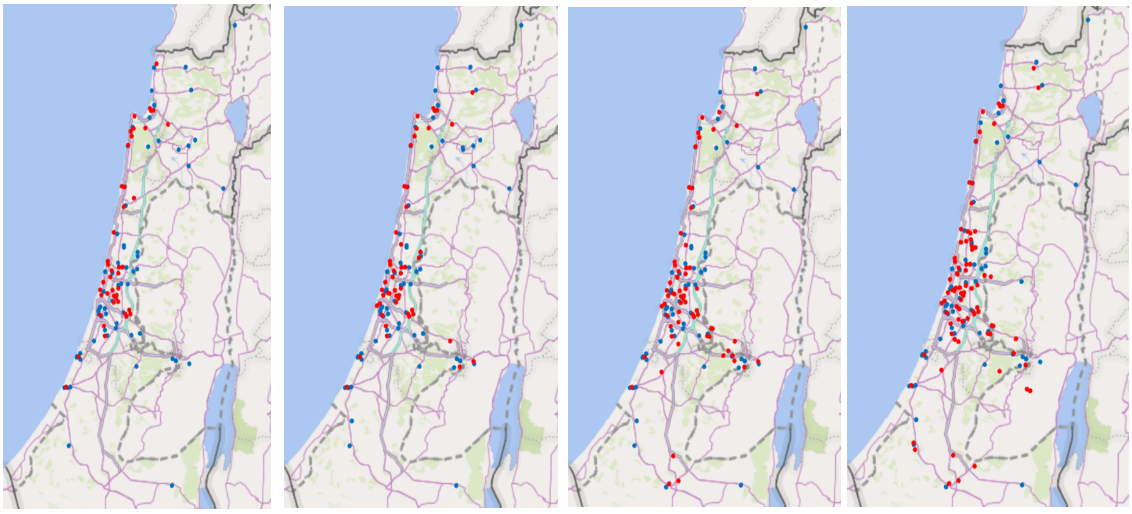


Aug. 2016 | Jul. 2017 | Jul. 2018 | Jul. 2019

Notes: The figures show the coverage of online service and the location brick-and-mortar stores for each year in our sample (2016, 2017, 2018, 2019). Panel I focuses on Rami Levy and Panel II on Victory. In 2016, both chains offered online service mostly at Tel Aviv metropolis. Over time, Rami Levy expanded its online service mostly towards the north and east. Victory expanded mostly towards the south of Israel.

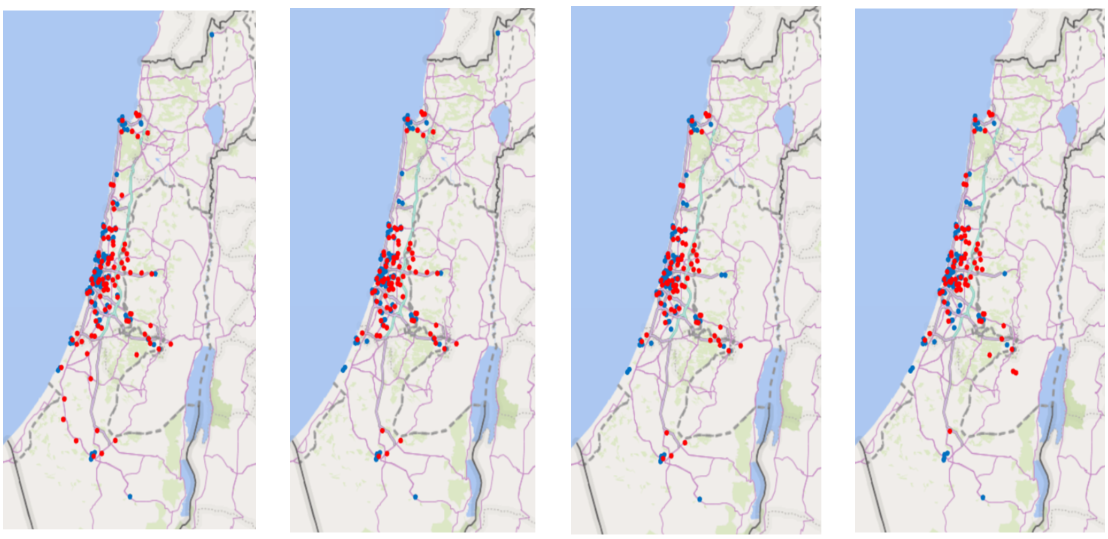
Figure A3: Chains' online service coverage (red) and location of traditional stores (blue) [Cont'd]

III. Yeinot Bitan



Aug. 2016 Jul. 2017 Jul. 2018 Jul. 2019

IV. Mega



Aug. 2016 Jul. 2017 Jul. 2018 Jul. 2019

Notes: The figures show the coverage of online service and the location brick-and-mortar stores for each year in our sample (2016, 2017, 2018, 2019). Panel III focuses on Yeinot Bitan and Panel IV on Mega. In 2016, Yeinot Bitan offered online service mostly at the Tel Aviv metropolis and along the northern coastal plain. Over time, it expanded primarily towards the east. Mega, the second largest chain in 2016, faced considerable difficulties and it limited its online service in some areas, such the southwest. Both Mega and Yeiont Bitan offer online service in regions where these chains operate brick-and-mortar stores.