

# Exercising Market Power Without Using Prices: Service Time in Online Grocery\*

Itai Ater<sup>†</sup> and Adi Shany<sup>§</sup>

<sup>†</sup>Tel Aviv University and CEPR

<sup>§</sup>Tel Aviv University

February 9, 2022

## Abstract

This paper studies how online grocers use service time to respond to local competition and demand conditions when prices are uniformly set at the national level. Using comprehensive data collected twice a week over three years from 180 Israeli localities, we first show that online grocers set identical prices in all markets where they operate. In contrast, service times are shorter in more competitive markets, on low-demand/low-utilization days of week, and for deliveries offered by high-priced grocers. Next, we exploit regional and temporal variation in entry decisions to show that incumbents reduce service time when facing entry, but only on low-demand/low-utilization days. This reduction begins shortly before entry and is greater in monopolistic markets and when the entrant poses a larger threat to the incumbent. Service time falls also in markets that do not experience entry yet are served by a fulfillment center serving markets facing entry. We use the newsvendor problem model to explain our findings, and emphasize the importance of both competitive and supply-side considerations when analyzing firms' responses, particularly when prices are unresponsive.

JEL: D83; L81; L66

Keywords: online grocery; service time; newsvendor problem; uniform pricing; entry

---

\*Itai Ater is an Associate Professor at the Coller School of Management, Tel Aviv University, and a Research Fellow at the CEPR. Adi Shany is an Assistant Professor at the Coller School of Management, Tel Aviv University. We thank Alon Eizenberg, Matthew Gentzkow, Lukasz Grzybowski, Oren Rigbi, Andrey Simonov, Kevin Tran and seminar and conference participants at Stanford GSB, Berkeley/SICS, IIOC, MaCCI, Paris Conference on Digital Economics, Tel Aviv University, Hebrew University, Bar Ilan University, Ben Gurion University and Bank of Israel for useful comments. Daniel Padon, Adi Omer and Daniel Caspi provided excellent research assistance. Financial support by Eli Hurvitz, Henry Crown, Falk Institutes and the Israeli Science Foundation (Grant No. 568/17) are gratefully acknowledged. E-mails: ater@post.tau.ac.il, adi.shany@taux.tau.ac.il

# 1 Introduction

Prices play a crucial role in the operation of markets. Standard models show that prices balance demand and supply, ensure efficient resource allocation and facilitate market clearing. Surprisingly, growing evidence shows that price-setting firms often behave very differently than what textbook models predict. In particular, multi-store retailers tend to set similar prices in environments characterized by very different demographic and competition conditions (e.g., [Cavallo et al. \(2014\)](#), [Cavallo \(2017\)](#), [Adams and Williams \(2019\)](#), [Hitsch et al. \(2021\)](#), [DellaVigna and Gentzkow \(2019\)](#)). Retailers do not adjust prices even when local demand and competition conditions drastically change ([Arcidiacono et al. \(2020\)](#), [Gagnon and López-Salido \(2020\)](#), [Goldin et al. \(Forthcoming\)](#)). These findings, which cast doubts on our understanding how markets operate, motivate our research questions: How do firms respond to changes in demand and competition without changing prices, and what is the role of operational capabilities in that respect? More broadly, how do firms exercise their market power, and how do markets clear when prices are unresponsive?<sup>1</sup>.

The online grocery market provides an excellent setting for addressing these questions and for studying the links between service quality, demand and competition. First, online grocers in many countries, including Israel which is the focus of this study, set identical prices in all local markets where they offer service ([Cavallo \(2017\)](#)). Second, sales in the online grocery have been growing rapidly and online retailers have been expanding into new local markets, already before the pandemic. In the U.S., the online grocery market more than doubled between 2016 and 2018, and it is the fastest growing purchase channel in the UK.<sup>2</sup> Our analysis exploits spatial and intertemporal changes in the competitive landscape to examine how online grocers adjust. Third, demand for online grocery is characterized by peak (pre-weekend) and off-peak (beginning of the week) demand periods. This within-week demand seasonality offers a unique opportunity to examine how incumbents respond to entry in distinct demand conditions in the same week and at the same market. Finally, service quality in online grocery is often determined at the local level, making an analysis that exploits variation in the nature of local demand and competition informative.

Our analysis focuses on service time, measured as the elapsed time between order time and the next available delivery time offered by a retailer. The prominence of service time, which is traditionally considered one of the most valuable measures of service in retail markets, has grown

---

<sup>1</sup>Recent papers also investigate how uniform pricing mitigates or exacerbates economic policies or shocks, such as minimum wage changes ([Leung \(2018\)](#)); propagation of local shocks across regions ([Daruich and Kozlowski \(2019\)](#); [Garcia Lembergman \(2020\)](#)); incidence of local tax changes ([Butters et al. \(2020\)](#)), and the provision of free-lunch in schools ([Handbury and Moshary \(2021\)](#)). Recent evidence shows that multi-unit firms often set uniform national wages ([Hazell et al. \(2021\)](#))

<sup>2</sup>See [www.businessinsider.com/online-grocery-report](http://www.businessinsider.com/online-grocery-report) and [www.statista.com/topics/3144/online-grocery-shopping-in-the-united-kingdom/](http://www.statista.com/topics/3144/online-grocery-shopping-in-the-united-kingdom/), respectively.

further with the rise of e-commerce and corresponding changes in customers' time preferences. Indeed, the success of companies such as Amazon, Fedex, Uber, Doordash, and Instacart depends on their ability to serve customers quickly, and before rivals do. Despite its importance, and probably due to data limitations, we are not aware of empirical studies that examine the impact of competition and demand conditions on service time. Service time in online grocery is a particularly important factor because online grocery shoppers know the available delivery times before they purchase. Recent surveys report that 46 percent of respondents abandoned their shopping carts online as a result of shipping times that were too long or not provided. Nearly 48 percent of shoppers used rapid delivery services.<sup>3</sup> Our findings show that firms strategically use service time when demand and competition conditions change, while operational considerations are also an important factor. For instance, incumbents improve service time more when facing entry in monopolistic markets compared to entry in competitive markets. The improvement in service time is considerably larger on low-cost/low-utilization days than on high-cost/high-utilization days.

To motivate our empirical analysis and to derive testable implications, in Section 2 we use the canonical newsvendor problem model (Arrow et al. (1951)). In the model, a retailer chooses capacity before knowing the actual demand level. The capacity choice highlights a classic trade-off between the costs of excess capacity (when demand turns out to be low), and the costs of limited capacity (when demand turns out to be high). Experiencing excess capacity implies unused costly resources, whereas limited capacity implies losing unserved orders today and future losses in case disgruntled customers buy elsewhere in subsequent purchases. We modify this trade-off and derive the following testable predictions. First, as the costs of adding capacity increase, online grocers choose a lower capacity level and offer longer service time. Second, high-priced online grocers, who are more concerned about not serving orders, choose a higher capacity level and offer shorter service time. Third, in environments where customers have more options to choose from, online grocers set shorter service time. Perhaps more importantly, we use the model to examine how entry by a competitor affects an incumbent's service time. We show that entry is expected to have a greater impact on service time (i) in more concentrated markets, (ii) when the capacity utilization rate is lower, and (iii) when the entrant poses a larger threat to incumbents.

The main data that we use to test these predictions, described in Section 3, include bi-weekly service time data for five online traditional grocery chains that were active between August 2016 and July 2019. During this period, we used a web crawler to collect data from 180 addresses that correspond to distinct local markets across Israel. The crawler was active twice a week, at midnight on Wednesday and on Saturday; representing high- (pre-weekend) and low- (weekend)

---

<sup>3</sup>See [www.mckinsey.com/industries/retail/our-insights/same-day-delivery-ready-for-takeoff](http://www.mckinsey.com/industries/retail/our-insights/same-day-delivery-ready-for-takeoff), and [coresight.com/research/from-quick-commerce-to-instant-needs-exploring-business-models-in-rapid-delivery/](http://coresight.com/research/from-quick-commerce-to-instant-needs-exploring-business-models-in-rapid-delivery/). We show that online shoppers are more likely not to buy from their regular grocer on days with long service time.

demand conditions, respectively.<sup>4</sup> For each market/address, and for each grocer serving that address, the crawler recorded the grocer’s available service time to that address, measured as the elapsed time between order time and promised delivery time. The number of retailers offering service to a particular address is our measure of competition in the corresponding market. Panel (a) of Figure 1 shows the relationship between service time and competition. The figure shows a clear pattern of a downward sloping service time curve for each of the five retailers. The larger the number of rivals in a market the shorter the service time offered. We supplement the crawler data with price data for the five online retailers active in the 180 local markets. We use the price data to show (Panel (b) of Figure 1) that each of the online grocers sets identical prices in all the local markets where it operates.

We take advantage of the panel structure of our data to identify the impact of entry on the incumbent’s service time. We implement a staggered difference-in-differences (DiD) design with two-way fixed effects estimation that exploits variation in the timing of entry of online grocers into new local markets. For instance, in the first month in our sample (8/2016), 72 local markets out of the 180 markets that we track were served by one online retailer. In the last month in our sample (7/2019), only 44 markets were local monopolies. The regression analysis compares service time offered by the incumbent in markets that experienced entry (treated markets) to service time in markets that did not experience entry (untreated markets) while controlling for time-invariant conditions within the same market, and time-variant effects which are fixed across markets. We use service times on high- and low- demand days to examine how the incumbent’s response differs across days characterized by high- and low- capacity utilization rates. The key assumption is that the timing of entry is uncorrelated with the incumbent’s service time, conditional on control variables. In Section 4.4 we provide evidence that entry decisions are likely driven by long-term demographic and regional operational considerations, and do not follow related expansions in the offline channel. In the analysis, we control for the presence of nearby physical stores operated by rivals, and verify that the results are unchanged when we use recent alternative staggered DiD estimation methods (Sun and Abraham (2020) and Borusyak et al. (2021)).

Our analysis includes both event-study DiD specifications, which accommodate the possibility of dynamic treatment effects, and static DiD specifications. The results, presented in Section 4, show that incumbents reduce service time when facing entry. The improvement in service time is larger and significant when the costs of reducing service time are relatively low, and when the benefits of doing so are higher. In particular, service time falls on low-demand/low-utilization days of the week, and when entry takes place into monopolistic markets. Our estimates show that

---

<sup>4</sup>We use longitudinal customer-level data from a large online grocery platform to show that demand for online grocery is considerably larger on pre-weekend days than on weekends. We also use these data to document switching patterns across online grocers, thereby identifying which retailers pose a larger threat to the incumbent.

incumbents' service time falls by about 13 percent in monopolistic markets and on low-demand days. The effect of entry is larger by 25 percent when we restrict attention to entry by rivals that pose a larger threat to the incumbent. In contrast, on high-demand/high-utilization days we do not find evidence for service time improvements surrounding market entry. Importantly, the drop in service time on low-demand days begins two months before actual entry takes place, suggesting that improvements are not driven by demand shifts that likely occur after entry. Thus, we interpret pre-entry improvements in service time as evidence that the incumbent strategically improves service time to accommodate entry. In contrast, the observed improvement in service time in the post-entry period can be attributed to both strategic motives and to the incumbent's available resources after consumers switch to the entrant. In the final step of the analysis, we explore how increased competition in one market affects service time in adjacent markets. We examine how entry in one market affects service time in markets that do not experience entry, yet are served by the same fulfillment center as markets that face entry. Our findings indicate that entry in one market triggers improvements also in adjacent markets, and that this improvement is greater when we focus on entry by aggressive entrants.

This paper contributes to several strands of literature. First, this is one of few studies that uses detailed market-level data on a measure of service, and to our knowledge, the first study that empirically examines the impact of competition on service time. While there exists an extensive theoretical literature on service time, capacity and competition (e.g., [Luski \(1976\)](#), [De Vany and Saving \(1977, 1983\)](#), [Allon and Federgruen \(2007, 2008, 2009\)](#), [Kalai et al. \(1992\)](#), and [Cachon and Harker \(2002\)](#)), empirical research is virtually nonexistent.<sup>5</sup> Due to lack of data, existing studies use the distance between sellers and buyers as a proxy for transaction cost and service time (e.g., for eBay ([Einav et al. \(2014\)](#), [Hortaçsu et al. \(2009\)](#)), and for Amazon ([Houde et al. \(2017, 2021\)](#)). Given the role of service industries in the world's GDP (e.g., [Buera and Kaboski \(2012\)](#)), the scarcity of empirical evidence concerning the determinants of service quality is quite striking. Moreover, with the rapid growth of e-commerce and online markets, the importance of service time is increasing, emphasizing the need to fill the gap in the literature. Second, our paper contributes to the literature on competition and non-price attributes. The intuition that firms with market power can maximize their profits by degrading the service they offer is often cited but rarely tested empirically. Perhaps as a result, competition policy tends to focus relatively little attention on service competition. We exploit cross-sectional and intertemporal variations in competition, service and demand levels, making it easier to infer causal relationships. The within-week and market variation in demand levels that we use is particularly important since it allows us

---

<sup>5</sup>[Allon et al. \(2011\)](#) uses annual measures of waiting time at fast-food restaurants to study their impact on market shares. Other empirical papers ([Lu et al. \(2013\)](#) and [Png and Reitman \(1994\)](#)) examine how waiting times affect purchase decisions, though not in the context of competition or demand conditions.

to examine how firms adjust service time when they experience different utilization rates. Probably closest to our study is the work by [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 does not examine how capacity considerations affect his findings.<sup>6</sup> A common feature of previous studies is that they rely on quality measures that are observed post-purchase (e.g., a flight’s on-time-performance) or only upon arriving at the store (e.g., product availability). These studies implicitly assume that consumers can compare quality attributes across retailers, and determine where to buy based on quality differences. In our case, service time is observed at the time of purchase and can be compared across different online retailers prior to the purchase decision.<sup>7</sup> Our findings also highlight the importance of capacity constraints when firms make choices regarding non-price attributes such as service time. These findings are related to the literature on productivity ([Syverson \(2011\)](#); [De Loecker and Syverson \(2021\)](#)), showing that competition positively affects productivity, measured by service time, though this effect depends on the capacity utilization rate (see [Butters \(2020\)](#) for a related argument).

Our paper is also related to the nascent literature on uniform pricing. Several papers show that multi-store firms often set similar prices in different environments (e.g., [DellaVigna and Gentzkow \(2019\)](#), [Hitsch et al. \(2019\)](#), [Cavallo et al. \(2014\)](#), [Adams and Williams \(2019\)](#), [Ater and Rigbi \(2020\)](#)). Recent studies also show that multi-store firms do not change prices following large demand and competition shocks ([Arcidiacono et al. \(2020\)](#), [Gagnon and López-Salido \(2020\)](#), [Goldin et al. \(Forthcoming\)](#)).<sup>8</sup> We add to this strand of literature by showing that firms use service time to cope with changes in demand and competition, when they are unable to change prices. Moreover, we highlight a novel channel through which welfare is reduced due uniform pricing. In particular, we provide evidence that uniform pricing hinders efficient resource allocation and results in longer service time. These findings are also related to the urban and transport economics literature. Economists have long advocated for the adoption of peak-load pricing to improve the use of public resources and reduce time inefficiencies ([Vickrey \(1963, 1969\)](#)). Our work demonstrates that competition might mitigate time-inefficiencies but are unlikely to eliminate them.

---

<sup>6</sup>Existing studies in this literature predominantly use measures of product quality, rather than service. These studies include [Olivares and Cachon \(2009\)](#) who study the relationship between the number of car dealers in the local market and inventory, [Berry and Waldfogel \(2010\)](#) who explore the relationship between restaurant quality and market size, and [Mazzeo \(2003\)](#) who investigate the relationship between an airline’s on-time performance and on-route competition. [Prince and Simon \(2014\)](#) show that airlines facing entry or a threat of entry by Southwest Airlines degrade on-time performance. [Orhun, Venkataraman, and Chintagunta \(2015\)](#) study how incumbents respond to entry in the US movie-exhibition industry. They find that an incumbent facing entry does not improve quality, measured by the extent to which it screens popular and recent movies.

<sup>7</sup>Few papers study online grocery and examine how behavior changes when consumers shop food online, and how the online channel affects traditional food stores ([Pozzi \(2012, 2013\)](#), [Chintagunta et al. \(2012\)](#), [Gil et al. \(2020\)](#)).

<sup>8</sup>Different explanations were proposed for why multi-store firms set uniform pricing. [DellaVigna and Gentzkow \(2019\)](#) suggest that firms set uniform pricing due to large managerial costs; [Hitsch, Hortaçsu, and Lin \(2021\)](#) claim that lack of data at the store level hinders optimal pricing decisions, whereas [Ater and Rigbi \(2020\)](#) point toward fairness and brand-image concerns as the main reason why food retailers adopt uniform pricing. In a similar vein, [Hazell et al. \(2021\)](#) suggest that firms set uniform wages because wage comparisons matter to workers.

## 2 Theoretical Framework for Service Time in Online Grocery

We use the newsvendor problem to motivate our empirical analysis and to derive testable predictions that we later examine 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. Grocers also need to recruit and train workers to collect ordered items, 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 locally.

The newsvendor problem offers a useful setting to examine a firm's optimal capacity choice when it faces 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 not purchase from the vendor, and also the goodwill costs borne when customers find out that they cannot complete the orders due to unavailability or long service times. Below, we assume that these goodwill costs are increasing with the number of alternatives that customers face. That is, when customers have more options to choose from they are more likely to switch when they realize that their regular vendor sets long service times. A related risk is that a customer who buys from a rival, may choose to continue buying from that rival also in the future. Choosing a high capacity level may reduce the risk of incurring overage costs but also entails a different types of costs, known as underage costs. In particular, if realized demand turns out to be below the capacity level, the retailer will not fully utilize its resources (e.g., redundant trucks or unproductive workforce). Thus, in selecting the capacity level, a retailer faces a trade-off between overage and underage costs. Below, we use the newsvendor problem to examine how the trade-off between overage and underage costs varies with the price that retailers set, the level of competition and the marginal cost of capacity. We also examine how entry changes the choice of optimal capacity. While the retailer may change the capacity in the long run, in the short run the retailer faces high adjustment costs, and uses the installed capacity in a given market in both low and high demand days.

### 2.1 Set up

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 available resources, such as the number of delivery trucks and labor (e.g., drivers, pickers). Let  $c$  be the

marginal cost associated with additional capacity, such as the availability of in-store labor to pick orders or the costs of additional delivery trucks. The demand for the online grocery service is uncertain, distributed with continuous cdf  $F(\cdot)$ , where  $R$  is a fixed margin earned for each order. Let  $\gamma$  represents the goodwill cost when the retailer cannot offer service to a customer or if the service time is excessively long. The goodwill costs are increasing in the number of alternatives a customer faces. Thus, a retailer decides on its optimal capacity,  $K$ , in order to maximize expected profits:

$$\text{Max}_K \int_0^K (Rx - cK)dF(x) + \int_K^\infty (RK - \gamma(x - K) - cK)dF(x)$$

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 unused resources:

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

This trade-off underscores the importance of three factors: 1) marginal cost of capacity ( $c$ ); 2) price ( $R$ ), and 3) goodwill cost ( $\gamma$ ). To apply this trade-off in our context, we assume that increased capacity translates into shorter service time, denoted by  $s$ , i.e.,  $\frac{\partial s}{\partial K} \leq 0$ . Positive service time (i.e., orders are not served immediately) is reasonable given that orders are made at different hours, and retailers deliver orders in trucks that contain several orders to the same locality. Changes in  $c$ ,  $R$  and  $\gamma$  are predicted to affect service time as follows. First, when marginal capacity costs are higher retailers are more willing to risk losing unserved customers (rather than to increase capacity) resulting in lower capacity and longer optimal service time ( $\frac{\partial s}{\partial c} > 0$ ). Second, a retailer who sets high prices ( $R$ ), is more concerned about losing customers, and will therefore invest in capacity and offer shorter service time ( $\frac{\partial s}{\partial R} < 0$ ). Third, when goodwill costs ( $\gamma$ ) are high retailers are concerned about losing customers, and therefore increase capacity and set shorter service time ( $\frac{\partial s}{\partial \gamma} < 0$ ). In Section 3.3 we use the data to test these predictions. Moreover, below we derive additional predictions that consider how changes in competition – an increase in the value of  $\gamma$  – affect service time offered by the incumbent. In particular, we examine how the incumbent responds to entry by a rival firm, and how this response depends on demand, competition and cost conditions. In the empirical analysis we take advantage of the panel structure of our data to test these predictions. Notably, since we examine how service time changes before and after entry in the same market, we are able to control for potential confounding factors that the analysis that uses only cross-sectional data does not.



## 2.2 The effects of entry on service time

Following entry of a rival firm,  $\gamma$  increases and the incumbent is interested in offering shorter service times ( $\frac{\partial s}{\partial \gamma} < 0$ ) to reduce the risk that customers will start using the entrant's services. We term this effect the *strategic effect* of entry. The magnitude of the strategic effect depends on the respective costs and benefits of improving service time. When the benefits are high or the costs are low, we expect that the incumbent will improve service times more than otherwise. Below we explain how we use pre-entry competition conditions, capacity utilization and the identity of the entrant to proxy for these costs and benefits.

**Pre-entry competition level.** As more online retailers operate in a market, the marginal effect of entry on service time that the incumbent firm sets falls. Formally, this prediction is captured by  $\frac{\partial^2 s}{\partial \gamma \partial \gamma} > 0$ . This prediction is a standard prediction in entry models that 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 utilization rate.** Changes in service time following entry depend on the extent to which an incumbent already utilizes its existing capacity. If the utilization rate is high, then the incumbent will find it costly to improve service time when a rival enters. In contrast, when the utilization rate is low then the incumbent can rely on available/non-utilized resources to improve service time. 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 days of the week. Accordingly, on low-demand days, when not all trucks or all workers are working to deliver orders, the utilization rate is low and the incumbent finds it easier to improve service time when facing entry. On high-demand days, the utilization rate is high and the incumbent cannot easily reduce service time.

**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, then the incumbent is more likely to respond by reducing service time. We consider entrants that are more likely to attract an incumbent's customers as more aggressive. For instance, when an entrant offers lower prices, the incumbent may be more concerned about customers switching, making the sensitivity of service time to  $\gamma$  greater. In [Section 3.3](#), we use customer level data to characterize customers' patterns of substitution across the online grocers and classifying entrants as aggressive.

**Pre and post effects of entry.** The main effect of entry on service time is the strategic effect, where the incumbent improves service time to cope with competition. A second, more nuanced, effect of entry on service time is through its potential indirect impact on capacity costs. Following entry, the number of orders received by the incumbent is expected to fall as at least

some customers shift to the entrant. As a result, the incumbent’s marginal cost of capacity,  $c$ , might change. The direction of this change depends on the shape of the service cost function. If delivery costs are convex, then the fall in the number of orders should result in lower  $c$ , which in turn leads to faster service time. We refer to this potential 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 the latter effect as a negative demand effect. Both the strategic and positive demand effects imply that incumbent’s service time decreases post-entry. To empirically separate these effects, with the broader aim identifying the strategic effect of service time, we look at how service time changes *before* a new rival enters. In particular, pre-entry changes in service time cannot be explained by demand changes and are therefore driven only by strategic considerations. Thus, improved service time before entry likely reflects an incumbent’s decision to allocate resources to improve customers’ goodwill, thereby reducing the likelihood of future switching to the entrant.

### 3 Industry Background, Data and Preliminary Evidence

#### 3.1 The online grocery market in Israel

In a standard online grocery service, consumers do not visit a physical store; instead they log-in a dedicated retailer’s website, select the items they wish to buy, choose the delivery time and pay. The ordered items are later delivered to their home-address at the promised delivery time.<sup>9</sup>

The market share of online grocery sales in Israel during the study period is estimated below 10%, and sales in the online channel have been growing, already before the pandemic. Our analysis focuses on the five supermarket chains that offered online grocery and traditional grocery service between 2016 and 2019: Shufersal, Mega, Rami Levy, Victory and Yenot Bitan. The joint market share of these supermarket chains in the retail food market was 68% in 2014.<sup>10</sup> Shufersal is the dominant player in the online segment. According to its 2018 annual financial report, 13.6% of its annual sales come from the online channel, up from 4.2% in 2014 and 11.5% in 2017. Shufersal’s market share in the online segment is estimated at about 70%.<sup>11</sup> Shufersal, with 283 physical stores in 2016, is also the largest player in the traditional segment. Mega, the second largest chain

<sup>9</sup>The first online grocery services were introduced in the US in the 1990’s. Initial prospects that online grocery will quickly become a primary shopping channel were not met. Early ventures failed due to logistical challenges in the “last mile” and in particular in delivering perishable goods in a timely manner to consumers’ home address. 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>.

<sup>10</sup>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>.

<sup>11</sup>See <https://www.ynet.co.il/articles/0,7340,L-4907570,00.html>.

in terms of number of stores, entered bankruptcy proceedings in early 2016 and divested many of its stores. In July 2016, Israel’s competition authority approved a merger between Yenot Bitan and Mega. Yet, the operations of these two chains, and particularly their online services were kept separate. The two remaining chains, Rami Levy and Victory underwent a rapid growth during the study period. Rami Levy, the second largest chain in terms of overall turnover, operated 27 stores in January 2015 and 52 stores in June 2019. Victory, the fifth largest chain in terms of overall volume increased its number of stores, from 29 stores to 51 stores. In 2019, 7.2% of Rami Levy’s sales and 4% of Victory’s sales were from the online channel.<sup>12</sup>

Online grocers set prices and delivery fees at the chain-national level. Prices and fees are identical across all the markets where the grocers offer service. Each chain operates an online channel that involves a dedicated website (e.g., Shufersal.co.il, www.rami-levy.co.il) where consumers can complete their order, observe delivery areas and available delivery time slots for each area/locality. Orders are delivered to the address specified by the customer at the time of purchase. Shufersal’s orders are delivered from 34 large distribution centers across Israel. Each of these centers serves several nearby localities, and in most cases is used also as a regular store that serves in-store consumers. According to Article 18A in the Israeli Consumer Protection Law, a delay of more than two hours in delivery may lead to a IS 300 fine (about \$90). Before retailers enter a new locality, they need to recruit workers (pickers/drivers), obtain specialized food delivery trucks, modify the website, and typically also the interior structure of the physical store where orders are picked and distributed from. Entry is also often accompanied with a local advertising campaign to raise awareness to the new service.

## 3.2 Data

Our main empirical analyses use service time and competition data that we obtained using a web-crawler. We augment these data with rich data on online grocery prices, the location of physical stores and demographic information. We also use customer-level data from a large online shopping grocery platform. Below we describe more details on each of the data sources that we use.

### 3.2.1 Service time and competition data

Our main data source is a web crawler that accessed the websites of each of the five supermarket chains described above, twice a week, each week between August 2016 and July 2019. The crawler was active at midnight on Wednesday and on Saturday, which we later show are days with high and low demand levels for online grocery service. On each visit to a chain’s website, the crawler recorded whether the retailer offered online service to any one of the 180 different addresses in

---

<sup>12</sup>The online grocery sales figures for Mega and Yenot Bitan, which are not publicly traded, are not available but are estimated to be lower than those of the other publicly-traded chains.

our sample and if yes, it also recorded the earliest available home-service time slot offered by each chain for each address. Each address corresponds to a different locality (i.e., an area served by a distinct local or municipal authority), and except the largest cities, retailers either offer online service to all addresses in a given locality or not at all. Accordingly, we consider each address as a separate market. To avoid over-identifying entries and exits that are driven by the malfunctioning of the crawler, we aggregate the crawler data to the monthly level. We use the crawler records to build our main variables of interest. The number of retailers that offer service to each address serves as our measure of local competition on a given date. This measure of competition is useful since consumers are likely to order groceries to their home-address. The elapsed time between the crawler recorded time and the earliest available home-service time slot is our measure for service time in each market on a given day.

### **3.2.2 Price data**

We use detailed data on the monthly average prices of 52 popular items sold by the five online retailers in all local markets where they operate. We use these prices to calculate the basket price sold by each of the five online grocers at each of the 180 local markets. For Shufersal, the incumbent, we also compute the basket price for Sunday and for Thursday following Saturday's and Wednesday's crawler times for each week in our sample. We obtained the price data from Pricez.co.il, a price comparison platform. These price data are available following Israel's 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 to demonstrate whether and how online grocers use prices in different demand and markets conditions.

### **3.2.3 Store and demographic data**

We used the chains' annual reports and media coverage to collect data on their physical stores including opening dates of new stores. We also identify the locations of Shufersal's 34 distribution centers, and match these centers to the 180 local markets based on the closest driving distance. Figure D1 in Appendix D shows in black dots the location of the 180 local markets in our sample and in red dots the locations of the incumbent's distribution centers. We also use demographic information on the 180 local markets. This information, obtained 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. The socioeconomic index for each locality is based on demographic and economic variables. The periphery index is based on the distance between each locality and Tel Aviv.

### 3.2.4 Online grocery shopping data

We use proprietary data from MySupermarket.co.il, an online platform that enables users to shop at each of the five online grocers. MySupermarket’s users can compare prices and contemporaneously observe available service times offered by each retailer. We use data on all orders performed through MySupermarket during the data collection period. These data cover about 700,000 orders by nearly 85,000 customers. About 85 percent of these customers live in one of the 180 localities that we track. We use these data to show that demand on pre-weekend days is considerably larger than on weekends; that customers are more likely to switch to a different online vendor on days with long service time, and that the online grocers, Rami Levy and Victory, pose a larger threat to Shufersal compared to Mega and Yenot Bitan. See Appendix A for more details on the data from MySuperMarket.

## 3.3 Preliminary evidence

Our sample is a balanced sample of 180 local markets. For each market, we construct the monthly average service time for potential orders made on Wednesday and on Saturday. Below we present evidence that supports the predictions described in Section 2.1, and that also serve as background for the estimation of the effect of competition on service time.

### 3.3.1 Service time, competition and prices

Figure 1 presents separately for each online retailer the relationship between competition and service times (Panel (a)) and between competition and prices (Panel (b)). Panel (a) plots the mean of the monthly average of service time (without distinguishing between Wednesday and Saturday) for each retailer against the number of active online retailers in the market. Panel (b) plots the monthly average price of a basket containing 52 popular items sold by each retailer in each local market against the number of active online retailers in that market.

In Panel (a) we observe a clear pattern of a downward sloping curve of service time, for each of the online grocers. Service time is considerably shorter in more competitive markets. For instance, Shufersal’s mean service time in markets where it is the only online grocer is 42 hours. In markets where Shufersal competes with four online retailers, its mean service time is only 22 hours. According to Panel (b) of Figure 1 an online grocer sets identical prices in all the markets that it serves, irrespective of the level of competition. Also, grocers choose different price levels and there exists a strong negative relationship between service time and the basket price offered by a given grocer: pricier retailers offer shorter service time. For instance, the chain that sets the lowest prices, Rami Levy, offers the longest service time. Shufersal offers short service times

and sets high prices. Overall, the patterns shown in Figure 1 regarding the relationship between competition and service time, and the relationship between price and service time, are consistent with the predictions outlined in Section 2.1.

### 3.3.2 Service time in different demand and capacity utilization conditions

To further explore the service time prediction derived in Section 2, we distinguish between days with low and high rates of capacity utilization. To this end, we first show that demand for online grocery on pre-weekend days is larger than on days at beginning of the week. Figure A3 presents the cumulative percent of orders for online grocery through MySupermarket on Tuesday and Wednesday, and on Friday and Saturday (i.e., 48 hours before the crawler was active on Wednesday and Saturday nights, respectively). The Figure shows that the cumulative percent of orders is about 3 times larger on Wednesdays than on Saturdays.<sup>13</sup> Second, we assume that available capacity in the online channel (i.e., labor and capital) on high-demand days is not considerably larger than on low-demand days. This assumption is reasonable given the large difference in demand for online grocery in pre-weekend and early days of the week, and also since 57.9% of sales in physical stores are also on pre-weekend days (Wednesday (19.4%), Thursday (22.9%) and Friday (15.6%)) (Storenext (2015)). Accordingly, in-store workers are unlikely available for work in the online channel on pre-weekend days. Also, food delivery trucks follow strict regulations and are generally not available on the rental market. Accordingly, the number of trucks is usually fixed within the same week, at least in the short-run. Taken together, it is reasonable to assume that grocers experience low utilization rates on early days of the week, while high utilization rates on pre-weekend days.

Panel (a) of Figure 2 builds on the distinction between high vs. low demand/utilization days, and presents Shufersal’s service times in markets with different competition levels. The figure shows that for a given competition level, service times on high-demand/high-utilization days are longer than on low-demand/low utilization days. Furthermore, service times are shorter and the differences in service times between high- and low- demand days become smaller as a market becomes more competitive. For instance, Shufersal’s mean service time in markets where it is a monopoly is 52 hours on Wednesdays and 36 hours on Saturdays. In markets with 5 online retailers, the mean service time is 25 hours on Wednesdays and 20 hours on Saturdays.<sup>14</sup> Panel (b) in Figure 2 presents a time series of Shufersal’s average basket price on Sunday and on Thursday in each

<sup>13</sup>Since service times are determined based on the back-log of orders and average service time is longer than 24 hours, it makes sense to aggregate orders over periods longer than 24 hours. Alternative definitions generate similar patterns. Panel (a) of Figure A4 also shows that MySupermarket customers are more likely to switch and buy from a vendor which is not their regular vendor on days characterized with long service time.

<sup>14</sup>In Israel grocery deliveries are unavailable on Friday evening and on Saturday. To take this into account, we subtract 37 hours (from Friday 6pm to Sunday 7am) from deliveries scheduled after Saturday. Ignoring this aspect, would make the differences in service times between low- and high- demand days (Saturday vs. Wednesday) even larger. Notably, this subtraction does not qualitatively affect any of the estimation results.

week. We chose Sunday and Thursday because these are the days following the crawler operating time at midnight on Saturday and Wednesday, respectively. As shown in the figure, unlike 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 on days where demand is low (Sundays) and on days where demand is high (Thursdays). The patterns shown in Figure 2 support the predictions laid out in Section 2.1. Figure B1 in Appendix B shows the patterns for the other retailers.

### 3.3.3 Market structure evolution and demographic differences

Panel (a) in Figure 3 shows the evolution of available online grocery service across the local markets in our sample. In August 2016, 72 markets were served only by Shufersal, and in 31 markets at least four online retailers were active. Over the 3 years competition intensified. In July 2019, 44 local markets were served only by Shufersal, and 49 markets were served by at least four online retailers. Panel (b) in Figure 3 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, Yenot Bitan and Rami Levy experienced massive growth in the number of markets that they serve, growing respectively from 27, 46 and 48 markets in August 2016 to 54, 80 and 96 markets in July 2019. Figure B2 in Appendix B shows the growth patterns in the number of physical stores operated by each retailer, except Shufersal, versus the growth in their online services. While Rami Levy, Victory and Yenot-Bitan have expanded both their online and traditional operations, we do not observe a clear association between the timeline of these expansions.

Overall, we observe 198 entries during the sample period. At least one entry took place in 129 markets, and in 55 of these markets the incumbent/Shufersal was a monopoly before entry. Our regression analysis examines the effect of entry on the incumbent’s service time by focusing on the 129 entries that are the first entry to a market during the sample period. Figure B3 in Appendix B plots the number of first entries that we observe in each month for all 129 markets, and for the 55 markets in which the incumbent was a monopoly before entry. The figure shows that the timing of entry to these markets is spread over three years of the sample period with no specific period of massive entries. We also observe some exits during the sample period and control for these exits in the regression analysis.

Table 1 presents demographic information on all 180 markets, classified according to whether they did or did not experience entry during the sample period. Odd columns 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 combined. Even columns show for each characteristic the mean difference between markets that experienced entry and those that did not

experience entry, alongside results of t-tests comparing these characteristics. The patterns suggest that online retailers are more likely to offer service in more populated and dense localities, 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 that did not, in particular for less competitive markets.

## 4 The effect of entry on service time

The empirical patterns presented above lend support to the service time predictions derived in Section 2.1. Nevertheless, we are cautious not to interpret these patterns as causal, since they do not take into account other factors that may affect service time in these markets. In particular, market density or different demand patterns may vary across markets and can explain why service time is shorter in localities where more retailers offer service. To address these concerns, in this section we examine how incumbents adjust service time once a new firm enters the market. Our focus is on markets that the incumbent was active during the all sample period and that experienced at least one entry (129 markets) or no change in competition level (51 markets) during the sample period. In markets that experienced multiple entries, we restrict attention to the first entry, which overall account for 70% of entries in the sample.

Figure 4 uses the raw service time data to show the mean service time of Shufersal in the 6 months before and after entry. The figure distinguishes between low- and high- demand days of the week and between different market structures (monopolies, duopolies and monopolies, and all markets). The figure shows that service times are shorter on low-demand days. Also, on both low- and high- demand days, service times are shorter when more grocers offer service. More importantly, the decline in service times occurs 2-3 months before entry and the reduction is more pronounced on low-demand days. The pre-entry change in service time is related to our discussion in Section 2.2, where we emphasized that entry could affect service time either by changing  $\gamma$  (a strategic effect) or through a change in  $c$  (a demand effect) due to a shift in demand after entry. Notably, pre-entry changes in service time are unlikely related to demand changes.

The patterns observed in Figure 4 motivate our empirical strategy. We employ a generalized difference-in-difference (DiD) design with staggered treatment using standard two-way fixed effect specification. This estimation strategy takes advantage of the massive expansion by online retailers into new local markets, and compares service time offered by the incumbent in markets that experienced entry (treated markets) to service time offered by the incumbent in markets that did not experience entry (untreated markets). The variation in the timing of entry into markets allows us to control for time-invariant conditions within the same market, and time-variant effects



which are fixed across markets. This approach mitigates concerns that contemporaneous trends confound with the effect of entry that we are interested in. Nevertheless, in order to identify the causal treatment effect of competition on service time, we must assume the existence of parallel trends. That is, absent the entry, the difference in potential service time offered by the incumbent would be the same across all markets and all months, conditional on market and month fixed effects. This requirement is likely to be satisfied in our setting, given that we focus on the service time offered by the incumbent (like Goolsbee and Syverson (2008) and Matsa (2011)). In Section 4.4 we further provide suggestive evidence that entry decisions are predominantly driven by the entrant’s operational capabilities rather than the incumbent’s capabilities. Moreover, if entrants do time their entry and focus on markets where the incumbent faces stricter capacity constraints, then our estimates are potentially biased downward.

We begin the analysis with event study DiD specifications, which accommodate the possibility of dynamic treatment effects on the incumbent’s service time before and after a rival enters. Next, we build on the event-study results to run a static DiD specifications (parametric) estimation which quantify the causal effect of entry on the incumbent’s service time. In both analyses we examine the incumbent’s response in different demand and competition conditions.

#### 4.1 Event-study estimation

Our first empirical exercise is a nonparametric estimation of an event study design. The primary advantage of this 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 an anticipation response before entry takes place. The basic event study specification has the following form:

$$\text{Log}(\text{delivery\_time})_{it} = \delta_i + \alpha_t + \sum_{k=-j}^{j+} \beta_k \mathbb{1}[t - \text{entry}_i = k] + u_i \quad (2)$$

where the dependent variable,  $\text{Log}(\text{delivery\_time})_{it}$ , is log of the average service time offered by Shufersal in locality  $i$  in month  $t$ .  $\delta_i$  and  $\alpha_t$  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.  $\text{entry}_i$  is the month of entry for market  $i$ , and  $\mathbb{1}[t - \text{entry}_i = k]$  is an indicator for being  $k$  months from entry. Standard errors are clustered at the locality level to account for within-market correlation in the error term. We focus on the coefficients of Shufersal’s (log) service time for each month relative to the month of entry (the event). Markets that did not experience entry during the sample period are used as control group. Since markets in the control group may experience different trends in service time, we use in the analyses both all untreated markets and only not-yet treated markets

(i.e., markets that did not experience entry, and have the same competition level as treated markets pre-entry).<sup>15</sup>

The key coefficients of interest are  $\beta_k$ , which capture the change in the dependent variable at a given  $k$  month relative to its average value in the excluded period, which are months earlier than the  $j$  months before entry. Since we want to allow the effect of entry on service time to materialize before entry, we use the  $j$  months before entry as the excluded period. In our baseline analysis, the subscript  $j$  is running from 6 months before entry to 6+ months after entry and the excluded period is more than 6 months before entry. We use six months before and after entry since we want to capture the short-term impact of entry. We estimate equation 2 separately for low- and high- demand days of the week (Saturday and Wednesday, respectively) and for sub-samples that include different pre-entry market structures. Including “lags” in equation 2 enables us to identify the timing of the pre-entry response and to test for parallel trends in the outcome variables for the different sub-samples and for low and high demand days.

Recent econometric literature shows that event-study coefficients might be biased if there are heterogeneity in treatment effects between groups of units treated at different times (De Chaisemartin and d’Haultfoeuille (2020); Goodman-Bacon (2021), Borusyak et al. (2021); Callaway and Sant’Anna (2020); Sun and Abraham (2020)). In these cases, each event time coefficient may be “contaminated” with effects from other cohorts.<sup>16</sup> In Appendix E, we verify that our findings are not sensitive to using alternative estimators proposed by Sun and Abraham (2020) and Borusyak et al. (2021) which allow for heterogeneous treatment effects.

#### 4.1.1 Results

Figure 5 presents the results of the event-study analysis. The figure graphs the point estimates and the 90 percent confidence intervals for the  $\beta_k$  coefficients in equation 2 where  $k$  runs from -6 (six months before entry) to 6 (six months after entry, and  $k=6$  equals one also for more than six months after entry). Estimation results are shown separately for low- and high- demand days of the week. Panel (a) reports the estimated effects of entry on the incumbent’s service time in markets which were monopolies before entry. Sub-figure (b) focuses on markets that were served by up to 2 online grocers, and sub-figure (c) reports the results for all markets. Dark signs are the coefficients from a sample that includes all markets that did not experience entry during the sample period as control group. Light signs are the estimated coefficients from a sample that uses

<sup>15</sup>Figure C1 in Appendix C also shows results from an analysis that do not include a control group and rely only on treated markets. All results are qualitatively the same.

<sup>16</sup>As shown by Goodman-Bacon (2021) and Callaway and Sant’Anna (2020), the inclusion of a control group can alleviate this issue as long as the control group is not treated yet (since already treated units may face a different trend in their outcome variable). In the presence of heterogeneous treatment effects, the ideal control group would be never or not-yet-treated markets that did not experience an entry during our sample period. Hence, in our main analysis, we report results using either a control group that includes all untreated markets or a control group that includes only untreated markets that have the same competition level as treated markets. Finally, in Figure C1 in Appendix C we report results from an analysis that only uses untreated markets.

includes as control markets that did not experience entry and have the same competition level as treated markets before entry (i.e., for treated monopoly markets, the untreated markets are markets where Shufersal was a monopoly throughout the sample period). Figure C1 in Appendix C shows estimation results when using only treated markets. Figure C2 in Appendix C shows the estimation results from a specification that expands the event window to 12 months before and after entry.

The results in Panel (a) show that that service time in pre-entry monopoly markets dropped by about 10 to 20 percent on low demand days. The drop in service time is statistically significant two months before actual entry took place. The post-entry coefficients are also negative and significant on low-demand days, and about the same magnitude as the coefficients in the two-months preceding entry. Our estimates for service time on high-demand days do not show a significant change in service time, before or after entry. Also, in more competitive markets (Panels (b) and (c)) we find a smaller impact on service time on low-demand days, and an insignificant change in service time on high-demand days. Overall, the event study results support the predictions in Section 2.2. We observe a decline in service time offered by the incumbent surrounding entry, and this decline is larger in more concentrated markets. Also, the effect is significant only on low demand days, when the rate of capacity utilization is lower. Moreover, we find that service time improves already before entry takes place. The results shown in Figures C1 and C2 are similar and strengthen the robustness of our analysis.

## 4.2 Difference-in-differences estimation

The event-study estimation results uncover two short-term patterns in response to entry: a significant drop in service time in the two months preceding entry, and a non-dynamic nature of response following entry. We build on these patterns and continue the analysis by using a parametric DiD estimation of the static effect of entry, while distinguishing between pre- and post- months of entry. In particular, we estimate the following two-way fixed effect DiD regression:

$$\text{Log}(\text{delivery\_time})_{it} = \delta_i + \alpha_t + \rho_1 \text{pre\_entry}_{it} + \rho_2 \text{post\_entry}_{it} + \lambda X'_{it} + u_i \quad (3)$$

where  $\text{pre\_entry}_{it}$  is a dummy for the 1-2 months preceding entry into the local market and  $\text{post\_entry}_{it}$  is a dummy for the months after entry into the local market. We also estimate specifications including  $X'_{it}$  which is a vector of time varying variables. These variables include the number of brick-and-mortar stores operated by rivals in the local market (we use the number of stores within a 10km radius of the address but results are similar when we use alternative definitions

as shown in Table C1 in Appendix C), and dummies for exits and subsequent entries in the same market to capture potential changes in the number of online retailers beyond the first entry. We also add a specific Shufersal’s fulfillment center linear time trend which captures potential time trend in service time (e.g., technological changes). Standard errors are clustered at the locality level to account for within-market correlation in the error term. Similar to the event-study estimation, we estimate equation 3 separately for low and high demand days, and for sub-samples of markets that include different pre-entry market conditions. We also use the parametric estimation to examine how the incumbent’s response varies with the identity of entrants, and to examine the effect of entry on service time in adjacent non-entered markets.

#### 4.2.1 Results

**Main results.** Table 2 presents the estimated results of equation 3. Columns 1-3 focus on low demand days and columns 4-6 on high demand days. Panel A reports the estimated effects of entry on the incumbent’s service time in pre-entry monopoly markets. Panel B reports the estimated effects of entry on the incumbent’s service time in markets that were served by up to 2 online grocers, and Panel C reports the estimated effects of entry for all markets. The results shown in Table 2 are based on an analysis that uses all untreated markets as the control group. Similar results are obtained when we use untreated markets with the same pre-entry competition level as the control group, or do not include a control group and exploit the variation in entry timing for identification (see Table C2 in Appendix C).

The results in Table 2 are consistent with the event-study results, and are not sensitive to the inclusion of time varying variables. On low-demand/low-utilization days and in pre-entry monopoly markets, a significant decline of 10-13 percent in service times is observed two months before entry. This drop continues at the same level also in the months after entry. The estimates in more competitive markets are smaller, and not always statistically significant. The estimates on high demand days, at all competition levels, are statistically insignificant. Moreover, the estimated effects of entry are not sensitive to the opening of a physical store by a rival nearby, and/or to subsequent changes in the number of online grocers.

**Response by entrant type.** The theoretical framework shows that the impact of entry by aggressive retailers on service time is expected to be larger. In that case, the incumbent is more concerned about consumers switching, and may choose to improve service time more than when a non-aggressive retailer enters. Below, we consider Rami Levy and Victory as aggressive online grocers, and examine how their entry affects service time by the incumbent.<sup>17</sup> Table 3 reports

---

<sup>17</sup>To identify aggressive and non-aggressive retailers, we use the longitudinal customer level data from MySuperMarket to show that Shufersal’s loyal customers are likely to switch to Rami Levy and Victory when they choose not to order from Shufersal (36% switch to Rami Levy and 28% switch to Victory). A loyal customer of Shufersal is a customer who used the online grocery platform more than 10 times, and ordered from Shufersal at least 60% of

the parametric estimation results, showing that on low demand days the incumbent’s service time falls when one of the aggressive retailers enters. The magnitude of the effect is nearly 25% larger than in the main specification and is significant also for entries into competitive markets. Thus, in pre-entry monopolistic markets (Panel A), the incumbent lowers service time by 16.2 percent before entry, and by 12.2 percent after entry. According to panel C, which shows the results for all markets, the incumbent reduces service time by 7.7 and 6.8 percent before and after entry, respectively. On high-demand days, we find the effect on post-entry service time is negative and marginally significant in monopolistic markets. These results are consistent with the theoretical predictions outlined in Section 2.2.

**Response in adjacent markets.** We also examine how service time changed in markets that were not entered but are adjacent to markets that experienced entry. We use this analysis to explore whether there are spillovers in the production of service time, taking advantage of the fact that several local markets are served by the same fulfillment center. In the analysis below, we distinguish between entry to nearby monopolistic markets and entry to nearby markets which are more competitive, and also between entries by aggressive retailers and all retailers. To conduct the analysis, we classify each of the 180 markets in our sample to Shufersal’s 34 fulfillment centers, and focus on the 51 markets that did not experience any change during the entire sample period (and are served by 22 fulfillment centers). We repeat the parametric estimation (equation 3) where the entry dummy variables refer to entry in a nearby market. In particular, these indicators receive the value of one for the first entry that occurred in a nearby local market that is served by the same fulfillment center.

Panel A in Table 4 reports the results when entry is by any retailer, and Panel B reports the results when entry is by an aggressive retailer. Columns 1, 2, 5 and 6 present the results for all entry events, and columns 3, 4, 7 and 8 focus on entry to monopolistic markets. The results suggest that when an aggressive retailer enters a nearby market, the incumbent improves service time by 8-10% in adjacent markets that are served by the same distribution center. This improvement is observed only on low demand days after entry. A possible explanation for this finding is that entry by an aggressive retailer leads to a significant decline in demand on the market that experienced entry, which frees resources that are used by the incumbent’s fulfillment center to improve service time in adjacent markets.<sup>18</sup> An alternative explanation for the drop in service time in adjacent markets is preemption, where entry in one market raises the propensity of entry in an adjacent market. Thus, the incumbent reduces service time in an effort to preempt these entries. To provide

---

those orders. In our data, there are 2,861 loyal customers of Shufersal. See Appendix A for more details. Figure 1 also shows that Rami Levy offers the cheapest basket and Victory offers the shortest service time. Forty percent of entries are by Rami Levy, and 60% of entries to monopolistic markets are by Rami Levy.

<sup>18</sup>The findings that service times do not change before entry may imply that our results in the main specification are not confounded by spillover effects to the 51 control markets. The negative effect on the control market after entry might suggest that our post-entry estimates in the main specification are a lower bound for the true effect.

very suggestive evidence that is consistent with a preemptive motive, in Panel C we distinguish between entries by aggressive retailer to nearby markets when the entrant (Rami Levy or Victory) was either already active or not in the adjacent market. In particular, we estimate:

$$\begin{aligned} \text{Log}(\text{delivery\_time})_{it} = & \delta_i + \alpha_t + \tau_1 \text{pre\_entry}_{it} + \tau_2 \text{pre\_entry}_{it} * \text{active\_entrant}_i \\ & + \tau_3 \text{post\_entry}_{it} + \tau_4 \text{post\_entry}_{it} * \text{active\_entrant}_i + \lambda X'_{it} + u_i \end{aligned} \quad (4)$$

where  $\text{pre\_entry}_{it}$  and  $\text{post\_entry}_{it}$  are dummy variables for the one or two months before entry, and for the months after entry by an aggressive entrant to a nearby market, respectively (as in Panel B in Table 4).  $\text{active\_entrant}_i$  is an indicator for whether the entrant is active in the adjacent market  $i$ . Panel C in Table 4 reports the estimated coefficients of  $\tau_1$  and  $\tau_3$  which refer to the effect in adjacent markets where the entrant was not active, and also the estimated linear combination of  $\tau_1 + \tau_2$  and  $\tau_3 + \tau_4$  which refer to the effect of entry in adjacent markets where the entrant was active. The results show that the reduction in service time in adjacent markets occurs only in markets that were not served by that retailer. In cases where the retailer already operated in the adjacent market at the time of a nearby entry, we do not find that the incumbent reduces service time. This finding may suggest that the incumbent offers better service time to deter subsequent entries in adjacent markets.

### 4.3 Interpretations

The empirical analysis shows that the incumbent sets shorter service times when it faces entry. Service times fall primarily on low-demand days, in concentrated markets and when a stronger rival enters. The change in service times begins before entry takes place and continues afterwards. Our preferred interpretation for these findings is that the incumbent exercises its market power using service time. The pre-entry improvements reflect strategic efforts by the incumbent to generate loyalty or lock-in among existing customers, making them less likely to switch to the rival after it enters. This loyalty interpretation is similar to what [Goolsbee and Syverson \(2008\)](#) propose as an explanation why incumbent airlines reduce prices before Southwest enters a route where they operate. In the theoretical framework presented in Section 2.2, the risk that a customer switches is captured by  $\gamma$ , and it rises when the entrant is more aggressive and when entry takes place into a monopolistic market. Accordingly, in these cases, we expect that the incumbent's response will be larger. Also, changes in service time due to entry might depend on the extent to which an incumbent utilizes its existing capacity. Our results show that when the utilization rate is high (i.e., on high demand days) the incumbent do not improve service time, probably since it is too expensive to do so.

Can alternative explanations give rise to the same patterns? One such explanation is that

the reduction in service time is a consequence of a drop in demand for the incumbent’s online service. If customers begin using the entrant’s service, then the incumbent may have available resources that it could use to offer short service time. Thus, this explanation posits that the effect of entry on service time is through the effect on  $c$  rather than through  $\gamma$ . To distinguish between the two alternative explanations, and to argue why we think that our findings reflect a deliberate attempt to fend off rivals, we distinguish between changes in service time before and after entry takes place. In particular, improvements in service time due to a change in  $c$  can materialize only after entry takes place. If service time falls before entry then this change is likely due a strategic response by the incumbent. Indeed, post-entry changes in service time can be explained by either strategic or cost reasons. Our analysis regarding the impact of entry by aggressive retailers on service in adjacent markets (panel C in Table 4) could suggest that strategic-preemptive reasoning are potentially important also after entry takes place.

Does the incumbent know that entrants intend to enter before they actually enter? While we do not have direct information on this issue, we note that offering online service requires non-trivial investments, such as recruiting and training new in-store workers, hiring specialized trucks, modifying physical stores for distribution and changes in the online grocery website. Also, before entry grocers sometimes engage in local advertising. Many of these actions are observable, certainly for rivals that operate in the same local market. Accordingly, it is plausible to assume that the incumbent knows that a rival intends to enter a local market few months before actual entry takes place. In fact, the fact that we observe a change in service time only 2-3 months before entry might strengthen our interpretation that this improvement is costly to implement but at the same time is required to strengthen loyalty among customers. Conversations we had with industry insiders confirm this assertion.

#### 4.4 Identification concerns

A causal interpretation of the impact of entry on service time might not be valid if the timing of entry is correlated with lower demand for the incumbent’s services. In such a case, the shorter service time is driven by unanticipated lower demand for the incumbent’s service rather than by a deliberate action by the incumbent. While we lack direct data on demand to test this conjecture directly, below we explain why we think that a rival’s entry is unlikely correlated with pre-entry demand for the incumbent’s online grocery service.

**Entry decisions.** Entry decisions depend on the socio-demographic characteristics of local markets, such as population size, expected population growth and average income. These factors are unlikely to significantly change during the time period we study, and the market fixed-effects that we include likely capture them. Figures D2 and D3 in Appendix D describe the expansion

of the four Shufersal’s rival retailers. The maps show for each point in time for four points in our sample period what are the markets that each retailer offers online services (red dots) and the location of the retailers’ physical stores (blue dots). The patterns shown in the figures 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. This implies that retailers tend to enter localities in regions where they already offer online service, thereby taking advantage of operational efficiencies (Holmes (2011)). Also, Figure B3 in Appendix B which show the distribution of entries that we are focus on in our analysis, further mitigating concerns about strategic timing of entry.

**Substitution between online and traditional channels.** Offering online service in a local market might be related to a prior decision to expand in the traditional channel in the same area. In such a case, the drop in the incumbent’s service time might be driven by reduced demand to its online service, as customers begin to buy at a newly-opened physical store. To address this concern, in the regression we flexibly control for the presence of physical stores (including new stores). The estimated results in Section 4.2.1 (columns 2, 3 5 and 6) account for the presence and for opening of physical stores in a 10km-radius around the crawler address of the market. Tables C1 in Appendix C show similar results when we use alternative definitions to account for the offline channel effect: presence of physical stores in a 5km- or 15km-radius around the crawler address of the market (columns 1, 2, 5 and 6) and the distance (in km driving) to the first or second physical store (columns 3, 4, 7 and 8). The results indicate that the effect of entry on the incumbent’s service time is not sensitive to the presence of or the distance to a rival store. Figure B2 in Appendix B and Figures D2 and D3 in Appendix D further indicate that the timing of entry does not seem to depend on the opening of a physical store in the local market. For instance, only four entries by Victory and Yenot-Bitan (two each) occurred one month after they opened a store in a 15km radius from the address served by the online service. All other entries we consider were at least 6 months after the opening of a new store in a 15-km radius.

**Local infrastructure.** Service times offered by the incumbent may improve due to local changes in infrastructure (e.g., roads). If these changes take place at the the same time that a rival firm decides to enters, then we may erroneously attribute the service time improvement to the impact of entry. We believe this concern is unlikely to hold given that we examine more than a hundred entry decisions, and that service time improves more when aggressive rivals enter and in more concentrated markets. These patterns are unlikely systematically related to improvements in infrastructure. Also, we do not find that service time improves on high-demand days. Arguably, if infrastructure changes are important then they should also reduce service time on high-demand



days. In addition, the estimated results in Section 4.2.1 (columns 3 and 6) account for specific Shufersal's fulfillment center linear time trend which captures potential time trend in service time (e.g., technological changes).

## 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 three years of bi-weekly longitudinal data on service time and prices in 180 markets, we first show that online grocers set shorter service times in more competitive markets and on low-demand days of the week. Also, high-priced retailers offer shorter service time. Our main empirical analysis takes advantage of the rapid expansion of online retailers into new local markets and considers the effect of entry on the incumbent's service time.

We find that incumbents improve service time shortly before a rival enters, and the effect is larger in concentrated markets and on low demand weekdays. Entry also affects service time in adjacent markets that are served by the same distribution center as markets that experienced entry. On high-demand days, when incumbents' utilization rate is high, we do not find that incumbents' service time changes. Overall, these results suggest that firms use service time to exercise their local market power. They strategically respond to competition and demand conditions, and operational considerations also affect the extent to which they respond. Using a non-price attribute, such as service time, is effective in a setting where firms adopt a uniform pricing strategy. Nevertheless, firms may and probably do use service time also in markets where prices vary with demand and competition. We note that the regression analysis captures the short-term effect of entry on service time. In the long-run, as likely reflected in the cross-sectional evidence, firms can more easily adjust their capabilities by adding relevant inputs or changing production technology. The distinction between a long and a short run response might explain why we find large differences in service time between low and high demand levels in the cross-sectional analysis. In the short-run, firms face high adjustment costs on high-demand days, and hence in the regression analysis we do not find that the incumbent improves service time on these days. We leave this issues for further research.

Our results also speak to the debate about uniform pricing. Growing evidence shows that national chains set similar prices in very different environments. These findings cast doubt on the relevancy of standard models of competition which emphasize the role of prices. In that sense, our findings can help explain how firms that set identical prices across markets use service time to

exercise their market power, indirectly also allowing markets to clear. A possible interpretation for our findings is that service time is 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, prices are expected to be lower in more competitive markets and in low-cost environments. In the standard model, entry has a greater impact on prices in monopolistic markets and when incumbents face low marginal costs. Remarkably, our findings offer a parallel evidence for service time in markets with fixed prices. Thus, service time is higher in monopolistic markets and on high demand days of the week. Also, 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 are used to exercise market power and eventually also facilitate market clearing.

## References

- Brian Adams and Kevin R Williams. Zone pricing in retail oligopoly. American Economic Journal: Microeconomics, 11(1):124–56, 2019.
- Gad Allon and Awi Federgruen. Competition in service industries. Operations Research, 55(1): 37–55, 2007.
- Gad Allon and Awi Federgruen. Service competition with general queueing facilities. Operations Research, 56(4):827–849, 2008.
- Gad Allon and Awi Federgruen. Competition in service industries with segmented markets. Management Science, 55(4):619–634, 2009.
- Gad Allon, Awi Federgruen, and Margaret Pierson. How much is a reduction of your customers’ wait worth? an empirical study of the fast-food drive-thru industry based on structural estimation methods. Manufacturing & Service Operations Management, 13(4):489–507, 2011.
- Peter Arcidiacono, Paul B Ellickson, Carl F Mela, and John D Singleton. The competitive effects of entry: Evidence from supercenter expansion. American Economic Journal: Applied Economics, 12(3):175–206, 2020.
- Kenneth J Arrow, Theodore Harris, and Jacob Marschak. Optimal inventory policy. Econometrica: Journal of the Econometric Society, pages 250–272, 1951.
- Itai Ater and Oren Rigbi. Price transparency, media and informative advertising. Working paper, 2020.
- Steven Berry and Joel Waldfogel. Product quality and market size. The Journal of Industrial Economics, 58(1):1–31, 2010.
- Kirill Borusyak, Xavier Jaravel, and Jann Spiess. Revisiting event study designs: Robust and efficient estimation. Unpublished working paper, version May, 19:2021, 2021.
- Timothy F Bresnahan and Peter C Reiss. Entry and competition in concentrated markets. Journal of Political Economy, 99(5):977–1009, 1991.
- Francisco J Buera and Joseph P Kaboski. The rise of the service economy. American Economic Review, 102(6):2540–69, 2012.
- R Andrew Butters. Demand volatility, adjustment costs, and productivity: An examination of capacity utilization in hotels and airlines. American Economic Journal: Microeconomics, 12(4): 1–44, 2020.

- R Andrew Butters, Daniel W Sacks, and Boyoung Seo. How do national firms respond to local shocks?: Evidence from excise taxes. Evidence from Excise Taxes (September 29, 2020), 2020.
- Gérard P Cachon and Patrick T Harker. Competition and outsourcing with scale economies. Management Science, 48(10):1314–1333, 2002.
- Brantly Callaway and Pedro HC Sant’Anna. Difference-in-differences with multiple time periods. Journal of Econometrics, 2020.
- Alberto Cavallo. Are online and offline prices similar? evidence from large multi-channel retailers. American Economic Review, 107(1):283–303, 2017.
- Alberto Cavallo, Brent Neiman, and Roberto Rigobon. Currency unions, product introductions, and the real exchange rate. The Quarterly Journal of Economics, 129(2):529–595, 2014.
- Pradeep K Chintagunta, Junhong Chu, and Javier Cebollada. Quantifying transaction costs in online/off-line grocery channel choice. Marketing Science, 31(1):96–114, 2012.
- Diego Daruich and Julian Kozlowski. Macroeconomic implications of uniform pricing. FRB St. Louis Working Paper, (2019-024), 2019.
- Clément De Chaisemartin and Xavier d’Haultfoeuille. Two-way fixed effects estimators with heterogeneous treatment effects. American Economic Review, 110(9):2964–96, 2020.
- Jan De Loecker and Chad Syverson. An industrial organization perspective on productivity. National Bureau of Economic Research, 2021.
- Arthur S De Vany and Thomas R Saving. Product quality, uncertainty, and regulation: The trucking industry. The American Economic Review, 67(4):583–594, 1977.
- Arthur S De Vany and Thomas R Saving. The economics of quality. Journal of Political Economy, 91(6):979–1000, 1983.
- Stefano DellaVigna and Matthew Gentzkow. Uniform pricing in us retail chains. The Quarterly Journal of Economics, 134(4):2011–2084, 2019.
- Liran Einav, Dan Knoepfle, Jonathan Levin, and Neel Sundareshan. Sales taxes and internet commerce. American Economic Review, 104(1):1–26, 2014.
- Etienne Gagnon and David López-Salido. Small price responses to large demand shocks. Journal of the European Economic Association, 18(2):792–828, 2020.
- Ezequiel Garcia Lembergman. Multi-establishment firms, pricing and the propagation of local shocks: Evidence from us retail. Available at SSRN 3813654, 2020.

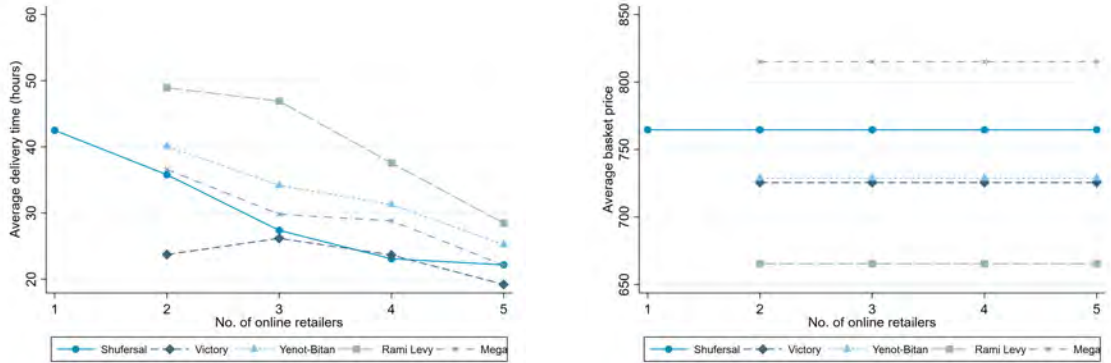
- Ricard Gil, Evsen Korkmaz, and Ozge Sahin. Can free-shipping hurt online retailers? Quantitative Marketing and Economics, 18(3):305–342, 2020.
- Jacob Goldin, Tatiana Homonoff, and Katherine Meckel. Issuance and incidence: Snap benefit cycles and grocery prices. American Economic Journal - Economic Policy, Forthcoming.
- Andrew Goodman-Bacon. Difference-in-differences with variation in treatment timing. Journal of Econometrics, 2021.
- Austan Goolsbee and Chad Syverson. How do incumbents respond to the threat of entry? evidence from the major airlines. The Quarterly Journal of Economics, 123(4):1611–1633, 2008.
- Jessie Handbury and Sarah Moshary. School food policy affects everyone: Retail responses to the national school lunch program. Available at SSRN 3897936, 2021.
- Jonathon Hazell, Christina Patterson, Heather Sarsons, and Bledy Taska. National wage setting. 2021.
- Günter J Hitsch, Ali Hortaçsu, and Xiliang Lin. Prices and promotions in us retail markets: Evidence from big data. University of Chicago, Becker Friedman Institute for Economics Working Paper, (2019-117), 2019.
- Günter J Hitsch, Ali Hortaçsu, and Xiliang Lin. Prices and promotions in us retail markets. Quantitative Marketing and Economics, pages 1–80, 2021.
- Thomas J Holmes. The diffusion of wal-mart and economies of density. Econometrica, 79(1):253–302, 2011.
- Ali Hortaçsu, F Martínez-Jerez, and Jason Douglas. The geography of trade in online transactions: Evidence from ebay and mercadolibre. American Economic Journal: Microeconomics, 1(1):53–74, 2009.
- Jean-François Houde, Peter Newberry, and Katja Seim. Economies of density in e-commerce: A study of amazon’s fulfillment center network. National Bureau of Economic Research, 2017.
- Jean-François Houde, Peter Newberry, and Katja Seim. The impact of distance and taxes on amazon. working paper, 2021.
- Ehud Kalai, Morton I Kamien, and Michael Rubinovitch. Optimal service speeds in a competitive environment. Management Science, 38(8):1154–1163, 1992.
- Justin H Leung. Minimum wage and real wage inequality: Evidence from pass-through to retail prices. The Review of Economics and Statistics, pages 1–47, 2018.

- Yina Lu, Andrés Musalem, Marcelo Olivares, and Ariel Schilkrut. Measuring the effect of queues on customer purchases. Management Science, 59(8):1743–1763, 2013.
- Israel Luski. On partial equilibrium in a queuing system with two servers. The Review of Economic Studies, 43(3):519–525, 1976.
- David A Matsa. Competition and product quality in the supermarket industry. The Quarterly Journal of Economics, 126(3):1539–1591, 2011.
- Michael J Mazzeo. Competition and service quality in the us airline industry. Review of Industrial Organization, 22(4):275–296, 2003.
- Marcelo Olivares and Gérard P Cachon. Competing retailers and inventory: An empirical investigation of general motors’ dealerships in isolated us markets. Management science, 55(9):1586–1604, 2009.
- A Yeşim Orhun, Sriram Venkataraman, and Pradeep K Chintagunta. Impact of competition on product decisions: Movie choices of exhibitors. Marketing Science, 35(1):73–92, 2015.
- Ivan PL Png and David Reitman. Service time competition. The Rand Journal of Economics, pages 619–634, 1994.
- Andrea Pozzi. Shopping cost and brand exploration in online grocery. American Economic Journal: Microeconomics, 4(3):96–120, 2012.
- Andrea Pozzi. The effect of internet distribution on brick-and-mortar sales. The RAND Journal of Economics, 44(3):569–583, 2013.
- Jeffrey T Prince and Daniel H Simon. Do incumbents improve service quality in response to entry? evidence from airlines’ on-time performance. Management Science, 61(2):372–390, 2014.
- Storenext. Summary of 2015, main trends in the israeli consumer product market. Technical report, StoreNext, 2015.
- Liyang Sun and Sarah Abraham. Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. Journal of Econometrics, 2020.
- Chad Syverson. What determines productivity? Journal of Economic literature, 49(2):326–65, 2011.
- William S Vickrey. Pricing in urban and suburban transport. The American Economic Review, 53(2):452–465, 1963.
- William S Vickrey. Congestion theory and transport investment. The American Economic Review, 59(2):251–260, 1969.

Figure 1: Service time and prices as a function of competition and demand levels

(a) Mean service time by no. of active retailers

(b) Mean basket price by no. of active retailers

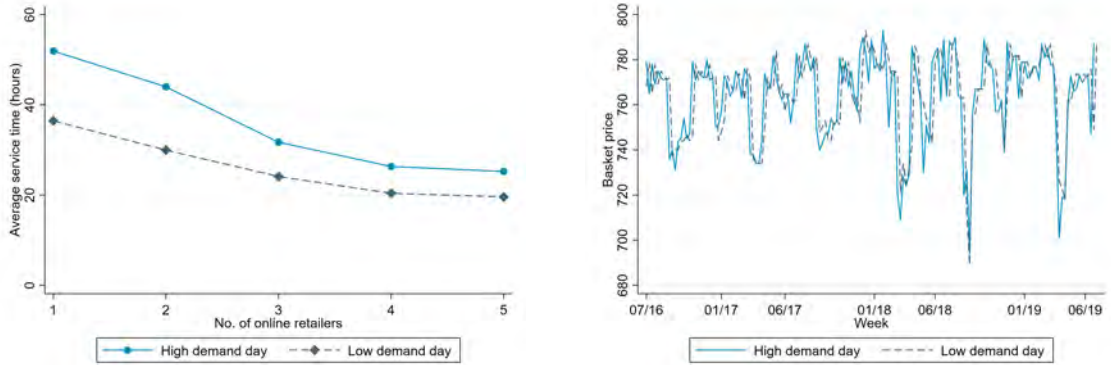


Notes: Panel (a) shows the average service time for each retailer by the number of active online retailers in each market. Panel (b) shows the average basket price for each retailer by the number of active online retailers in each market. Both graphs are based on monthly data from August 2016 to July 2019 (prices for Victory are based on monthly data from November 2017 to July 2019, since before November 2017 Victory was not active in a market with only two active retailers). 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. For instance, Shufersal’s mean service time in markets where it is the only online grocer is 42 hours. In markets where Shufersal competes with four online retailers, its mean service time is only 22 hours. Panel (b) shows that different grocers choose different price levels, but these price levels are identical across markets characterized with different levels of competition. Finally, we observe a strong negative relationship between service times and prices. Pricier 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 sets high prices.

Figure 2: Service time and prices as a function of competition & demand (incumbent only)

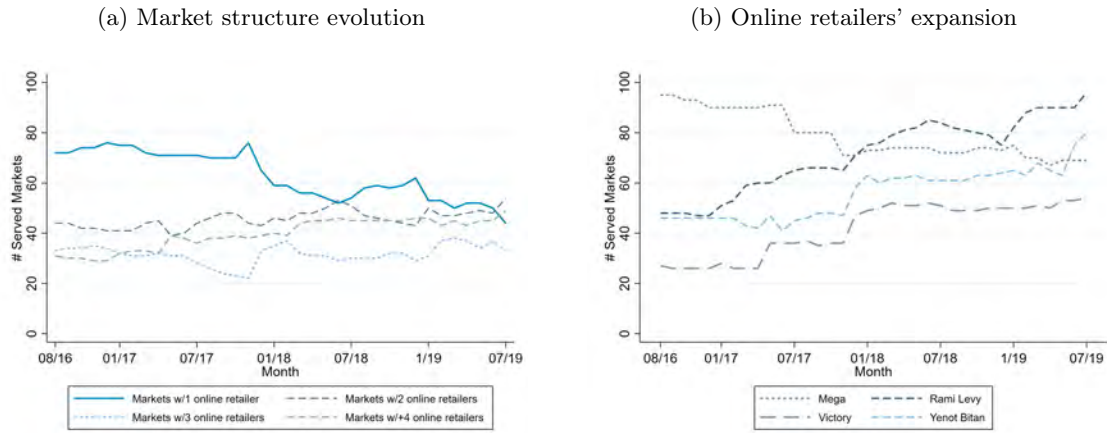
(a) Mean service time by low/high demand days

(b) Basket price by low/high demand days



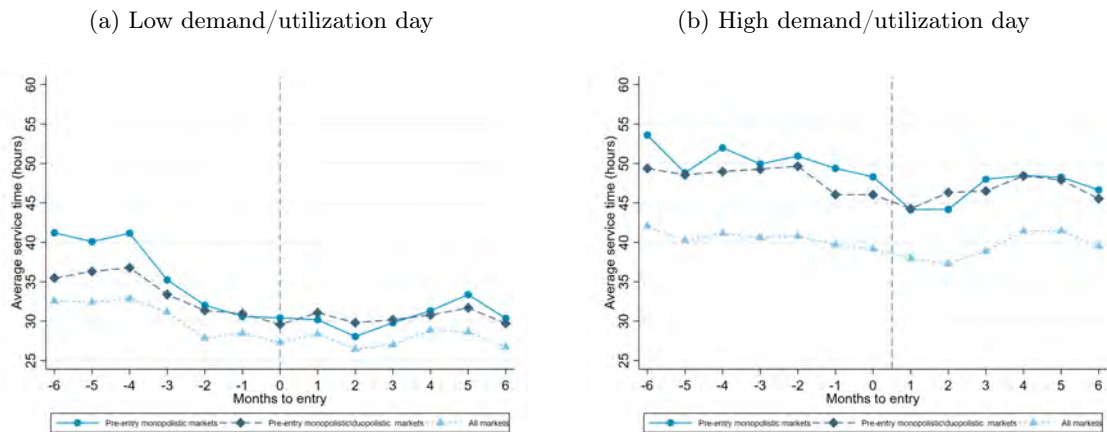
Notes: Panel (a) shows the average service time of Shufersal as a function of the number of active online retailers in each market, separately for low- demand/low utilization days and for high demand/high utilization days, based on monthly data from August 2016 to July 2019. Panel (b) shows the daily price of a basket of 52 products sold by Shufersal’s online channel, separately for the days following the crawler operating time – Sundays (low demand day) and Thursdays (high demand day) – for each week from August 2016 to July 2019. The figure shows that service times on high-demand/high-utilization days are longer than on low-demand/low utilization days. Service times are shorter and the differences in service times between high- and low- demand days are smaller in more competitive markets. Unlike 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 on days where demand is low (Sundays) and on days where demand is high (Thursdays).

Figure 3: Changes in market structure and online retailers' expansion



Notes: Panel (a) shows the number of markets at different competition levels in each month during the sample period. In August 2016, 72 markets were monopolies, and there were only 31 markets in which at least four online retailers were active. Over the 3 years, competition intensified, and in July 2019, 44 local markets were served by one retailer, and 49 markets were served by at least four online retailers. Panel (b) displays, for each online retailer, the number of markets served by that retailer over the sample period. We exclude Shufersal from this figure since it operates in all 180 markets throughout the sample period. As can be seen in the figure, Victory, Yeinet Bitan and Rami Levy experienced massive growth in the number of markets that they serve, growing respectively from 27, 46 and 48 markets in August 2016 to 54, 80 and 96 markets in July 2019. Also, Mega, which faced considerable financial difficulties during the period, exited many of the local markets it served. Overall, we observe at least one entry in 129 of the markets in our sample.

Figure 4: Service time before/after entry, by competition and demand levels

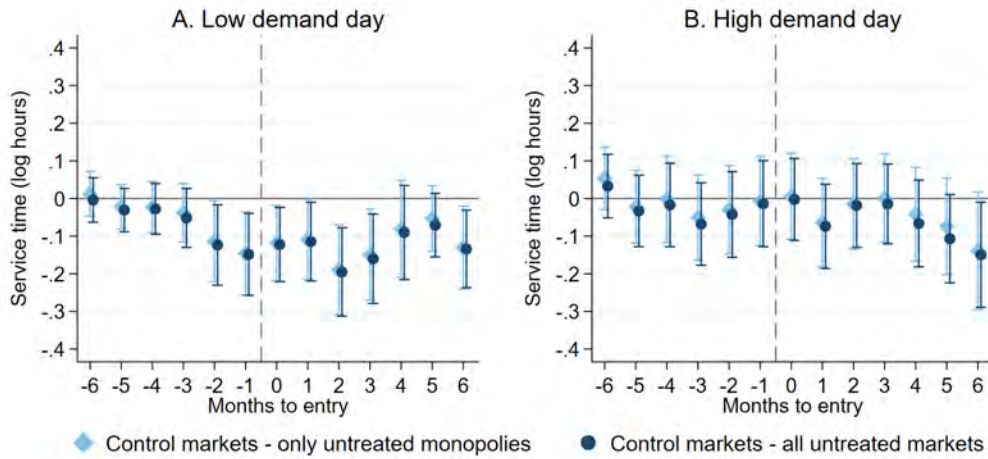


Notes: The figure plots average service times of the 129 markets that experienced entry as a function of the number of months before and after the first entry of a rival during the sample period. The figure distinguishes between low (Panel (a)) and high (Panel (b)) demand/utilization days of the week, and between different competition levels. The figure shows that service times are shorter on low-demand/utilization days. Also, on both low- and high-demand/utilization days, service times are shorter in markets with more online grocers. The decline in service times occurs 2-3 months before entry, and this reduction is more pronounced on low demand/utilization days. This reduction, as measured by the slope of the service time curve is larger in monopolistic markets than in competitive markets.

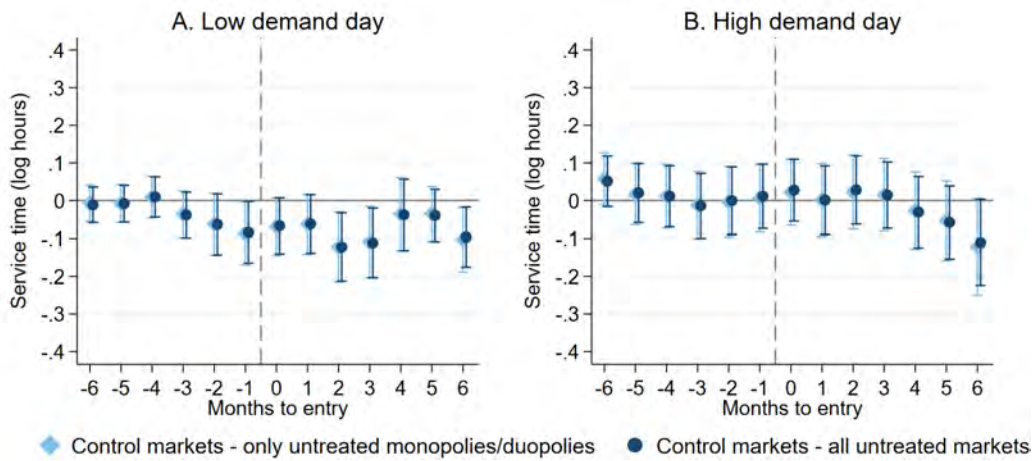


Figure 5: The effect of entry on service time, by competition and demand level

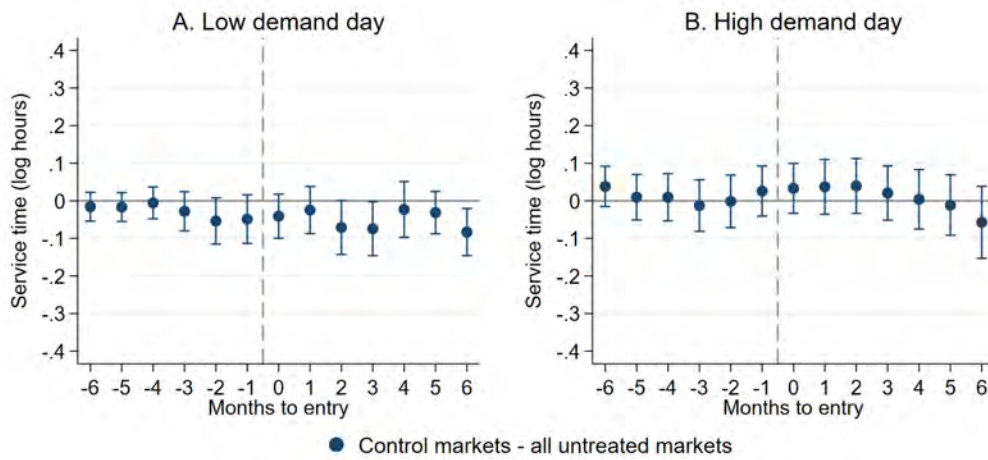
(a) Pre-entry monopoly markets



(b) Pre-entry monopoly/duopoly markets



(c) All markets



Notes: The figures plot the coefficients of  $\beta_j$  for  $j$  running from -6 to 6 and their 90-percent confidence intervals from a regression of equation 2 for different sub-samples. Standard errors are clustered at the market level. The dependent variable is Shufersal's (the incumbent) log service time in the local market, and results are presented separately for low-demand and high-demand days. Panel (a) reports the estimated effects of entry in pre-entry monopoly markets. Panel (b) considers markets that were served by up to 2 online grocers before entry and Panel (c) on all other markets. Dark signs are the coefficients from a sample that includes all markets that did not experience entry during the sample period as control group. Light signs are the estimated coefficients from a sample that includes as control markets that did not experience entry and have the same competition level as treated markets. All specifications include market fixed effects and month fixed effects. Results suggest that incumbents reduce service time when facing entry, but only on low-demand/low-utilization days. This reduction begins shortly before entry and is greater in pre-entry monopoly markets.

Table 1: Market demographic characteristics, by entry and competition level

	Pre-entry monopolistic markets		Pre-entry monopolistic/ duopolistic markets		All markets	
	Markets with entry	$\Delta$ Markets w/o entry	Markets with entry	$\Delta$ Markets w/o entry	Markets with entry	$\Delta$ Markets w/o entry
	(1)	(2)	(3)	(4)	(5)	(6)
Population (K)	29.62 (20.68)	-2.840 [4.358]	41.83 (98.01)	-13.41 [16.03]	59.62 (108.1)	-23.33 [15.58]
Density (population/km)	5946 (4357)	-1364 [1022]	7311 (7131)	-2999** [1360]	8990 (7342)	-3271*** [1220]
Average income per capita	9932 (2054)	9.722 [459.0]	10153 (2252)	38.65 [423.5]	10369 (2318)	452.6 [381.3]
Vehicle per capita	0.407 (0.593)	-0.084 [0.107]	0.382 (0.471)	-0.055 [0.077]	0.379 (0.392)	-0.025 [0.056]
Socioeconomic index [1-low to 10-high]	6.309 (1.698)	-0.180 [0.382]	6.386 (1.684)	-0.097 [0.325]	6.566 (1.643)	0.199 [0.275]
Periphery index [1-v.perif. to 10-not.perf.]	4.618 (1.661)	-0.102 [0.352]	4.977 (1.681)	-0.161 [0.315]	5.605 (1.897)	-0.134 [0.309]
Markets	55	31	88	38	129	51

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Notes: The table reports characteristics of markets that experienced entry (means with standard deviations in parentheses) alongside mean differences as compared with markets that did not experience entry (t-test standard errors in brackets). Column 1 include markets where only Shufersal was active before the first rival entered during the sample period (55 markets). Column 2 includes markets where only Shufersal was active during the whole sample period (31 markets). Column 3 includes the same markets as in column 1 and markets where Shufersal and one more rival were active before the first rival entered during the sample period. Column 4 includes the same markets as column 2 and markets where Shufersal and one more rival were active during the whole sample period. Column 5 includes all markets that faced entry during the sample period. Column 6 includes all markets with a constant number of active firms during the whole sample period. The socio-demographic characteristics show that markets that had more active firms before entry were more densely populated and located closer to the center of Israel. Nevertheless, there is no discernible difference in these characteristics, at least for monopolistic markets, between markets that experienced entry during the sample period vs. markets those that did not experience entry.

Table 2: The effect of entry on service time, by competition and demand level

	Low-demand day			High-demand day		
	(1)	(2)	(3)	(4)	(5)	(6)
<b>Panel A: pre-entry monopolistic markets</b>						
Pre entry	-0.127** (0.058)	-0.128** (0.058)	-0.129** (0.055)	-0.011 (0.055)	-0.011 (0.056)	-0.003 (0.047)
Post entry	-0.119** (0.053)	-0.120** (0.053)	-0.093* (0.049)	-0.084 (0.054)	-0.080 (0.054)	-0.018 (0.042)
Markets			106			
Markets with entry			55			
N			3,804			
<b>Panel B: pre-entry monopolistic / duopolistic markets</b>						
Pre entry	-0.067 (0.042)	-0.067 (0.042)	-0.068* (0.039)	0.014 (0.041)	0.014 (0.041)	0.020 (0.035)
Post entry	-0.078** (0.038)	-0.077** (0.038)	-0.056* (0.033)	-0.055 (0.042)	-0.052 (0.042)	0.007 (0.036)
Markets			139			
Markets with entry			88			
N			4,988			
<b>Panel C: all markets</b>						
Pre entry	-0.039 (0.032)	-0.039 (0.032)	-0.052* (0.031)	0.020 (0.030)	0.021 (0.030)	0.004 (0.028)
Post entry	-0.051* (0.029)	-0.050* (0.029)	-0.046* (0.025)	-0.014 (0.034)	-0.010 (0.034)	-0.002 (0.029)
Markets			180			
Markets with entry			129			
N			6,456			
Additional controls:						
No. of rivals' offline stores (10km radius)		✓	✓		✓	✓
Exits and additional entries indicators		✓	✓		✓	✓
Fulfilment center linear time trend			✓			✓

\* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$

Notes: The table reports estimation results for equation 3. Standard errors in parentheses are clustered at the market level. The dependent variable in columns 1-3 is Shufersal's log service time in the local market on Saturday night. The dependent variable in columns 4-6 is Shufersal's log service time in the local market on Wednesday night. *pre\_entry* is an indicator for one or two months before entry. *post\_entry* is an indicator for the month when entry takes place and for the following months. The sample in Panel A includes treated markets where Shufersal were active before the entry. The sample in Panel B includes treated markets where Shufersal and one more rival were active before entry, and the sample in Panel C includes all treated markets. In all specifications we use untreated markets (i.e. markets without entries) as the control group. The regression also includes market fixed effects and month fixed effects. According to the regression results, on low-demand/low-utilization days and in pre-entry monopoly markets, a significant decline of 10-13 percent in service times is observed two months before entry and in the months after entry. The estimates in more competitive markets are smaller and not always statistically significant. The estimates on high-demand days of the week are generally negative but statistically insignificant.

Table 3: The effect on service time by aggressive retailers, by competition and demand level

	Low demand day			High demand day		
	(1)	(2)	(3)	(4)	(5)	(6)
<b>Panel A: pre-entry monopolistic markets</b>						
Pre entry	-0.143*	-0.144**	-0.160**	0.007	0.006	0.004
	(0.073)	(0.073)	(0.071)	(0.062)	(0.063)	(0.055)
Post entry	-0.142**	-0.143**	-0.122**	-0.111*	-0.105*	-0.037
	(0.065)	(0.064)	(0.059)	(0.062)	(0.062)	(0.047)
Markets				93		
Markets with entry				42		
N				3,339		
<b>Panel B: pre-entry monopolistic / duopolistic markets</b>						
Pre entry	-0.089	-0.089	-0.103*	0.025	0.025	0.032
	(0.056)	(0.056)	(0.053)	(0.048)	(0.048)	(0.051)
Post entry	-0.103**	-0.101**	-0.093**	-0.076	-0.073	-0.002
	(0.048)	(0.048)	(0.042)	(0.051)	(0.051)	(0.041)
Markets				114		
Markets with entry				63		
N				4,093		
<b>Panel C: all markets</b>						
Pre entry	-0.063	-0.063	-0.077*	0.031	0.032	0.025
	(0.043)	(0.043)	(0.040)	(0.037)	(0.037)	(0.031)
Post entry	-0.074*	-0.073*	-0.068**	-0.038	-0.034	0.005
	(0.038)	(0.038)	(0.032)	(0.043)	(0.043)	(0.034)
Markets				139		
Markets with entry				88		
N				4,988		
Additional controls:						
No. of rivals' offline stores (10km radius)		✓	✓		✓	✓
Exits and additional entries indicators		✓	✓		✓	✓
Fulfilment center linear time trend			✓			✓

\* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$

Notes: The table reports estimation results for equation 3. Standard errors in parentheses are clustered at the market level. The dependent variable in columns 1-3 is Shufersal's log service time in the local market on Saturday night. The dependent variable in columns 4-6 is Shufersal's log service time in the local market on Wednesday night. *pre\_entry* is an indicator for one or two months before an aggressive online grocer (Rami Levy or Victory) enters the local market. *post\_entry* is an indicator for the month of entry and for the following months. The sample in Panel A includes treated markets where only Shufersal was active before entry, Panel B includes treated markets where Shufersal and one another grocer were active before entry in Panel C we include all treated markets. In all specifications, we use untreated markets (i.e. markets that did not experience entry) as the control group, and include market and month fixed effects. The results show that on low-demand days the incumbent retailer improves service time in all pre-entry market conditions, where the effect diminishes with the level of competition. The improvement begins before entry takes place and its magnitude is nearly 25% larger than in the main specification. On high-demand days, we find that the effect on service time is negative and marginally significant in monopolistic markets after entry takes place.

Table 4: The effect on service time in adjacent markets, by demand level and entrant's identity

	Low demand day				High demand day			
	Entry to all markets		Entry to monopolistic markets		Entry to all markets		Entry to monopolistic markets	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<b>Panel A: Entry by all retailers</b>								
Pre entry	0.017 (0.025)	0.019 (0.026)	-0.010 (0.033)	-0.011 (0.034)	0.036 (0.065)	0.046 (0.062)	0.083 (0.061)	0.085 (0.061)
Post entry	-0.021 (0.041)	-0.011 (0.039)	-0.058 (0.035)	-0.053 (0.036)	-0.035 (0.079)	0.006 (0.080)	0.044 (0.072)	0.068 (0.070)
Markets					51			
N					1,830			
<b>Panel B: Entry by aggressive retailers</b>								
Pre entry	-0.027 (0.038)	-0.027 (0.039)	-0.031 (0.040)	-0.031 (0.040)	-0.040 (0.060)	-0.033 (0.057)	0.030 (0.067)	0.036 (0.065)
Post entry	-0.091* (0.051)	-0.087 (0.053)	-0.089* (0.046)	-0.085* (0.046)	-0.120 (0.087)	-0.087 (0.088)	-0.015 (0.084)	0.012 (0.079)
Markets					51			
N					1,830			
<b>Panel C: Entry by aggressive retailers when that retailer is not active in the adjacent market</b>								
Pre entry	-0.050 (0.046)	-0.050 (0.047)	-0.037 (0.050)	-0.038 (0.051)	-0.060 (0.073)	-0.055 (0.070)	0.044 (0.081)	0.049 (0.079)
Post entry	-0.106* (0.059)	-0.101* (0.060)	-0.105* (0.055)	-0.101* (0.054)	-0.143 (0.100)	-0.111 (0.100)	-0.014 (0.096)	0.012 (0.090)
Pre entry+ pre entry*active entrant	0.055 (0.048)	0.056 (0.046)	-0.015 (0.045)	-0.013 (0.044)	0.022 (0.073)	0.039 (0.074)	-0.016 (0.070)	-0.005 (0.071)
Post entry+ post entry*active entrant	-0.033 (0.047)	-0.027 (0.046)	-0.028 (0.041)	-0.020 (0.041)	-0.022 (0.065)	0.018 (0.067)	-0.021 (0.073)	0.018 (0.075)
Markets					51			
N					1,830			
Additional controls:								
No. of rivals' offline stores (10km radius)	✓		✓		✓		✓	
Exits and additional entries indicators	✓		✓		✓		✓	

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Notes: Panels A and B report estimation results for regression similar to equation 3 and Panel C reports estimation results for equation 4 using a sample that includes only markets that experienced neither entry nor exit during the sample period. Standard errors in parentheses are clustered at the market level. The dependent variable in columns 1-4 is Shufersal's log service time in the local market on Saturday night. The dependent variable in columns 5-8 is Shufersal's log service time in the local market on Wednesday night. *pre\_entry* is an indicator for one or two months before the first entry in nearby market served by the same fulfillment center. *post\_entry* is an indicator for the month of entry in nearby market and for the following months. Entry indicators in columns 1, 2, 5 and 6 refer to all entries in nearby markets, and in columns 3, 4, 7 and 8 to entries only to monopolistic nearby markets. Entry indicators in Panel A refer to entries by all retailers, and in Panels B and C only to entries by aggressive retailers. In Panel C the specification includes also interaction between the entry indicators to indicators for markets where the entrant rival was active. The regressions also include market and month fixed effects. The results suggest that when an aggressive retailer enters one local market, the incumbent improves service time on low-demand days also in adjacent markets which are served by the same distribution center. This improvement is larger and statistically significant after entry takes place and when the entrant is not active in the market.

## Appendix A Online grocery platform data

We use proprietary data from MySupermarket.co.il, an online platform that enables users to shop at each of the five online retailers. MySupermarket users can compare prices and contemporaneously observe available service times offered by each retailer. Figures A1 and A2 below show examples of screens observed by users of MySupermarket. After compiling a list of items that they want to purchase, users transfer the list of items to the website of a particular retailer and complete the transaction there. We use data on all such orders performed through MySupermarket during the data collection period. The individual customer/order data from MySupermarket cover about 700 thousand orders by nearly 85,000 customers. About 85 percent of these customers live in localities that we track. 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. 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 price is about 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: 1) to examine how the number of online grocery orders changes over days of the week (Figure A3), 2) to explore how the level of daily demand is related to customers' decision to switch, i.e. order from a retailer other than their "regular vendor" (Panel (a) in Figure A4), 3) to examine substitution patterns across retailers, and accordingly characterize entrants as aggressive (Panel (b) in Figure A4).

Figure A3 presents the cumulative percent of orders for online grocery Tuesday and Wednesday, and on Friday and Saturday (i.e., 48 hours before the crawler was active on Wednesday and Saturday nights, respectively). The figure shows that the cumulative percent of orders is about 3 times larger on Wednesdays than on Saturdays. Figure A4 shows switching patterns of loyal customers who use MySupermarket. A loyal customer is defined as an individual who used MySupermarket more than 10 times during the sample period, and at least 60 percent of times bought from the same online grocer. There are 9,182 loyal customers in the sample, 2,861 are Shufersal's loyal customers. Panel (a) shows the percentage of orders made by all 9,182 loyal customers and examine on which days these customers do not purchase from their regular retailer. More than 17 percent of switches by loyal customers occur on Thursday, compared to about 12.5 percent of switches to a non-regular vendor on Saturday and on Sunday. According to the figure, on days characterized

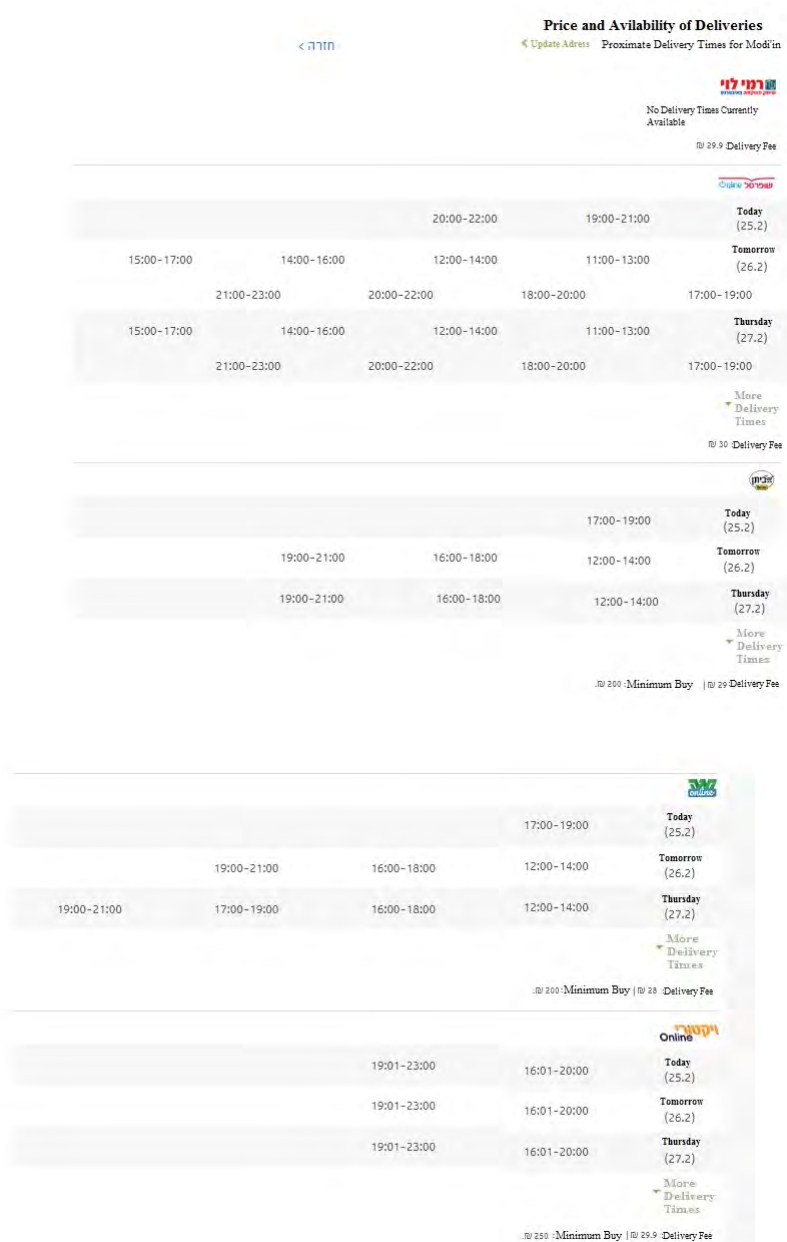
with long service time (e.g., Thursday) loyal customers are more likely to switch to an alternate retailer, arguably since they are unsatisfied with the service time offered by their regular vendor. This provides additional support for our assertion that customers care about service time when choosing where to buy. Panel (b) focuses on Shufersal's loyal customers, and shows the percentage of orders from other retailers. According to the figure, about 64 percent of switches by Shufersal's loyal customers are to Rami Levy and to Victory, which we consider as aggressive entrants.

Figure A1: Online shopping platform - basket price



Notes: The figure shows a screenshot from MySupermarket.co.il webpage where consumers observe the basket price offered by each of the online grocers that offer service to their address, and can choose the retailer they want to order from. For instance, Rami Levi, offers the cheapest price for this basket (23 products, IS 749.37).

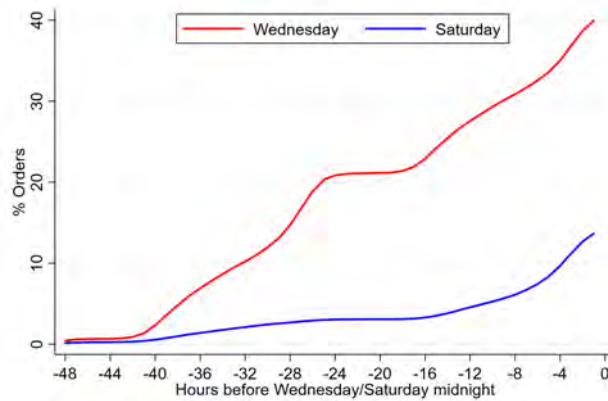
Figure A2: Online shopping platform - service time



Notes: The figure shows a screenshot from MySupermarket.co.il where consumers observe available delivery slots offered by online retailers to their address.



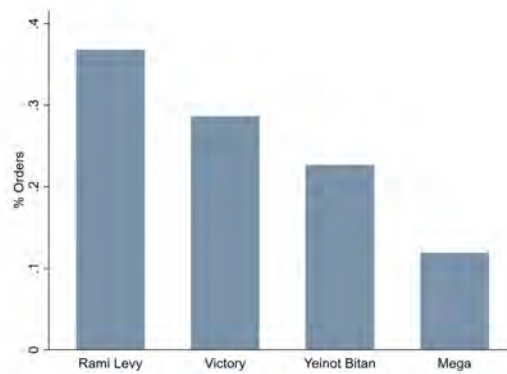
Figure A3: Cumulative number of orders before the crawler time on Wednesday & Saturday



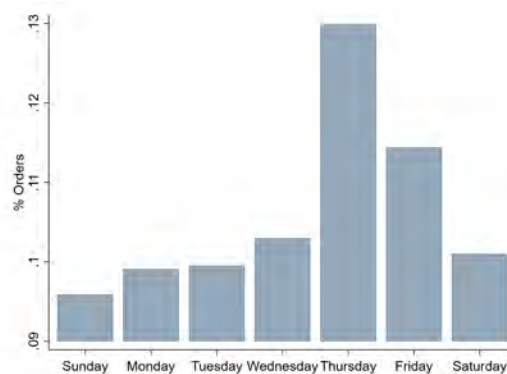
Notes: The figure shows a normalized measure of the share of orders through MySupermarket in the 48 hours that precede the crawler time (midnight on Saturday and on Wednesday). The figure demonstrates that demand is considerably higher on pre-weekend days compared to weekend demand.

Figure A4: Customers' switching patterns at MySupermarket

(a) Switching patterns across days of the week



(b) Switching patterns across online grocers

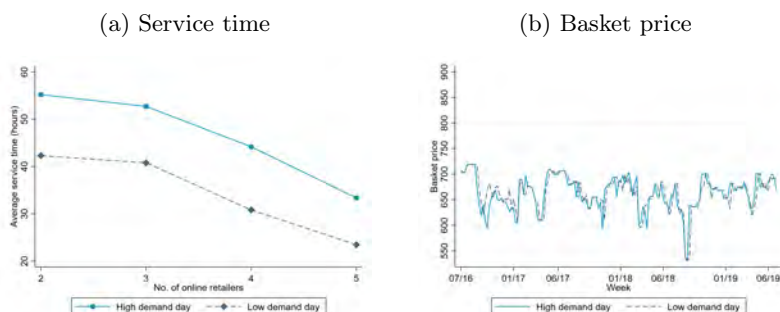


Notes: The figures show switching patterns by loyal customers who use MySupermarket.co.il to purchase online grocery. A loyal customer is defined as an individual who used MySupermarket more than 10 times during the sample period, and at least 60 percent of times bought from the same online grocer. There are 9,182 loyal customers in the sample, 2,861 are Shufersal's loyal customers. Panel (a) focuses on Shufersal's loyal customers, and shows the percentage of orders from other retailers. According to the figure, about 64 percent of switches by Shufersal's loyal customers are to Rami Levy and to Victory, which we consider as aggressive entrants. Panel (b) shows the percentage of orders made by all 9,182 loyal customers and examine on which days these customers do not purchase from their regular retailer. More than 17 percent of switches by loyal customers occur on Thursday, compared to about 12.5 percent of switches to a non-regular vendor on Saturday and on Sunday. According to the figure, on days characterized with long service time (e.g., Thursday) loyal customers are more likely to switch to an alternate retailer, arguably since they are unsatisfied with the service time offered by their regular vendor.

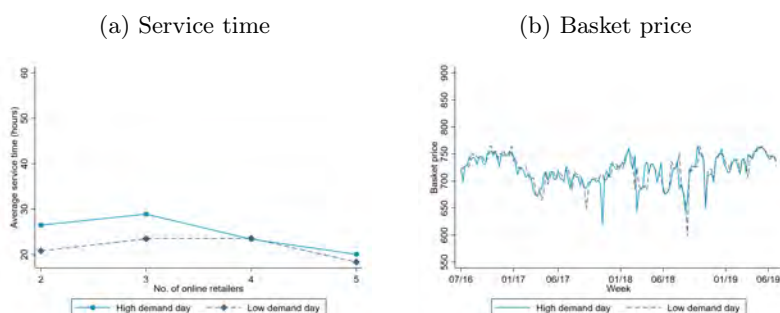
## Appendix B Entrants' service time, prices and stores

Figure B1: Service time and prices as a function of competition & demand (entrants)

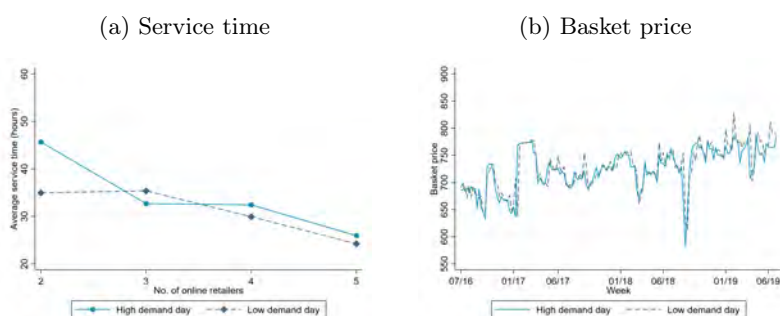
### A. Rami Levy



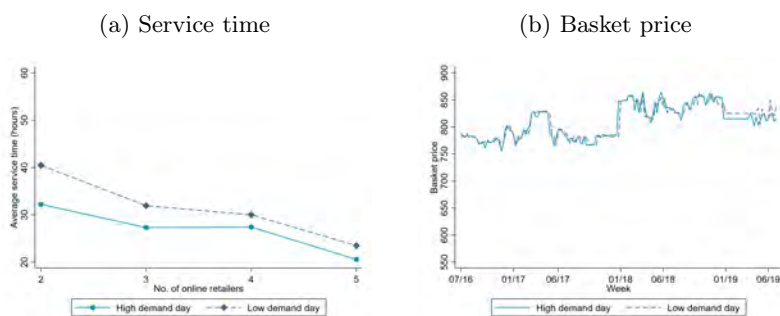
### B. Victory



### C. Yenot-Bitan

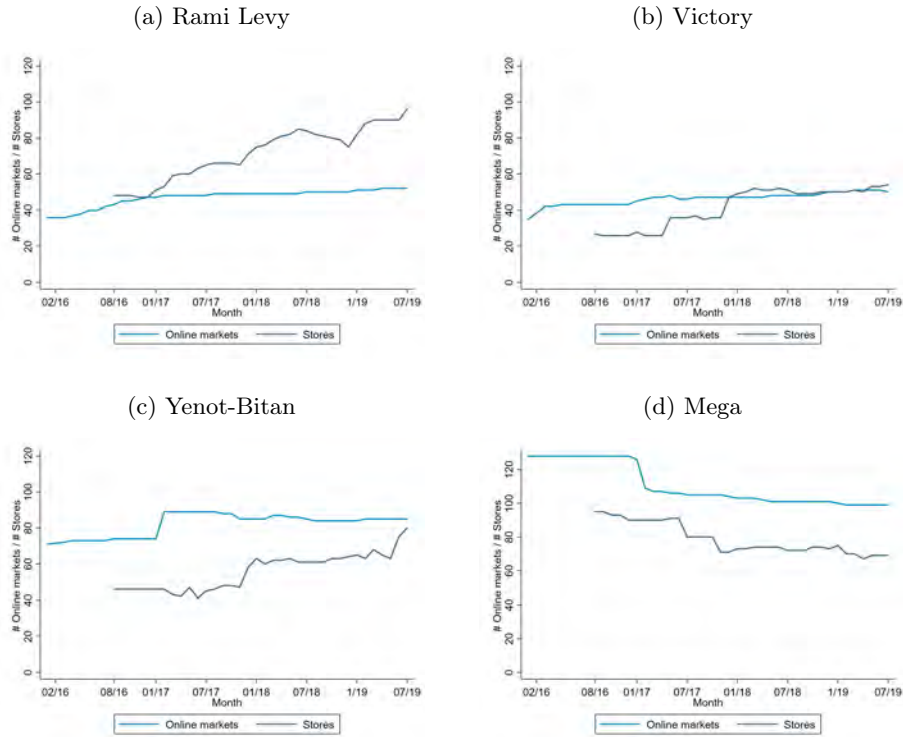


### D. Mega



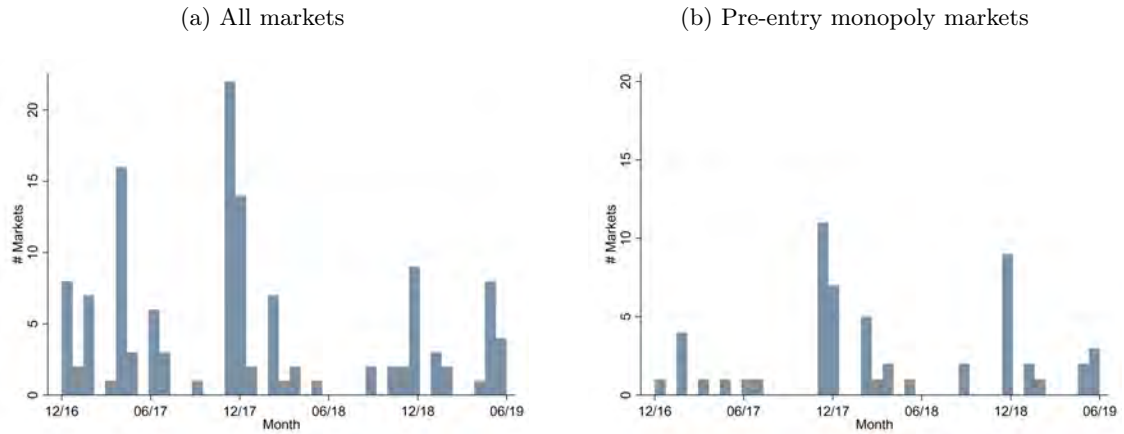
Notes: Panels (a) show the average service time offered by each of retailers (except Suhfersal) as a function of the number of active online retailers in each market, separately for low- demand/low utilization days and for high demand/high utilization days, based on monthly data from August 2016 to July 2019. Panels (b) shows the daily price of a basket of 52 products sold by offered by each of retailers (except Suhfersal) online channel, separately for Sundays (low demand day) and Thursdays (high demand day) for each week from August 2016 to July 2019.

Figure B2: The number of physical stores operated by a grocer vs. online expansion by the grocer



Notes: The figures show for each online retailer, the number of markets in the sample where the retailer offers online grocery service and the number of physical stores operated by that retailer over the sample period.

Figure B3: The distribution of timing of first entry

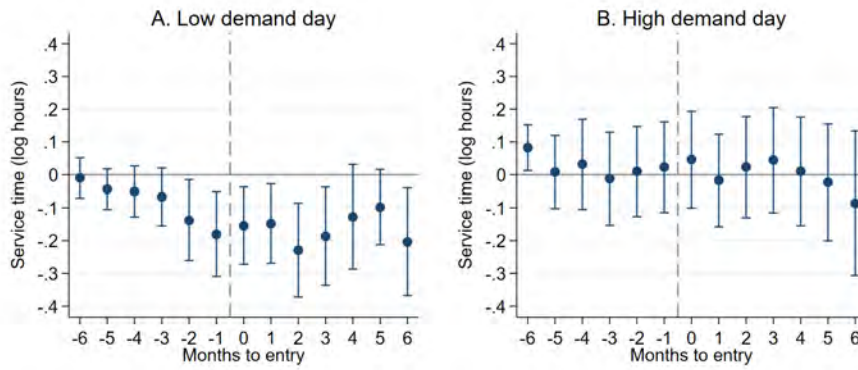


Notes: Panel (a) shows the number of markets that experienced entry in each month during the sample period. Panel (b) shows the number of monopoly markets that experienced entry in each month during the sample period. The patterns of timing of entry do not reveal a pattern of strategic timing of entry decisions during the 3 years.

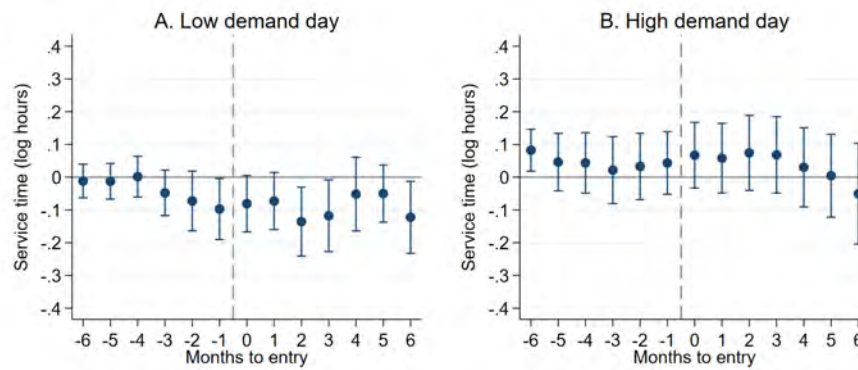
## Appendix C Robustness checks

Figure C1: The effect of entry on the incumbent's service time using treated markets only

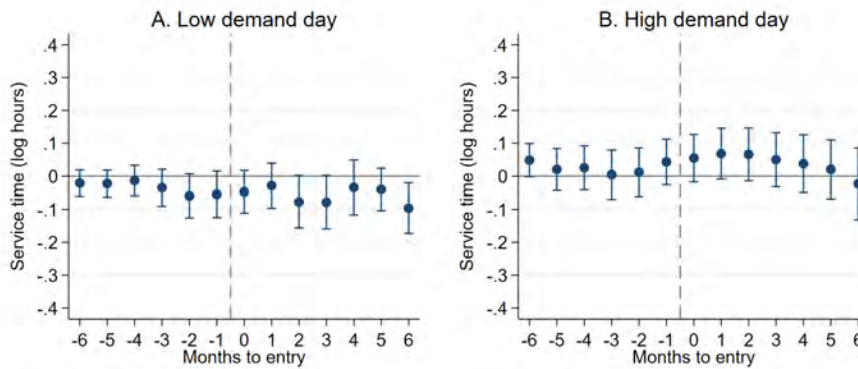
(a) Pre-entry monopoly markets



(b) Pre-entry monopoly / duopoly markets



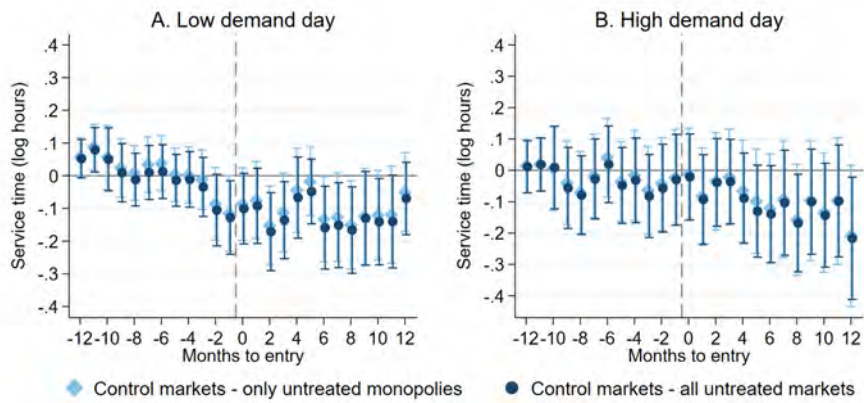
(c) All markets



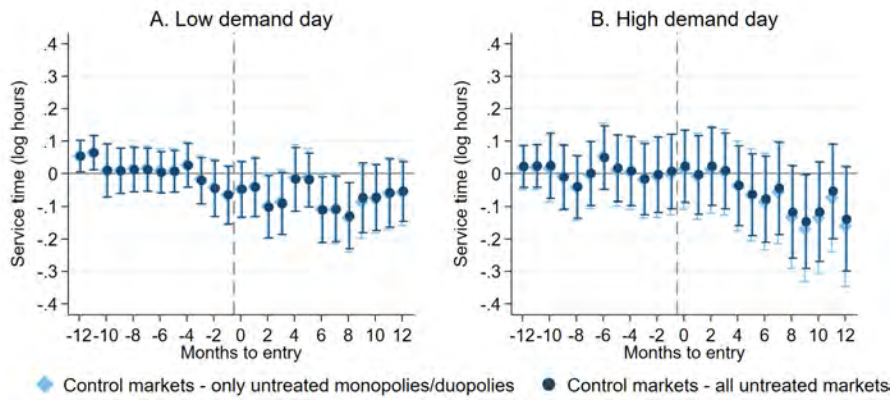
Notes: The figures plot the coefficients of  $\beta_j$  for  $j$  running from -6 to 6 and their 90-percent confidence intervals from a regression of equation 2 for different sub-samples including only treated markets (markets that experienced an entry during the sample period). Standard errors are clustered at the market level. The dependent variable is Shufersal's (the incumbent's) log service time in the local market. Estimated results are shown separately for low-demand days and for high-demand days. Panel (a) reports the estimated effects of entry in markets which were monopolies before entry. Panel (b) reports the estimated effects of entry in markets that were served by up to 2 online retailers, and Panel (c) reports the results for all markets. All specifications include market and month fixed effects. Results are qualitatively similar to the results in the main text.

Figure C2: The effect of entry on the incumbent's service time using a 12-months window

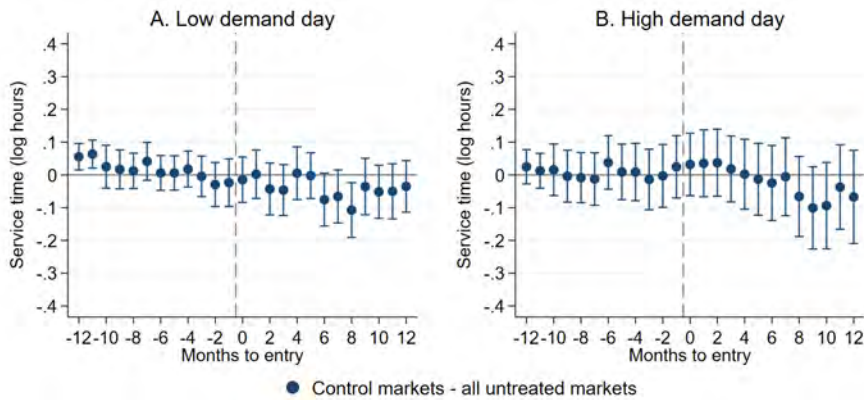
(a) Pre-entry monopoly markets



(b) Pre-entry monopoly / duopoly markets



(c) All markets



Notes: The figures plot the coefficients of  $\beta_j$  for  $j$  running from -12 to 12 and their 90-percent confidence intervals from a regression of equation 2 for different sub-samples. Standard errors are clustered at the market level. The dependent variable is Shufersal's (the incumbent) log service time in the local market. Estimated results are shown separately for low-demand days and for high-demand days. Panel (a) reports the estimated effects of entry in markets which were monopolies before entry. Panel (b) reports the estimated effects of entry in markets that were served by up to 2 online retailers, and Panel (c) reports the results for all markets. Dark signs are the coefficients from a sample that includes all markets that did not experience any entry during the sample period as control group. Light signs are the estimated coefficients from a sample that includes as control only markets that did not experience entry and have the same competition level as treated markets before entry. All specifications include market and month fixed effects. Results are qualitatively similar to the results in the main text.

Table C1: The effect of entry on the incumbent's service time accounting for competition from physical stores

	Low-demand day				High-demand day			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<b>Panel A: pre-entry monopoly markets</b>								
Pre entry	-0.128** (0.055)	-0.128** (0.055)	-0.129** (0.055)	-0.129** (0.055)	-0.003 (0.047)	-0.005 (0.046)	-0.003 (0.048)	-0.004 (0.047)
Post entry	-0.092* (0.049)	-0.093* (0.048)	-0.089* (0.048)	-0.091* (0.049)	-0.019 (0.042)	-0.016 (0.042)	-0.026 (0.042)	-0.024 (0.042)
Markets				106				
Markets with entry				55				
N				3,804				
<b>Panel B: pre-entry monopoly / duopoly markets</b>								
Pre entry	-0.068* (0.039)	-0.066* (0.039)	-0.067* (0.039)	-0.069* (0.039)	0.020 (0.035)	0.017 (0.034)	0.018 (0.035)	0.019 (0.034)
Post entry	-0.057* (0.033)	-0.056* (0.033)	-0.056* (0.033)	-0.059* (0.033)	0.007 (0.036)	0.005 (0.036)	0.005 (0.036)	0.001 (0.036)
Markets				139				
Markets with entry				88				
N				4,988				
<b>Panel C: all markets</b>								
Pre entry	-0.053* (0.031)	-0.050* (0.030)	-0.052* (0.031)	-0.053* (0.031)	0.005 (0.028)	0.003 (0.028)	0.003 (0.028)	0.003 (0.028)
Post entry	-0.047* (0.026)	-0.045* (0.025)	-0.046* (0.025)	-0.048* (0.026)	-0.001 (0.029)	-0.003 (0.028)	-0.004 (0.028)	-0.006 (0.028)
Markets				180				
Markets with entry				129				
N				6,456				
Additional controls:								
No. of rivals' offline stores (5km)	✓				✓			
No. of rivals' offline stores (15km)		✓				✓		
Driving distance to rivals' 1st store			✓				✓	
Driving distance to rivals' 2nd store				✓				✓

\* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$

Notes: The table reports estimation results for equation 3. Standard errors in parentheses are clustered at the market level. The dependent variable in columns 1-4 is Shuseral's log service time in the local market on Saturday night. The dependent variable in columns 5-8 is Shufersal's log service time in the local market on Wednesday night. *pre\_entry* is an indicator for one or two months before entry. *post\_entry* is an indicator for the month when entry takes place and for the following months. The sample in Panel A includes treated markets where only Shufersal was active before the entry. The sample in Panel B includes treated markets where Shufersal and another grocer were active before entry, and in Panel C the sample includes all treated markets. In all specifications, we use untreated markets (i.e. markets without entries) as the control group and include market and month fixed effects. The results suggest that the effect of an online grocer's entry on the incumbent's service time are not sensitive to the presence of a nearby traditional store.

Table C2: The effect of entry on the incumbent's service time using alternate control markets

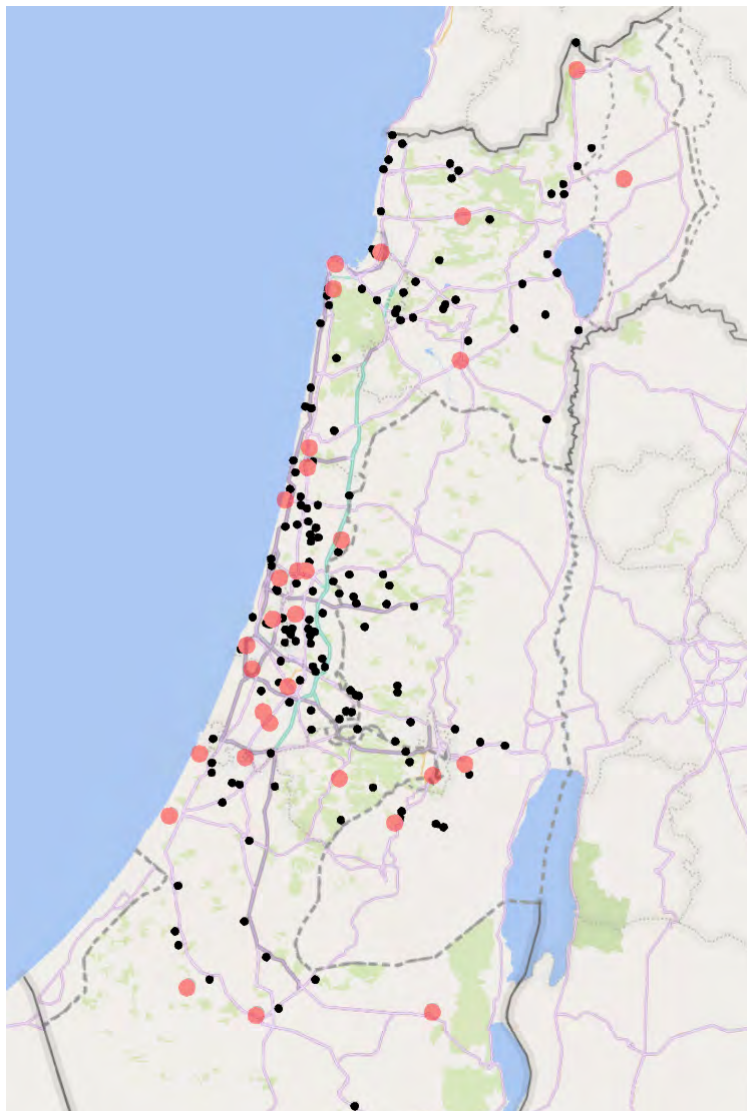
	Low-demand day		High-demand day	
	(1)	(2)	(3)	(4)
<b>Panel A: pre-entry monopoly markets</b>				
Pre entry	-0.139** (0.057)	-0.129** (0.055)	0.027 (0.052)	0.004 (0.045)
Post entry	-0.136** (0.060)	-0.101** (0.050)	0.023 (0.058)	-0.004 (0.043)
Markets	55	86	55	86
Markets with entry	55	55	55	55
N	1,978	3,093	1,978	3,093
<b>Panel B: pre-entry monopoly / duopoly markets</b>				
Pre entry	-0.069* (0.041)	-0.071* (0.040)	0.029 (0.036)	0.016 (0.034)
Post entry	-0.062 (0.038)	-0.062* (0.034)	0.033 (0.041)	0.005 (0.038)
Markets	88	126	88	126
Markets with entry	88	88	88	88
N	3,162	4,528	3,162	4,528
<b>Panel C: all markets</b>				
Pre entry	-0.049 (0.032)	-0.052* (0.031)	0.015 (0.029)	0.004 (0.028)
Post entry	-0.042 (0.029)	-0.046* (0.025)	0.022 (0.030)	-0.002 (0.029)
Markets	129	180	129	180
Markets with entry	129	129	129	129
N	4,630	6,462	4,630	6,462
Additional controls:				
No. of rivals' offline stores (10km radius)	✓	✓	✓	✓
Exits and additional entries indicators	✓	✓	✓	✓
Fulfilment center linear time trend	✓	✓	✓	✓

\* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$

Notes: The table reports estimation results for equation 3. Standard errors in parentheses are clustered at the market level. The dependent variable in columns 1-2 is Shuseral's log service time in the local market on Saturday night. The dependent variable in columns 3-4 is Shufersal's log service time in the local market on Wednesday night. *pre\_entry* is an indicator for one or two months before entry. *post\_entry* is an indicator for the month when entry takes place and for the following months. The sample in Panel A includes treated markets where Shufersal were active before the entry. The sample in Panel B includes treated markets where Shufersal and one more rival were active before entry, and the sample in Panel C includes all treated markets. In columns 1 and 3 the sample includes only treated markets and in columns 2 and 4 the sample includes also control group which is markets that did not experience entry and have the same competition level as treated markets before entry. The regression also includes market fixed effects and month fixed effects.

## Appendix D Maps

Figure D1: Online local markets (black) and Shufersal's fulfillment centers (red)

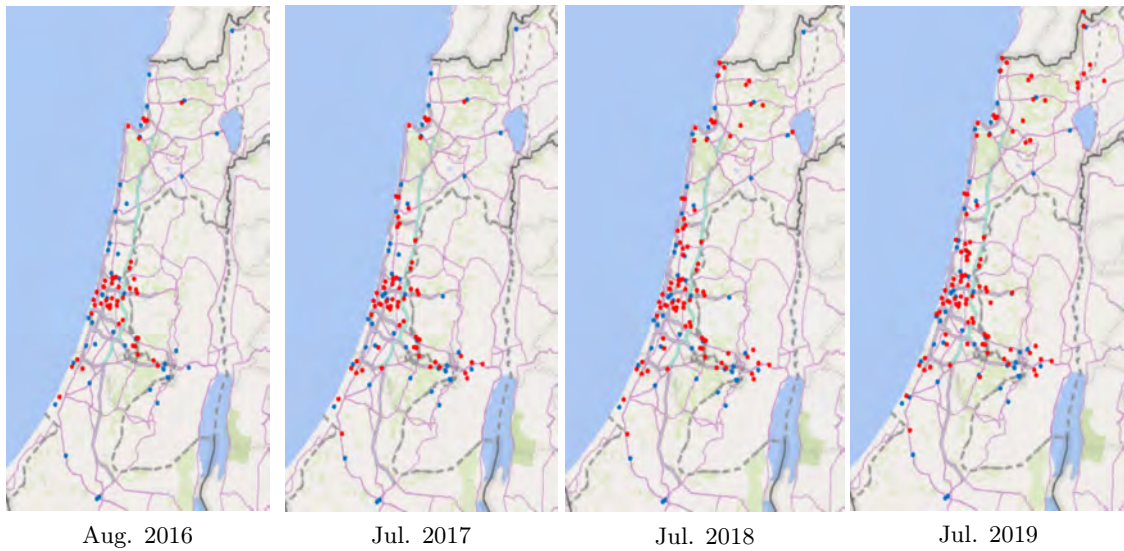


Notes: Black dots show the location of the 180 local markets covered in our sample. Red dots show the location of Shufersal's 34 fulfillment centers.

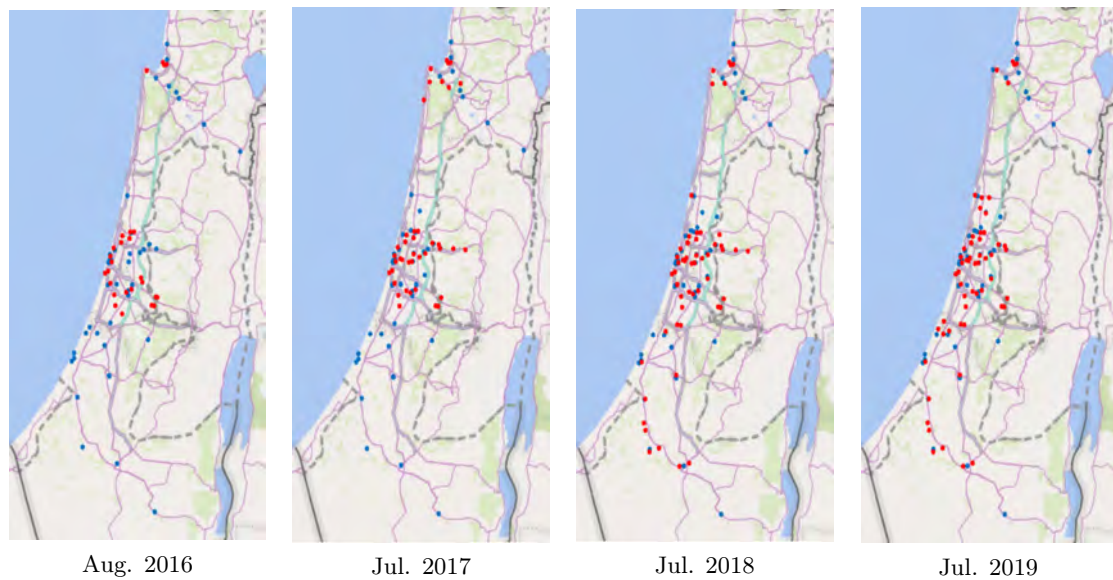


Figure D2: Chains' online service coverage (red) and location of traditional stores (blue)

I. Rami Levy



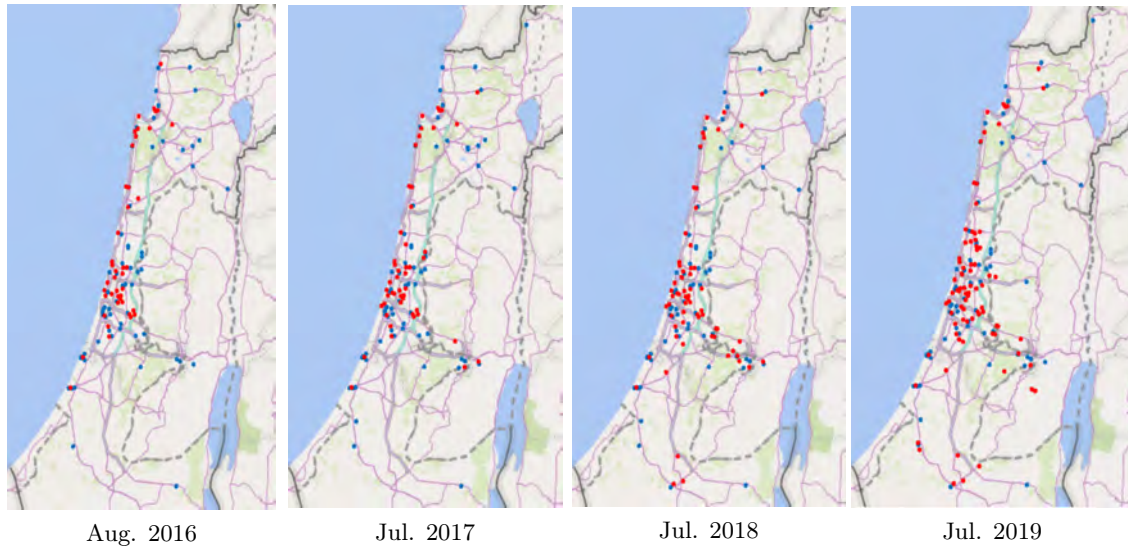
II. Victory



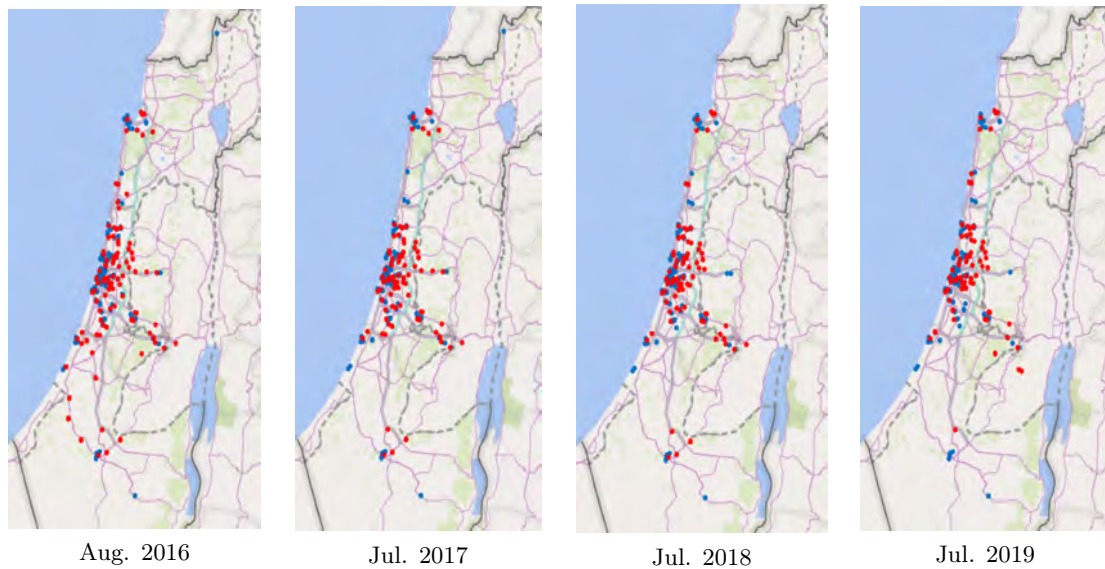
Notes: The figures show the coverage of online service (red dots) and the location brick-and-mortar stores (blue dots) for each year in our sample (2016, 2017, 2018, 2019). Panel I focuses on Rami Levy and Panel II on Victory. In 2016, both chains offered online service mostly at Tel Aviv metropolis.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

Figure D3: Chains' online service coverage (red) and location of traditional stores (blue)

### III. Yeinot Bitan



### IV. Mega



Notes: The figures show the coverage of online service (red dots) and the location brick-and-mortar stores (blue dots) 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 as the southwest. Both Mega and Yeiont Bitan offer online service in regions where these chains operate brick-and-mortar stores.

## Appendix E Alternative estimators for TWFE DiD

As mention in Section 4.1, the event study coefficient might be biased if there are heterogeneity in treatment effects between groups of units treated at different times. Recent advances in econometric theory suggest that event study coefficient under staggered treatment represents a weighted average of cohort-specific average treatment effects from units treated at different times (Sun and Abraham (2020); De Chaisemartin and d’Haultfoeuille (2020); Goodman-Bacon (2021); Borusyak et al. (2021) and Callaway and Sant’Anna (2020)). The presence of heterogeneous treatment effects and negative weights could generate invalid results. Here, we provide additional supporting evidence for the validity of our estimates by using alternative estimators proposed by Sun and Abraham (2020) and Borusyak et al. (2021) that are robust to heterogeneous treatment effects.

Sun and Abraham (2020) method estimates the dynamic effect for each treatment cohort, and then calculates the weighted average of these cohort-specific estimates, with weights equal to each cohort’s respective sample share, when using either never-treated as controls or “last cohort treated” if no never-treated.<sup>19</sup> Specifically, each event time coefficient from this estimation is a weighted average of the cohort-specific ATE, where the weights are given by the share of cohorts that experienced at least  $t$  periods relative to treatment and normalized by the total event time periods we are estimating. Figure E1 shows estimation results using Sun and Abraham (2020) approach while dark signs are the estimated coefficients from an estimation using never-treated markets as control group, i.e. markets that did not experience entry and have the same competition level as treated markets before entry and light signs are the estimated coefficients from an estimation using “last cohort treated” (markets with entry at the last month of the sample) as control group.<sup>20</sup> The results are qualitatively similar to the results in our main analysis. Sun and Abraham (2020) require unconditional parallel trend assumption and no anticipation during the pre-treatment period. While we discuss the parallel trend assumption in Section 4.4, the anticipation in the two months before entry might bias the results. Accordingly, we also use Borusyak et al. (2021) estimator to verify that our results are unchanged.

Borusyak et al. (2021) provide an imputation estimator which is constructed in three steps. First, unit and period fixed effects are fitted by regression on untreated observations only. Second, they are used to impute the untreated potential outcomes and therefore obtain an estimated treatment effect for each treated observation. Finally, a weighted average of these treatment

---

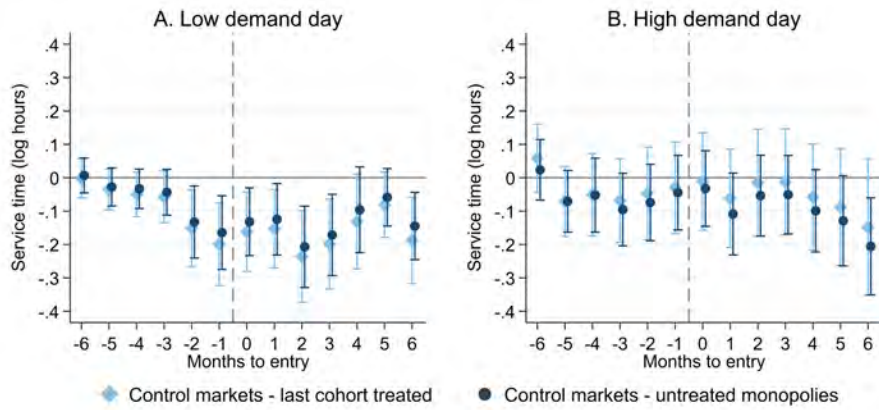
<sup>19</sup>Sun and Abraham (2020) can be considered as a specific case of Callaway and Sant’Anna (2020) estimator. Callaway and Sant’Anna (2020) propose a group-time average treatment effect based on calendar time while Sun and Abraham (2020) propose a regression-based estimator of cohort-specific average treatment effects based on event time. In a setting where there is no never-treated group, Sun and Abraham (2020) use the last cohort to be treated as control, whereas Callaway and Sant’Anna (2020) use the set of not-yet-treated cohorts.

<sup>20</sup>We do not use all untreated markets as control since according to Sun and Abraham (2020) always treated units should be dropped.

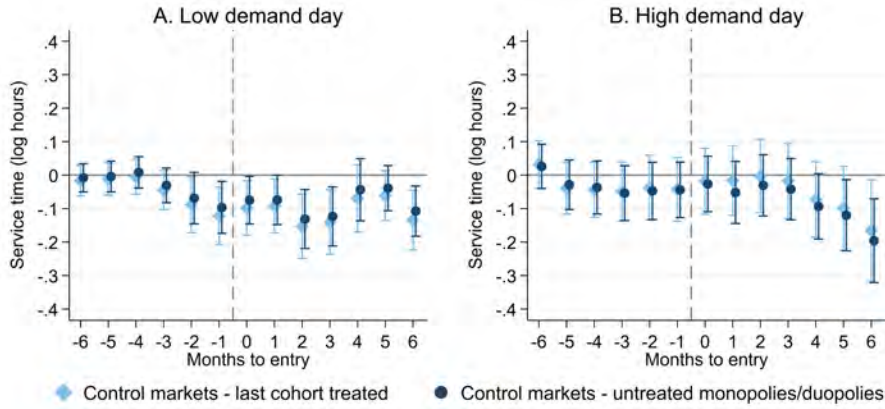
effect estimates is taken with weights, corresponding to the estimation target. [Borusyak et al. \(2021\)](#) require that the parallel trend assumption based on a linear function of unit and time fixed effects holds, and allows for a shift in the treatment period when there is known pre-treatment anticipation. Hence, we are able to allow for two months anticipation in the [Borusyak et al. \(2021\)](#) estimation method. [Figure E2](#) shows estimation results using [Borusyak et al. \(2021\)](#) approach, assuming a two-months shift in treatment effect, i.e. in  $t - 2$ , and using all untreated markets (dark signs) or only untreated markets that have the same competition level as treated market pre-entry (light signs). The results show similar patterns to the results presented in [Figure 5](#), suggesting that our two-way fixed effects estimates are free of contaminated effects from other periods, and heterogeneity treatment effects.

Figure E1: Sun and Abraham (2020) estimator for the effect of entry on incumbent’s service time

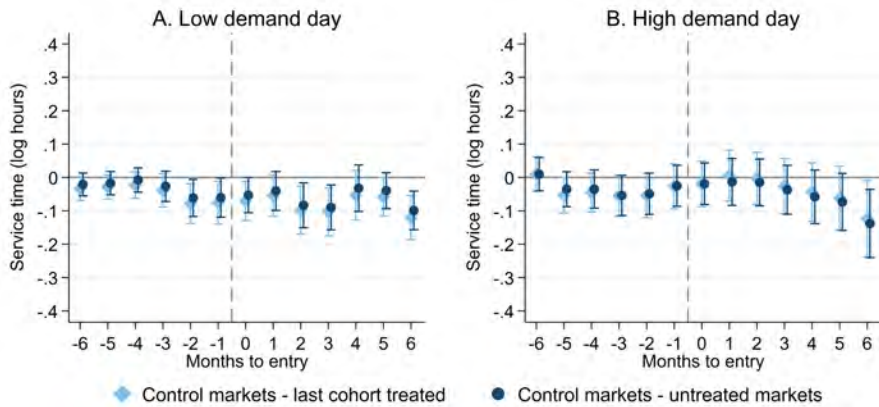
(a) Pre-entry monopoly markets



(b) Pre-entry monopoly / duopoly markets



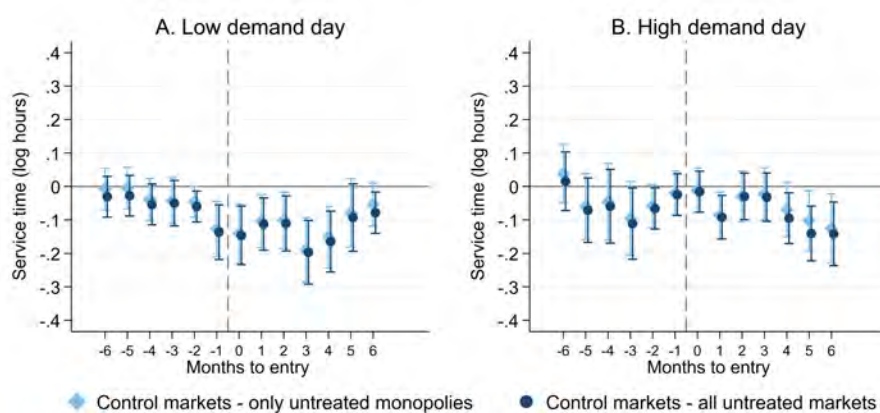
(c) All markets



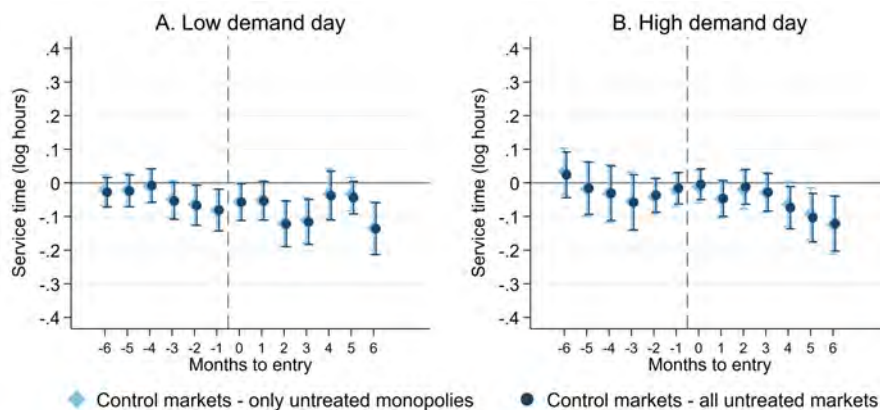
Notes: The figures plot the coefficients of  $\beta_j$  for  $j$  running from -6 to 6 and their 90-percent confidence intervals from a regression of equation 2 for different sub-samples using Sun and Abraham (2020) estimation method. Standard errors are clustered at the market level. The dependent variable is Shufersal’s (the incumbent’s) log service time in the local market. Estimated results are shown separately for low-demand days and for high-demand days. Panel (a) reports the estimated effects of entry in markets which were monopolies before entry. Panel (b) reports the estimated effects of entry in markets that were served by up to 2 online retailers, and Panel (c) reports the results for all markets. Dark signs are the estimated coefficients from an estimation using never-treated markets as control group, i.e. markets that did not experience entry and have the same competition level as treated markets before entry (we do not use all untreated markets as control since according to Sun and Abraham (2020) always treated units should be dropped). Hence, in Panel A never-treated markets are markets where Shufersal is a monopoly during the all sample period. In Panel B never-treated markets are markets where Shufersal is a monopoly or share the markets with only one additional retailer during the all sample period and in Panel C never-treated markets are all markets without entry, excluding markets where all the 5 retailers are active. Light signs are the estimated coefficients from an estimation using “last cohort treated” (markets with entry at the last month of the sample) as control group. All specifications include market and month fixed effects. Results are qualitatively similar to the two-way fixed effects specification in the main text.

Figure E2: [Borusyak et al. \(2021\)](#) estimator for the effect of entry on incumbent's service time

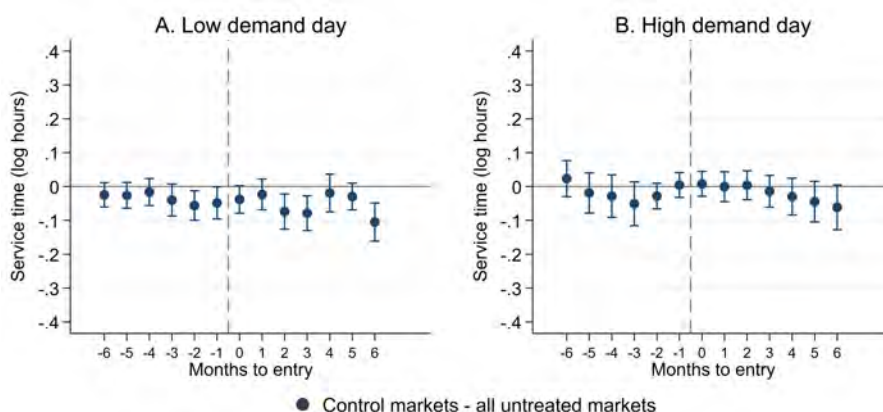
(a) Pre-entry monopoly markets



(b) Pre-entry monopoly / duopoly markets



(c) All markets



Notes: The figures plot the coefficients of  $\beta_j$  for  $j$  running from -6 to 6 and their 90-percent confidence intervals from a regression of equation 2 for different sub-samples using [Borusyak et al. \(2021\)](#) estimation method and assuming 2 months of shift in treatment period ( $t - 2$ ). Standard errors are clustered at the market level. The dependent variable is Shufersal's (the incumbent's) log service time in the local market. Estimated results are shown separately for low-demand days and for high-demand days. Panel (a) reports the estimated effects of entry in markets which were monopolies before entry. Panel (b) reports the estimated effects of entry in markets that were served by up to 2 online retailers, and Panel (c) reports the results for all markets. Dark signs are the coefficients from a sample that include all markets that did not experience any entry during the sample period as control group. Light signs are the estimated coefficients from a sample that includes as control only markets that did not experience entry and have the same competition level as treated markets before entry. All specifications include market and month fixed effects. Results are qualitatively similar to the two-way fixed effects specification in the main text.