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Centre for Economic Policy Research
33 Great Sutton Street, London EC1V 0DX, UK
Tel: +44 (0)20 7183 8801
www.cepr.org

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JEL Classification: D83, L81, L66

Keywords: N/A

Itai Ater - itai.ater@gmail.com
Tel Aviv University and CEPR

Adi Shany - adishany@tauex.tau.ac.il
Tel Aviv University

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Itai Ater[†] and Adi Shany[§]

[†]Tel Aviv University and CEPR
[§]Tel Aviv University

September 30, 2021

Abstract

This paper studies how firms use service time to respond to local competition and demand conditions when their 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-cost days of the week, and for deliveries offered by high-priced grocers. Next, we exploit regional and temporal variation in entry decisions to examine how incumbents respond. We find 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 entrants pose 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 classic newsvendor problem model to explain our findings, and in doing so emphasize the importance of accounting for both competitive and supply-side considerations when analyzing firms' response, particularly when prices are unresponsive.

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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@tauex.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. (2019), DellaVigna and Gentzkow (2019)). Moreover, retailers also do not change 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 using prices? How do operational capabilities or supply-side considerations affect firms' responses, and indirectly how markets clear when prices are unresponsive?[1]

We address these questions by investigating how online grocers use service time to cope with changes in local demand and competition conditions. The online grocery market is well-suited for studying the links between service time, demand and competition. First, 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.[2] Our analysis exploits changes in the competitive landscape to examine how online grocers respond to such changes. Second, 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 facing entry respond in distinct demand conditions. Third, online grocers' decisions are often determined locally. Accordingly, it is meaningful to examine how conduct changes when the local environment changes. With regard to our specific research questions, we later show that the Israeli online grocers set identical prices in markets characterized by very different competition conditions. Our analysis focuses on service time which has long been recognized as valuable for consumers and firms. The prominence of service time has grown further with the rise of e-commerce and corresponding changes in customers' time preferences. Specifically, consumers in the online grocery market observe service time before they buy, and service time affects their decisions where

[1] 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)).

[2] See www.businessinsider.com/online-grocery-report. and www.statista.com/topics/3144/online-grocery-shopping-in-the-united-kingdom/, respectively.

to buy.[3] Notably, we are not aware of previous empirical studies that consider the link between competition, demand and service time.

Our findings show that firms strategically use service time when demand and competition conditions change. The magnitude of this response is significantly smaller when the costs of providing timely service are high, or when the benefits of improving service time are low. For instance, we do not find evidence that incumbents who face entry improve service time on high-cost/high utilization days. Also, the effect of entry on the incumbent's service time is considerably larger in pre-entry monopolistic markets compared to entry to more competitive markets. Thus, our findings suggest that both competitive and operational considerations determine how retailers use service time to address changes in competition and demand conditions.

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 unserved 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 also examine how entry by a new 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 entrants pose a larger threat to incumbents.

The main data we use to test these predictions, described in Section 3, include bi-weekly service time data for the five online grocery chains that were active in Israel 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) demand conditions, respectively. 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

[3] Survey evidence shows that nearly half of online grocery shoppers consider speed an important factor. Two-thirds of respondents would consider switching vendors if delivery time offered by their normal retailer is not within a two-day window. See `www.statista.com/statistics/630351/factors-when-buying-food-online-in-the-united-kingdom-uk/`, and `getfabric.com/2019-grocery-report/`. We also provide evidence that consumers tend to switch online vendors on days with long service 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 different competitive markets.

To offer a causal interpretation for the effect of competition on service time, we take advantage of the panel structure of our data to estimate how entry of a new competitor into a given market affects the incumbent grocer's service time. We implement a staggered difference-in-differences (DiD) design with two-way fixed effects (TWFE) estimation that exploits the massive expansion of online retailers into new local markets during the sample period.[4] 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.[5] Moreover, since we record service time on both high- and low- demand days of the week, we can examine how the incumbent's response to entry (in terms of service time) differs across days characterized by high- and low- capacity utilization rate. Our analysis includes both event study DiD specifications, which accommodate the possibility of dynamic treatment effects, and static DiD specifications.

The event-study and static DiD estimation results, presented in Section 4, show that incumbents reduce service time when facing entry. However, the improvement in service time is large and significant when the costs of reducing service time are relatively low and when the benefits of doing so are high. In particular, we find that service time falls on low-demand/low-utilization days of the week, and when entry takes place into monopolistic markets. Our estimates show that 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 entries by rivals that pose a larger threat to the incumbent.[6] Importantly, the improvement in service time begins already before entry takes place and therefore points towards a strategic response by the incumbent rather than a mechanical drop in service time due to reduced demand to the incumbent's online

[4] 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.

[5] In Section 5.1 we address concerns that entry is not random and that the parallel-trends assumption for valid DiD estimation might not hold. We provide evidence that entry decisions are driven by long-term demographic and regional operational considerations. We also show that controlling for the presence of nearby stores do not affect the results. Moreover, using recent alternative staggered DiD estimation methods also do not alter the results.

[6] We use longitudinal customer-level data from an online grocery platform to identify which retailers pose a larger threat to the incumbent. We also use these data to show that demand for online grocery is considerably larger on pre-weekend days than on weekends.

service after a rival enters. In contrast, on high-demand/high-utilization days we do not find evidence for service time improvements surrounding market entry. Our final analysis explores how competition in one market affects service time in nearby markets. In particular, we examine how entry in one market affects service time in adjacent markets that do not experience entry, yet are served by the same fulfillment center. Our findings suggest that entry in one market triggers improvements in service time also in adjacent markets. This improvement is greater when we focus on entry by aggressive entrants, and is smaller in magnitude compared to the main effect.

This paper contributes to several strands of literature. First, to our knowledge, this is the first study that empirically examines the links between service time, demand and competition. While there exists an extensive theoretical literature examining how service times, capacity and competition interact (e.g., Luski (1976), De Vany and Saving (1977, 1983), Allon and Federgruen (2007, 2008, 2009), Kalai et al. (1992), and Cachon and Harker (2002)), empirical research is virtually nonexistent. With the rapid growth of e-commerce and online markets, the importance of service time is increasing, emphasizing the need to fill this gap in the literature. Some 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)).

Second, our findings highlight the importance of capacity constraints when firms make choices regarding non-price attributes, and in particular service time. While several papers examine the relationship between competition and broadly-defined quality attributes, to our knowledge, these papers do not take into account capacity or cost considerations that firms face when making these choices. In that regard, our findings add to the literature on productivity (Syverson (2011); De Loecker and Syverson (2021)), showing that competition has a positive impact on productivity, as measured by service time, though this effect depends on the rate of capacity utilization (see also Butters (2020) for a related argument). 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 could not examine how capacity concerns in in different demand conditions affect his findings.[7] 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). Thus, 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

[7]Other studies in this literature 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 its quality, as measured by the extent to which it screens popular and recent movies.

is observed at the time of purchase and can be compared across different online retailers prior to the purchase decision.[8]

Third, our paper adds to the literature on firms' non-optimal price-setting behavior and to the implications of uniform pricing. Several papers show that multi-store firms tend to 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)).[9] 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 an additional channel through which welfare is reduced due uniform pricing. In particular, we provide evidence that uniform pricing hinders the efficient allocation of resources 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.[10]

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 at the regional and at the local store levels.

The newsvendor problem offers a useful setting to examine a firm's optimal capacity choice

[8] Empirical papers also examine how waiting times affect purchase decisions, though not in the context of competition or demand conditions. Allon et al. (2011) studies the impact of waiting times in the fast food industry, and Lu et al. (2013) and Png and Reitman (1994) examine how the length of a queue and waiting times affect purchasing decisions in retail stores and gasoline stations, respectively. Finally, some studies use a single firm data to examine how consumer's behavior changes when shopping food online, and how the online grocery channel affects traditional food stores (Pozzi (2012, 2013), Chintagunta et al. (2012), Gil et al. (2020)).

[9] 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 (2019) claim that lack of data at the store level hinders optimal pricing decisions, whereas Ater and Rigbi (2020) claim that fairness concerns are the main reason why Israeli food retailers adopt uniform pricing after food prices became transparent.

[10] Somewhat in contrast, recent studies also examine how the use of sophisticated pricing schemes by ride-hailing platforms affects, among other things, service time (e.g., Hall et al. (2021) and Liu et al. (2021)).

when facing uncertain demand for its service. If realized demand is above the chosen capacity, the retailer forgoes the opportunity cost of lost sales, incurring what is often referred to as overage costs. Overage costs include both the direct one-time lost margin from customers who do dot purchase, and indirectly also the goodwill costs borne when customers are unable to complete their orders. Below, we assume that goodwill costs increase with the number of alternatives that customers face. That is, when customers have more options to choose from they are more likely to switch to these alternatives when their regular vendor is unavailable. Also, if a customer buys from a rival once he may later choose to continue buying from that rival. However, if realized demand is below the chosen capacity level, the retailer is not fully utilizing its resources and is incurring underage costs. Thus, in selecting the optimal capacity level, a retailer faces a trade-off between overage and underage costs. We use the newsvendor problem to show how this trade-off varies with the price that retailers set, the level of competition and the marginal cost of capacity.

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 inputs such as the number of delivery trucks and manpower. Let c be the marginal cost associated with installing additional capacity. Demand for service is uncertain, distributed with continuous cdf $F(\cdot)$, where R is a fixed margin earned for each order. Let γ represents the goodwill cost when the retailer cannot offer service to a customer. This goodwill cost increases in the number of alternatives a customer faces. Thus, a retailer decides on its optimal capacity, K, in order to maximize expected profits:

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

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

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

This trade-off underscores the importance of three factors: 1) marginal cost of capacity (c); 2) price (R), and 3) goodwill cost (γ). To apply this trade-off in our context, we assume that increased capacity translates into shorter service time, denoted by s, i.e., $\frac{\partial s}{\partial K} \leq 0$.[11] Changes in c, R and γ 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

[11] 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.

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 are 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 (γ) are high retailers are concerned about losing customers, and therefore increase capacity and reduce service time ($\frac{\partial s}{\partial \gamma} < 0$). In Section 3.3 we use our data to test these predictions. Moreover, below we derive additional predictions that consider how changes in competition – an increase in the value of γ – affect service time offered by the incumbent. In particular, we examine how the incumbent responds to entry of a new rival, 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 only uses cross-sectional data does not.

2.2 The effects of entry on service time

Following entry of a new rival, γ increases and hence incumbents will increase capacity and offer shorter service time ($\frac{\partial s}{\partial \gamma} < 0$). 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. 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 the market, the marginal effect of an additional entrant on service time offered by the incumbent diminishes. Formally, this prediction is captured by $\frac{\partial^2 s}{\partial \gamma \partial \gamma} > 0$. This prediction is a standard prediction in entry models 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 might depend on the extent to which an incumbent utilizes its existing capacity. If the utilization rate is high, then the incumbent will find it expensive 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 γ 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. A second, more nuanced, effect of entry on service time is through its indirect impact on capacity costs. Following entry, the number of orders received by the incumbent is expected to fall as at least some customers switch. As a result, the incumbent's marginal cost of capacity, c, might change. The direction of this change depends on the shape of 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 incumbents' service time decreases post-entry. To empirically separate these effects, with the broader aim identifying the strategic effect on 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 changed and are therefore driven only by strategic considerations. An improvement before entry may reflect retailers' attempt to improve customers' goodwill, presumably to reduce the likelihood of future switching to the entrant.

3 Industry Background, Data and Descriptive Statistics

3.1 The online grocery market in Israel

Online grocery sales in Israel have been growing rapidly in recent years, since even before the COVID-19 pandemic. Our analysis focuses on the five traditional supermarket chains that offered online grocery service between 2016 and 2019: Shufersal, Mega, Rami Levy, Victory and Yeinot Bitan. The joint market share of these supermarket chains in the traditional retail food market was 68% in 2014.[12]

Shufersal is the dominant player both in traditional stores and in the online segment, operating

[12] 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.

283 stores at the beginning of 2016. Industry insiders estimate that the market share of Shufersal is about 70% of the online grocery market.[13] According to its annual financial report, 13.6% of Shufersal's annual sales come from the online channel, up from 4.2% in 2014 and 11.5% in 2017. Shufersal's home deliveries are distributed from 34 large stores across Israel, with each distribution center serving several nearby localities. Mega, the second largest chain, suffered substantial losses and entered bankruptcy proceedings in early 2016. Consequently, Mega divested many of its stores, and is the only chain out of the five studied to have decreased the number of stores over the data collection period: from 172 stores in January 2015 to 125 stores in the following year, and to 99 in mid 2019. Yeinot Bitan, the third largest chain, increased the number of physical stores it operated, from 72 in January 2016 to 88 in mid-2019 accordingly. In July 2016, Israel's competition authority approved a merger between Yeinot Bitan and Mega. Yet, the operations of the two chains, and particularly their online services were kept separate. The online sales figures for Mega and Yeinot Bitan, which are not publicly traded, are not available but are estimated to be lower than those of the three other publicly-traded chains.

The two remaining chains, Rami Levy and Victory underwent a rapid growth during the data collection period and increased the number of stores they operated. Rami Levy, the second largest chain in terms of overall turnover, is well known for its low-price strategy. Rami Levy operated 27 stores in January 2015 and 52 stores in June 2019. Victory, the fifth largest chain in terms of overall volume also substantially increased its number of stores, from 29 storesto 51 stores. In 2019, 7.2% of Rami Levy's sales and 4% of Victory's sales were from the online channel.

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

3.2 Data

Below we describe the different data sources that we use. 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. Finally, in some analyses we use customer-level data from an online shopping grocery platform.

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

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 as 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 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 since retailers either offer online service to all addresses in a given locality or not at all, we consider each address as a separate market.[14] 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 data on the total number of retailers that offer service to each address serve as our measure of local competition. We use variation in this measure to identify entries and exits to and from a local market. 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.

3.2.2 Price data

We use detailed data on the 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 monthly average of the price of this basket 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 obtain the product-store-day 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 collected from chains' annual reports data on physical stores operated by the five chains and on the locations of Shufersal's 34 distribution centers. We match these 34 distribution centers to the 180 local markets based on the closest driving distance. Appendix Figure C1 shows in black dots the location of the 180 local markets in our sample and in red dots the locations

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

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.[15]

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 MySpermarket 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 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 Yeinot Bitan. See Appendix A for more details.

3.3 Descriptive statistics

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 descriptive statistics that support the predictions described in Section 2.1.

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 mean of the monthly average of basket price sold by each retailer against the number of active online retailers in the market. The monthly average price is calculated for a basket of 52 similar popular items sold by the online grocer in all the markets served by that retailer in each month.

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 44 hours. In markets where Shufersal competes with four online retailers, its mean service time is only 22

[15] 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.

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 local competition. Also, grocers choose different price levels and there exists a strong negative relationship between service time and prices 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, lend support to the predictions outlined in Section 2.1.

3.3.2 Service time in different demand and capacity utilization conditions

To further explore the validity of the service time trade-off in equation 1, we want to examine how service times vary with capacity utilization. To this end, we distinguish between low and high demand days of the week, assuming that the same capacity (e.g., trucks) is used on both low and high demand days of the week in the same market. Therefore, grocers experience low utilization rate and low marginal costs on low demand days, while high utilization rate and high marginal costs on high demand days.[16]

Panel (a) of Figure 2 builds on the distinction between high vs. low demand days and presents Shufresal's service times in markets with different competition and utilization conditions. The figure shows that 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 are smaller in more competitive markets. 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.[17] For completeness, Panel (b) in Figure 2 presents a time series of Shufersal's average price of the basket containing the 52 products on Sunday and on Thursday in each 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

[16] To support the distinction between low- and high- demand days of the week, Figure A3 presents the cumulative percent of orders through MySupermarket in the 48 hours before the time the crawler was active on Wednesday and Saturday. 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 the orders over periods longer than 24 hours. The Figure shows that the cumulative percent of orders is about 3 times larger on Wednesdays than on Saturdays. This pattern supports our assumption that demand – as well as the corresponding capacity utilization rate – is higher on Wednesdays than on Saturdays. Also, Panel (b) of Figure A4 shows that on days characterized with long service time, customers are more likely to switch and buy from a vendor which is not their regular vendor.

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

demand is low (Sundays) and on days where demand is high (Thursdays).[18] The patterns shown in Figure 2 support the predictions laid out in Section 2.1.

3.3.3 Market structure evolution and demographic differences

Our regression analysis takes advantage of online grocers' expansion decisions to identify the effect of competition on the incumbent's service time. Panel (a) in Figure 3 presents the evolution of market structures in our sample. 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) 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, Yeinot 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. Overall, we observe at least one entry in 129 of the markets in our sample. We also observe exits during our sample period, mainly by Mega. We control for these exits in the empirical analysis.

Figure 4 uses the raw service time data to show the mean service time 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 (pre-entry monopolies, pre-entry monopolies and duopolies, 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 that this reduction is more pronounced on low- demand days. Moreover, the reduction in service time, as measured by the slope of the service time, is larger in monopolistic markets than in competitive markets.

Table 1 presents demographic information on all 180 markets, classified according to whether they did or did not experience entry during the sample period. In our sample 129 markets experienced at least one entry, and in 55 of these markets, the incumbent was a monopoly before entry. 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 more online retailers operate 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

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

that did not, in particular for less competitive markets.

4 Estimation and Results

The descriptive statistics patterns presented above are consistent with the predictions derived from the service time trade-off described in Section 2.1. Nevertheless, we are cautious not to interpret these findings as causal, since they do not take into account other factors that may affect service time offered in these markets. In this section, we address these concerns by examining how incumbents respond to competition once a new firm enters a local market. We focus 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 that we observe.[19]

We implement a staggered difference-in-difference (DiD) design with two-way fixed effects (TWFE) estimation. This estimation strategy takes advantage of the massive expansion by online retailers into new local markets, and compares service time offered by the incumbent firm in markets that experienced entry (treated markets) to service time in markets that did not experienced entry (untreated markets). The variation in the timing of entry to different 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. Since our measure of local competition is based on deliveries to customers' home address we are not concerned about defining the geographical local market.

The validity of our estimation strategy requires that the parallel-trends assumption holds. We comprehensively address this issue in Section 5.1. Here we briefly mention the following. First, our analysis focuses on the incumbent's response to entry rather than the entrant's behavior (like Goolsbee and Syverson (2008) and Matsa (2011)). Second, Figure B1 in Appendix B shows that entry decisions are spread over the three years, mitigating concerns about strategic timing of entry. Figures C2 and C3 in Appendix C show that retailers tend to enter localities in regions where they already operate, thereby taking advantage of operational efficiencies (Holmes (2011)). Taken together, we claim that the incumbent's service time is unlikely driving the timing of entry nor the specific market that is entered. Finally, our setting allows us to examine the effect of entry on low and high demand days of the week in the same local market. This within-market comparison allows to examine pre-entry trends, and presumably rule out concerns that the timing of entry is driven by changes at the market level.

We begin the analysis with event study DiD specifications, which accommodate the possibility

[19] About 70% of entries in the sample are first entries.

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:

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

where the dependent variable, $Log(delivery\_time)_{it}$, is log of the average service time offered by Shufersal in locality i in month t. δ_i and α_t are locality and month-year fixed-effects, respectively. Locality fixed-effects account for market characteristics that may have affected entry decisions. Month-year fixed-effects account for seasonal and other trends at the national level. $entry_i$ is the month of entry for market i, and $\mathbb{1}[t - entry_i = k]$ 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.

The key coefficients of interest are β_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. Following Goolsbee and Syverson (2008) and since we expect that the effect of entry on service time may take place even 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 (or control group). 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. To interpret the event-study monthly coefficients in equation 2 as the causal effect of entry requires that the parallel trends assumption holds. Including "lags" in equation 2 enable us to test for the parallel trajectories of the outcomes before the onset of treatment. We discuss the validity of this assumption in greater detail in Section 5.1.

4.2 Event study 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 β_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 retailers, 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 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 (i.e., for pre-entry monopolies treated markets, the untreated markets are markets where Shufersal was a monopoly during the entire sample period).

According to Panel (a) in Figure 5, service times in pre-entry monopoly markets dropped by about 10 to 20 percent on low demand days. The drop in service time materialized 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 times on high-demand days. Figure B2 in Appendix B reports the results from a specification that expands the event window to 12 month before and after entry. Figure B3 in Appendix B reports the results from estimating equation 2 using a sample of only markets that experienced entry (only treated markets) and relying only on the variation in timing of entry for causal identification. The results from these analyses are consistent with our main findings. We now turn to the parametric DiD estimation which enables to directly test the predictions developed in Section 2.2.

4.3 Difference-in-differences estimation

The event study estimation uncovers two important patterns in the short-term response to entry. The first is a significant drop in service time in the two months preceding entry, and the second is a non-dynamic nature of the 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 TWFE DiD regression:

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

where pre_entry_{it} is a dummy for the 1-2 months preceding entry into the local market and $post\_entry_{it}$ is a dummy for the months after entry into the local market. 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 but results are similar with different definitions as reported by Appendix Table B1), and dummies for exits and subsequent entries 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).

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 nearby non-entered markets. In our main analysis we use all untreated markets as the control group, though results are similar when we use only treated markets or untreated markets with the same pre-entry competition level as treated markets (see Table B2).

4.4 Results of DiD estimation

4.4.1 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 markets which were served by only one online retailer before entry. Panel B focuses on markets that were served by up to 2 online retailers, and Panel C reports the results for all markets. 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 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, at all competition levels, are statistically insignificant. Tables B1 and B2 in Appendix B show that the estimated effects of entry on the incumbent's service time are not sensitive to alternate definitions of control markets and to rivals' physical stores in the market.

Overall the results in Table 2 support the theoretical predictions outlined in Section 2.2, suggesting that increased competition triggers shorter service time, particularly in concentrated markets and on low-demand/low-utilization days.

4.4.2 Response by entrant type

Our theoretical framework distinguishes between entry by aggressive and non-aggressive retailers. We consider the retailers Rami Levy and Victory as aggressive retailers. Figure 1 shows that Rami Levy offers the cheapest basket and Victory offers the shortest service time. In contrast, Mega, is the most expensive chain and Yeinot Bitan offers medium prices and long service times. Moreover, in Appendix A we use the longitudinal customer level data from MySupermarket, an online grocery platform, to show that Rami Levy and Victory are closer substitutes to Shufersal. That is, Shufersal's online loyal customers are likely to buy from these these chains when they choose not to order from Shufersal (36% switch to Rami Levy and 28% switch to Victory).[20]

Table 3 reports the results of the parametric estimation only for entries by Rami Levy and Victory. The results show that the incumbent retailer, Shufersal, improves its service time on low-demand days when one of the aggressive retailers (Rami Levy or Victory) enters. The magnitude of the effect is nearly 25% larger than in the main specification, and is significant also for entries into non pre-entry monopolistic markets. Thus, in pre-entry monopolistic markets (panel A), the incumbent reduces service time by 16.2 percent before entry and 12.2 percent after entry. According to Panel C, which shows the results for all markets, the incumbent reduces service time before and and after entry by 7.7 and 6.8 percent, respectively. On high-demand days, we find the the effect on post-entry service time is negative and marginally significant in monopolistic markets. The results are consistent with the theoretical predictions outlined in Section 2.2

4.4.3 Supply-side externalities

Our last exercise examines how incumbents improve service times in markets that were not entered but are adjacent to markets that experienced entry. We are interested in understanding whether there are positive or negative spillovers in service time to markets that are served by the same fulfilment center. To examine this, we classify each of the 180 markets in our sample to 34 fulfillment centers that Shufersal uses to pick and distribute online orders. Next, we focus on the 51 markets that did not experience any change during the sample period, and repeat the parametric estimation (equation 3) where the entry dummy variables refer to entry in adjacent markets. In particular, these indicators receive the value of one if entry occurred in another local

[20] Panel (a) in Figure A4 shows switching patterns for Shufersal's loyal customers across the four retailers. We define a loyal customer as a customer who used the online grocery platform more than 10 times over the time period, and ordered from the same online grocer in at least 60% of those orders. In our data, there are 2,861 loyal customers of the incumbent firm, Shufersal.

market that is served by the same fulfillment center. The 51 markets that did not experience any entry in the sample are served by 22 fulfillment centers. Fifteen of these centers experienced entry to at least one of the local markets that they serve. In the analysis, we distinguish between entry to pre-entry monopolistic markets (where we previously found a large impact on service time) and entry to other markets, and also between entries by aggressive retailers to entries by other retailers.

Table 4 reports the results using specification similar to equation (3) without the fulfillment center linear time trend.[21] Panel A reports the results when entry is by any retailer, and Panel B reports the results when entry is by aggressive retailers. 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 only. The results suggest that when an aggressive retailer enters one local market, the incumbent firm improves service time in adjacent markets that are served by the same distribution center. This improvement is observed only on low demand days, and it occurs after entry takes place. One possible explanation can be that the decline in demand on markets where an aggressive retailer entered, freed resources that enables the incumbent to offer better service in adjacent markets.[22]

5 Threats to Identification Strategy

5.1 The timing of entry decisions

The casual interpretation of our analysis relies on the parallel trends assumption, implying that the trend of service time should be the same for treated and untreated markets in the absence of treatment. In this section, we discuss why we think that this assumption likely holds in our setting. That is, why the decision whether and when to enter is uncorrelated with unobserved factors that are also associated with the service time offered by the incumbent.

First, our analysis focuses on service time offered by the incumbent. Accordingly, the concern is that the timing of entry is correlated with the incumbent's online capabilities or demand in that market. For instance, a retailer will enter a market in 2017 instead of 2018 because the incumbent's service time capabilities are temporarily damaged. Below, we argue that entry decisions are predominantly driven by the entrant's operational 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 biased downward.

Second, entry decisions likely depend on the socio-demographic characteristics of local markets, such as population size, expected population growth and average income (Table 1). These factors

[21] In the sample of the 51 markets we observe only few markets for each fulfilment center (between one to five market for each). Hence, we can not include fulfillment center linear time trend in this analysis.

[22] The findings that service times do not change before entry to adjacent markets could imply that our results regarding pre-entry effect on service time 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 is a lower bound for the true effect.

are unlikely to significantly change during the time period we study, and are likely captured by the market fixed-effects that we include in the analysis. Moreover, short-lived changes in population are also less relevant since entry decisions are likely based on long-term market characteristics of the local market. Likewise, the incumbent's infrastructure was in place at the beginning of the time period we study, and to our knowledge has not changed significantly. Also, as discussed above, controlling for the number of physical stores operated by rivals does not affect our results. Nevertheless, if unobserved time variant factors affect demand for online service and also influence the timing of entry, then our estimates are potentially biased.

Third, entry decisions are predominantly driven by entrants' operational concerns rather than on the incumbent's service time. Offering online service requires non-trivial investments, such as training workers, converting trucks into food-delivery trucks, modifying physical stores for distribution, and investing in local advertising. These investments depend on a retailer's capabilities and available infrastructure in the respective region. To save costs retailers offer service to several localities in the vicinity of the same distribution center. Figures C2 and C3 in Appendix C show the geographical expansion of online service offered by each of the four chains. The figures also present the location of the brick and mortar stores of each of the retailers. The patterns shown in the 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. Our assumption is that these patterns are not driven by unobserved time-variant factors that affect service time by the incumbent. Finally, our analysis compares the response to entry in high and low demand periods. As entry occurs in both high and low demand periods, the comparison between low and high demand periods is not sensitive to concerns about endogenous entry. Moreover, the fact that on high demand weekday and on more competitive markets we do not find any change in service time lends additional support that unobserved time-variant factors are not driving our results.

5.2 Staggered TWFE DiD designs pitfalls

Recent advances in econometric theory suggest that staggered DiD designs using TWFE may not provide valid estimates of the causal estimands of interest. i.e. the average treatment effect (ATE) or the average treatment effect on the treated (ATT), even under random assignment of treatment (e.g., De Chaisemartin and d'Haultfoeuille (2020), Sun and Abraham (2020), Callaway and Sant'Anna (2020), Goodman-Bacon (2021), Borusyak et al. (2021)). The main pitfall is that static estimation produce a weighted average of dynamic (vary over time) and heterogeneous (vary over treatment-timing groups). In a setting where there is a staggered timing of treatment assignment and no treatment effect heterogeneity across units or over time, the TWFE DiD estimates are unbiased. A dynamic estimation by event study can provide unbiased estimates even if treatment effect vary over time but only under the assumption of homogeneity treatment effect across units.

Our event study estimation provides unbiased estimates, at least in the short run, if the homogeneity treatment effect assumption holds. Accordingly, the static TWFE DiD estimation also provides unbiased estimates for the short term effect. The homogeneity assumption in the short term and the restrictions on the leads in our specification (impose zero effect for more then j months before entry) can be justified by our theoretical framework. First, the model assumes that capacity is pre-determined and cannot change quickly. Second, the incumbent's response in the short-term depends on the competition level and its capacity utilization which vary by the day of the week. Hence, the model assumes homogeneity conditional on pre-entry competition and utilization/demand levels. Third, since the incumbent's response depends only on γ that can change (c and R are fixed), we able to impose zero effect for long period before the treatment (entry).

The homogeneity assumption might not be hold if there are specific cohorts treatment effect which means that different treated cohorts (markets with entry in different timing) respond differently to the entry. In that case, conditioning on the pre-entry competition and demand levels as we do in our analysis will not solve the problem, and could yield biased estimates. To mitigate this concern we use two alternative estimation methods by Sun and Abraham (2020) and Borusyak et al. (2021) that enable us to obtain unbiased estimates under heterogeneity treatment effect. We apply these methods and present the results in Figures D1 and D2 in Appendix D. The Sun and Abraham (2020) estimators are remarkably similar (slightly larger) to our TWFE estimators, suggesting that our baseline results are unbiased. Likewise, the estimation results using Borusyak et al. (2021) are similar to our main results, suggesting that our TWFE DiD estimates are unbiased. In Appendix D we provide more details on the application of these methods in our setting.

6 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 new rival enters, and the effect is larger in concentrated markets and on low demand weekdays. On high-demand days, when incumbents' utilization rate is high, we do not find that incumbents respond to entry. Overall, these results suggest that firms strategically use service time to respond to changes in competition and demand conditions. Nevertheless, firms' operational considerations also determine how retailers respond to competition.

We also note that our event-study and static DiD estimation results capture the short-term effect of entry on service time. In the long-run, as presumably reflected in the cross-sectional evidence, firms are able to change capacity, by adding relevant inputs or changing production technology. This distinction between the response in the long and and in the short run might explain why the cross-sectional variation reveals large differences in service time between low and high demand levels, whereas the intertemporal variation following entry suggests otherwise. We leave this issues for further research.

Our results speak to the debate about uniform pricing. Growing evidence shows that national chains set similar prices in very different environments. 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 respond to competition and demand conditions, and eventually markets clear. Perhaps more broadly, the patterns we uncover for service time in different demand and competition conditions offer a mirror image to what standard models of competition predict for prices. In particular, according to a Bertrand with differentiated-products model with fixed quality, prices are expected to be lower in more competitive markets and in low-cost environments. Also, in this standard model entry has a greater impact on prices in monopolistic markets and when incumbents face low marginal costs. Remarkably, our findings offer 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. Moreover, 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 facilitate market clearing.

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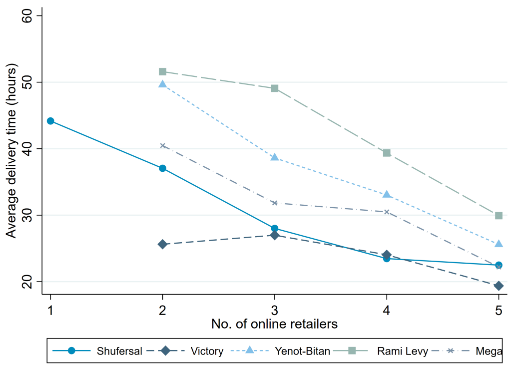
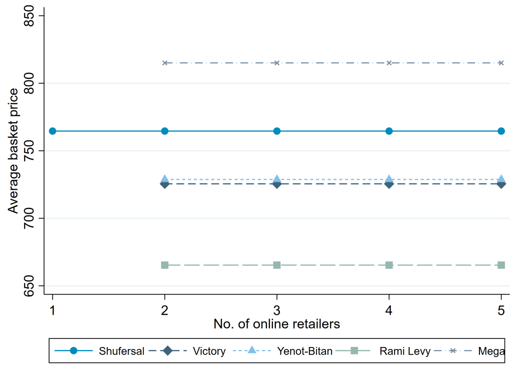
Figure 1: Service time and prices as a function of competition and demand levels

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



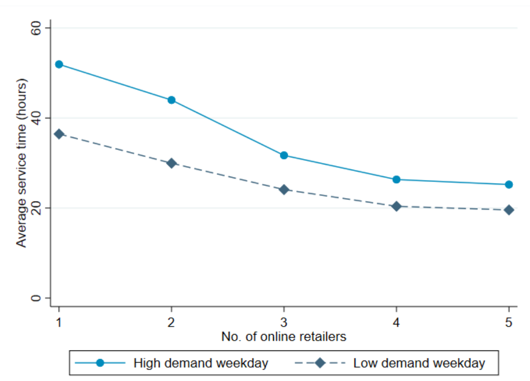
(b) Mean basket price by no. of active retailers



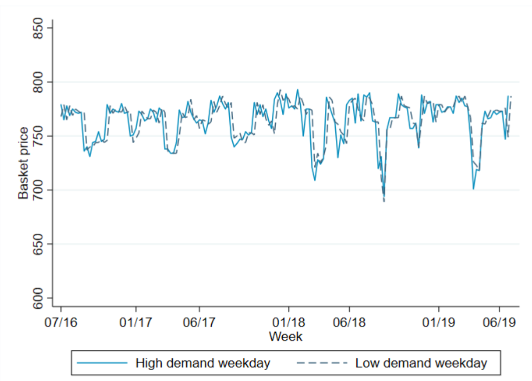
Notes: Panel (a) shows the average service time for each retailer by the number of active online retailers in each market. Panel (b) shows the average basket price for each retailer by the number of active online retailers in each market. Both graphs are based on monthly data from August 2016 to July 2019. 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 44 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



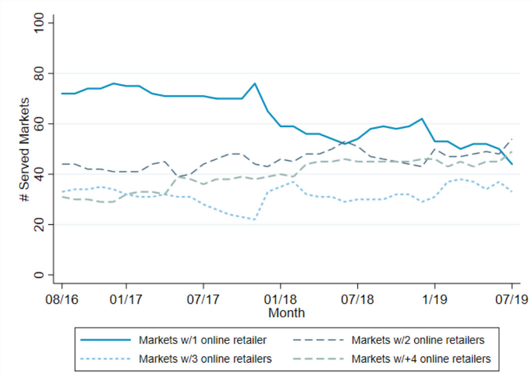
(b) Mean basket price by low/high demand days



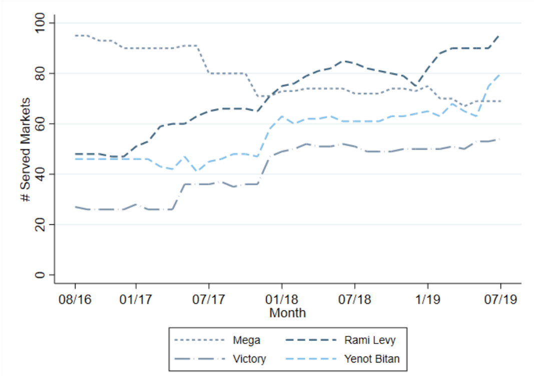
Notes: Panel (a) shows the average service time of Shufersal as a function of the number of active online retailers in each market, separately for low- demand/low utilization days and for high demand/high utilization days, based on monthly data from August 2016 to July 2019. Panel (b) shows the daily price of a basket of 52 products sold by Shufersal's online channel, separately for 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. Panel (b) presents a time series of Shufersal's mean basket price, focusing on the basket price on Sunday and on Thursday in each week (the days following the crawler operating time). 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

(a) Market structure evolution



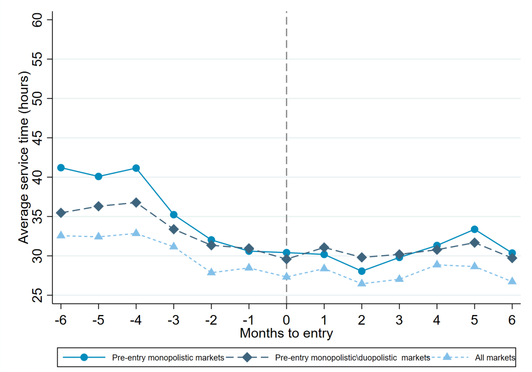
(b) Online retailers' expansion



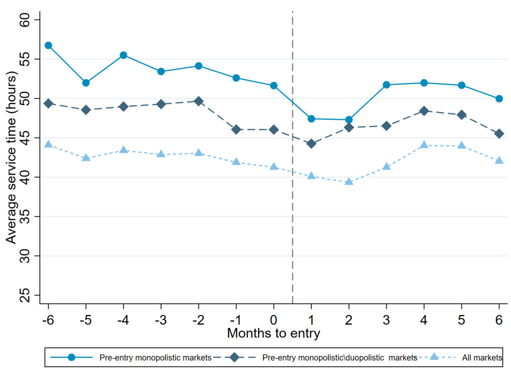
Notes: Panel (a) shows the number of markets at different competition levels in each month during the sample period. In August 2016, 72 markets were monopolies, and there were only 31 markets in which at least four online retailers were active. Over the 3 years, competition intensified, and in July 2019, 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, Yeinot 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 market competition and demand levels

(a) Low demand day



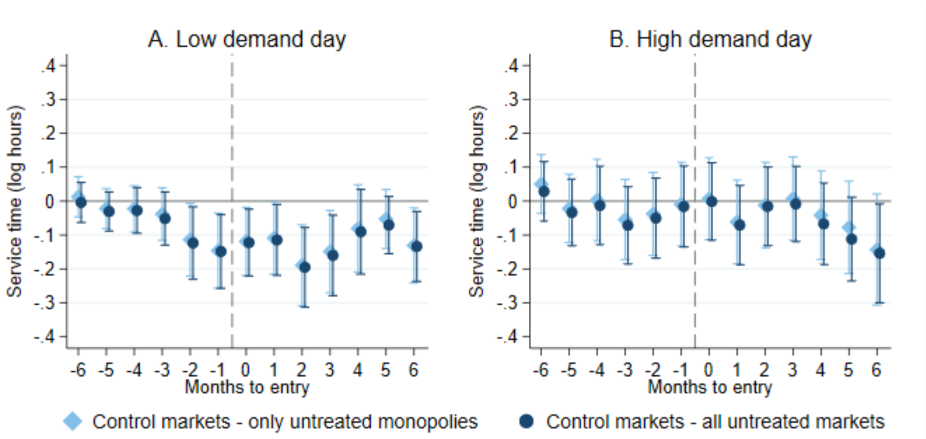
(b) High demand day



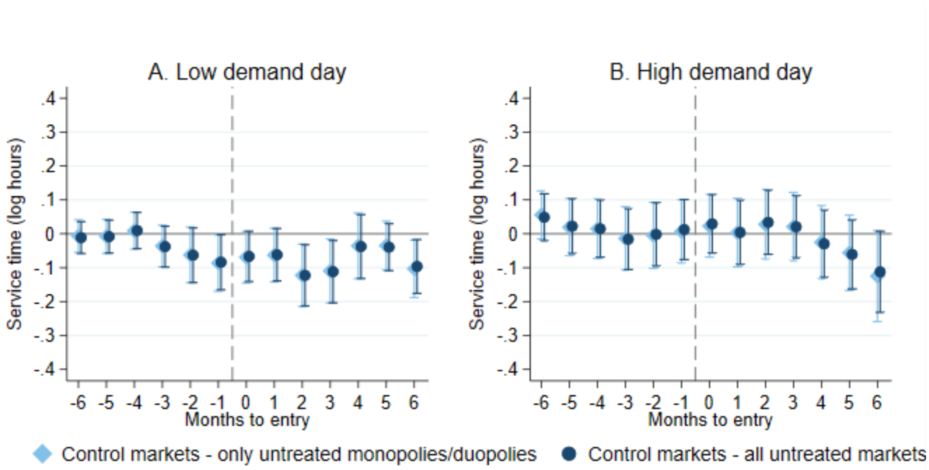
Notes: The figure plots average service times of the 129 markets that experienced entry as a function of the number of months before and after the first entry of a rival during the sample period. The figure distinguishes between low (Panel (a)) and high (Panel (b)) demand days of the week, and between markets with different numbers of active retailers before entry. 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 this reduction is more pronounced on low-demand days. Moreover, the reduction in service time, as measured by the slope of the service time, is larger in monopolistic markets than in competitive markets.

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

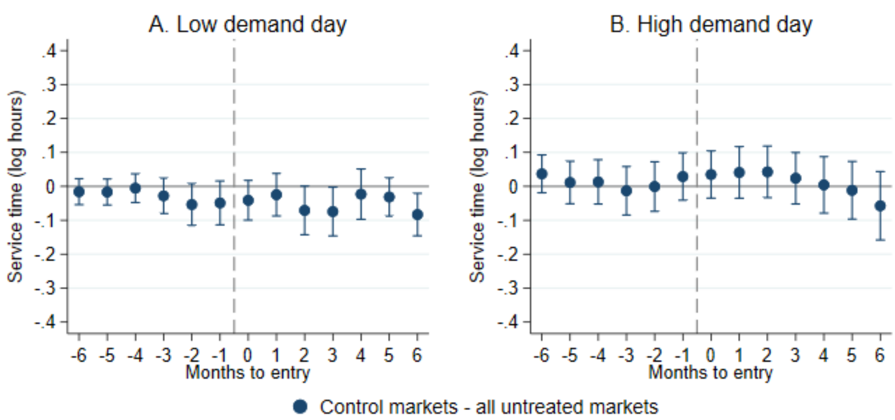
(a) Pre-entry monopolistic markets



(b) Pre-entry monopolistic/duopolistic markets



(c) All markets



Notes: The figures plot the coefficients of β_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-damned and high-demand days. Panel (a) reports the estimated effects of entry in pre-entry monopolistic 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 monopolistic markets.

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

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

	Low-demand day			High-demand day		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: pre-entry monopolistic markets						
pre_entry	-0.127**	-0.129**	-0.130**	-0.015	-0.015	-0.005
	(0.058)	(0.058)	(0.055)	(0.058)	(0.058)	(0.050)
post_entry	-0.119**	-0.120**	-0.093*	-0.085	-0.080	-0.014
	(0.053)	(0.053)	(0.0488)	(0.056)	(0.056)	(0.045)
Markets				106		
Markets with entry				55		
N				3,804		
Panel B: pre-entry monopolistic / duopolistic markets						
pre_entry	-0.067	-0.067	-0.068*	0.014	0.015	0.021
	(0.042)	(0.042)	(0.039)	(0.042)	(0.042)	(0.036)
post_entry	-0.078**	-0.077**	-0.056*	-0.054	-0.051	0.009
	(0.038)	(0.038)	(0.033)	(0.044)	(0.044)	(0.038)
Markets				139		
Markets with entry				88		
N				4,988		
Panel C: all markets						
pre_entry	-0.039	-0.039	-0.052*	0.022	0.023	0.005
	(0.032)	(0.032)	(0.031)	(0.032)	(0.032)	(0.029)
post_entry	-0.051*	-0.049*	-0.045*	-0.013	-0.009	-0.003
	(0.029)	(0.029)	(0.025)	(0.036)	(0.036)	(0.030)
Markets				180		
Markets with entry				129		
N				6,456		
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 Shuseral'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: Effect of entry by aggressive retailers on service time, by competition and demand level

	Low demand day			High demand day		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: pre-entry monopolistic markets						
pre_entry	-0.143*	-0.145**	-0.162**	0.004	0.003	0.002
	(0.073)	(0.073)	(0.071)	(0.064)	(0.065)	(0.058)
post_entry	-0.142**	-0.143**	-0.122**	-0.111*	-0.107	-0.036
	(0.065)	(0.064)	(0.060)	(0.065)	(0.064)	(0.050)
Markets	93					
Markets with entry	42					
N	3,339					
Panel B: pre-entry monopolistic / duopolistic markets						
pre_entry	-0.089	-0.089	-0.103*	0.025	0.025	0.033
	(0.056)	(0.056)	(0.053)	(0.050)	(0.050)	(0.043)
post_entry	-0.103**	-0.101**	-0.093**	-0.077	-0.074	-0.001
	(0.048)	(0.048)	(0.042)	(0.053)	(0.053)	(0.043)
Markets	114					
Markets with entry	63					
N	4,093					
Panel C: all markets						
pre_entry	-0.063	-0.063	-0.077*	0.033	0.033	0.026
	(0.043)	(0.043)	(0.040)	(0.038)	(0.038)	(0.033)
post_entry	-0.074*	-0.073*	-0.068**	-0.039	-0.034	0.005
	(0.038)	(0.038)	(0.032)	(0.045)	(0.045)	(0.035)
Markets	139					
Markets with entry	88					
N	4,988					
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)
Panel A: Entry by all retailers								
pre_entry	0.017	0.019	-0.010	-0.012	0.033	0.044	0.082	0.083
	(0.025)	(0.026)	(0.033)	(0.034)	(0.069)	(0.065)	(0.065)	(0.065)
post_entry	-0.021	-0.010	-0.058	-0.052	-0.036	0.006	0.048	0.072
	(0.041)	(0.038)	(0.035)	(0.035)	(0.084)	(0.084)	(0.076)	(0.074)
Panel B: Entry by aggressive retailers								
pre_entry	-0.027	-0.027	-0.031	-0.032	-0.045	-0.036	0.030	0.036
	(0.038)	(0.039)	(0.040)	(0.040)	(0.064)	(0.060)	(0.071)	(0.069)
post_entry	-0.091*	-0.085	-0.089*	-0.084*	-0.124	-0.090	-0.012	0.016
	(0.051)	(0.052)	(0.046)	(0.046)	(0.092)	(0.092)	(0.089)	(0.084)
Markets	51							
N	1830							
rivals' offline stores (10km radius)		✓		✓		✓		✓
exits and additional entries indicators		✓		✓		✓		✓

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

Notes: The table reports estimation results for equation 3 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 an adjacent market served by the same fulfillment center. *post_entry* is an indicator for the month of entry in the adjacent market and for the following months. Entry indicators in columns 1, 2, 5 and 6 refer to all entries in adjacent markets, and in columns 3, 4, 7 and 8 to entries only to monopolistic adjacent markets. Entry indicators in Panel A refer to entries by all retailers, and in Panel B only to entries only by aggressive retailers. 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.

Appendix A Online grocery platform data

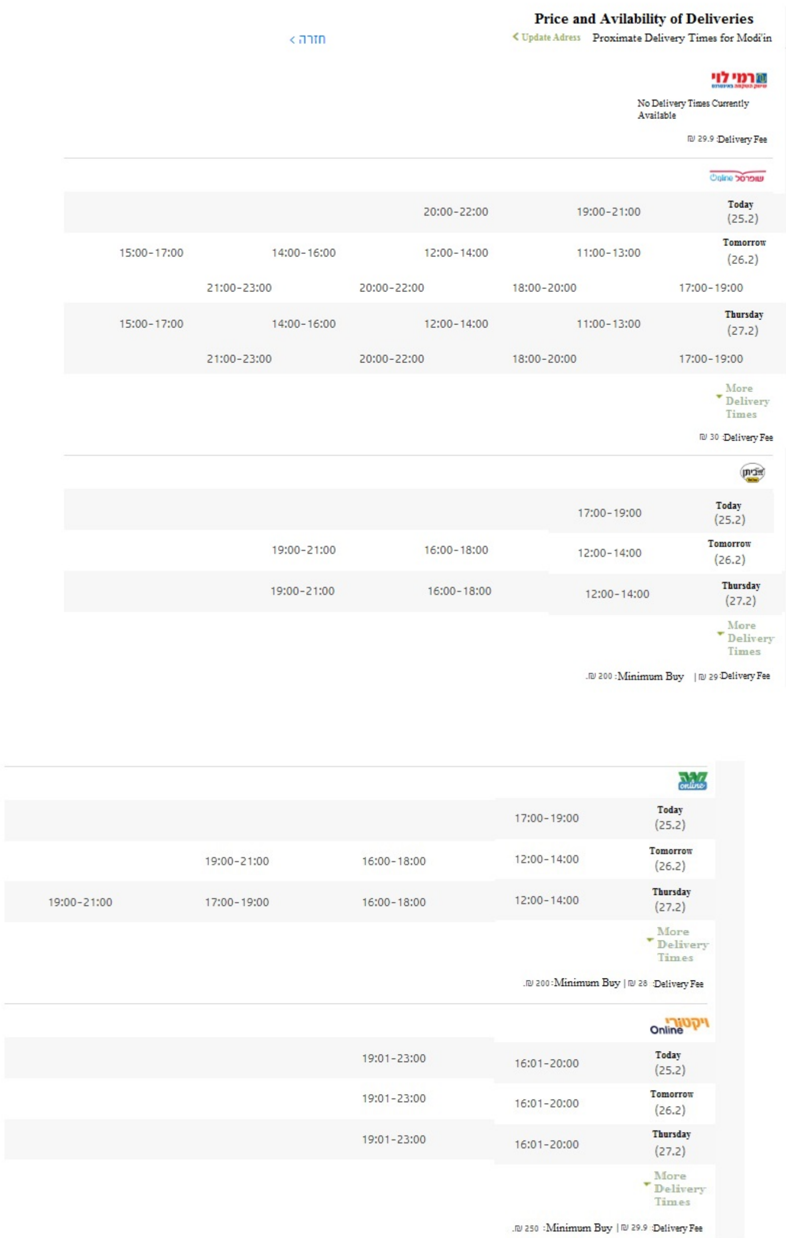
We use proprietary data from MySupermarket.co.il, an online platform that enables users to shop at each of the five online retailers. MySupermarket users can compare prices and contemporaneously observe available service times offered by each retailer. Figures A1 and A2 below show examples of screens 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 MySpermarket 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 the MySupermarket data in three ways: 1) to examine how the number of online grocery orders changes over days of the week, 2) to examine substitution patterns across retailers, and accordingly characterize entrants as more vs. less aggressive (Panel (b) in Figure A4), 3) 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). This latter analysis provides additional support for our assertion that customers care about service time when choosing where to buy.

Figure A1: Online shopping platform - basket price

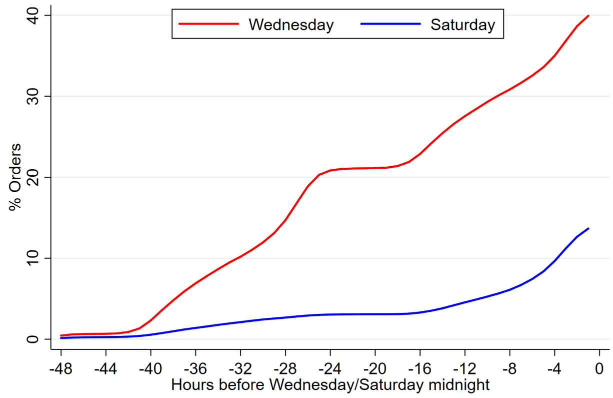
Notes: The figure shows a screenshot from MySupermarket.co.il webpage where consumers observe the basket price offered by each of the online grocers that offer service to their address, and can choose the retailer they want to order from. For instance, Rami Levi, offers the cheapest price for this basket (23 products, NIS749.37).

Figure A2: Online shopping platform - service time



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

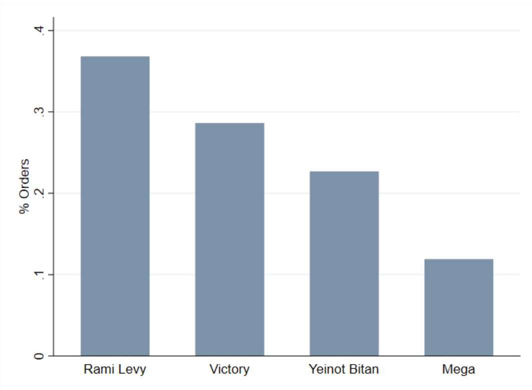
Figure A3: Cumulative orders before crawler time on MySupermarket.co.il



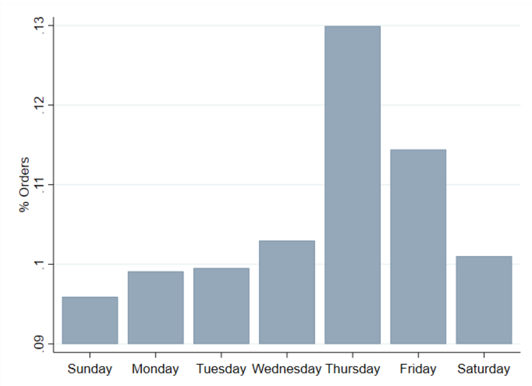
Notes: The figure shows a normalized measure of the number of consumers that order through MySupermarket. It plots the cumulative percent of orders over the 48 hours that precede the crawler time (midnight on Saturday and on Wednesday). The figure demonstrate that demand is considerably higher on pre-weekend days compared to weekend demand.

Figure A4: Customers' switching patterns at MySupermarket.co.il

(b) Switching patterns across online grocers



(a) Switching patterns across days of the week

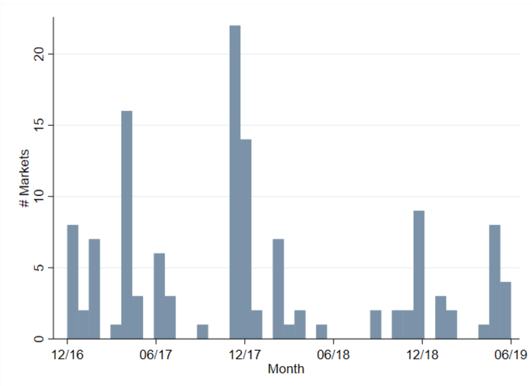


Notes: The figures show switching patterns of loyal customers who using MySupermarket.co.il to purchase online groceries. A loyal customer is defined as an individual who used the MySupermarket platform more than 10 times during the sample period, and at least 60 percent of times bought from the same retailer. There are 9,182 loyal customers in the sample, 2,861 are Shufersal's loyal customers. Panel (a) focuses on Shufersal's 2,861 loyal customers and shows the percentage of orders made by these customers who choose to purchase from other retailers. According to the figure about 64 percent of switches by Shuferasl's loyal customers are to Rami Levy and Victory, which we consider as aggressive entrants. Panel (b) shows the percentage of orders made by all loyal customers (both of Shufersal and of the other four retailers) who choose not to purchase from their regular retailer on each day of the week. More than 17 percent of switches by the 9,182 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 before the weekend (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.

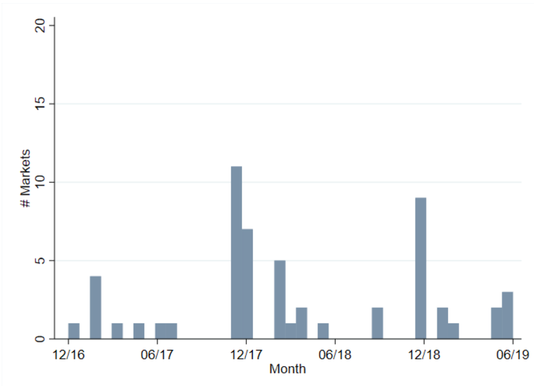
Appendix B DiD estimation supplements

Figure B1: The distribution of timing of first entry

(a) All markets



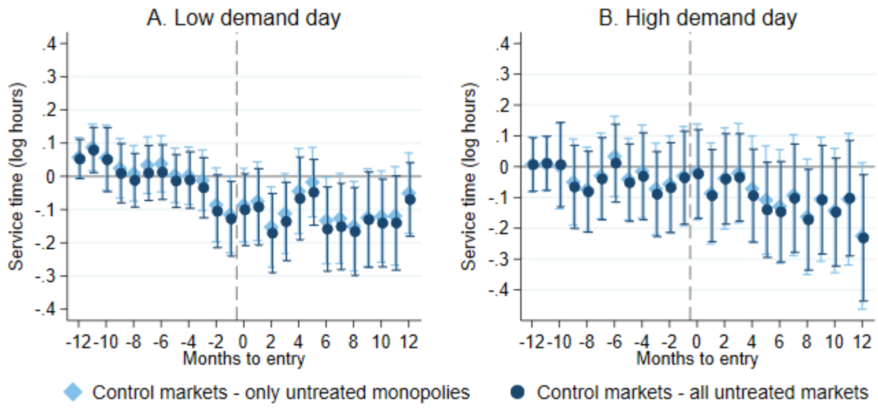
(b) Pre-entry monopolistic markets



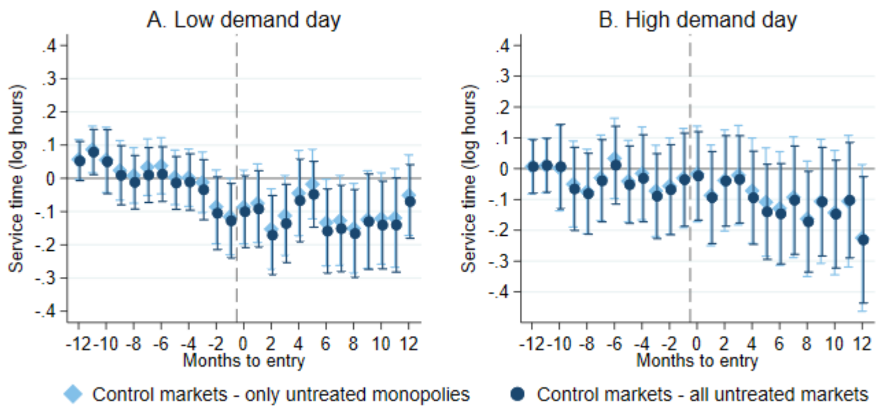
Notes: Panel (a) shows the number of markets that experienced entry in each month during the sample period. Panel (b) shows the number of monopolistic markets that experienced entry in each month during the sample period. The patterns of timing of entry do not reveal a pattern of strategic timing of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

Figure B2: The effect of entry on incumbent service time with 12 months window

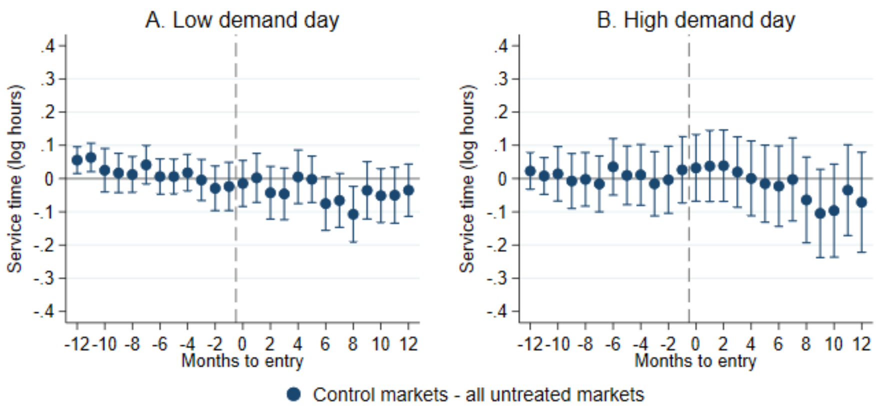
(a) Pre-entry monopolistic markets



(b) Pre-entry monopolistic / duopolistic markets



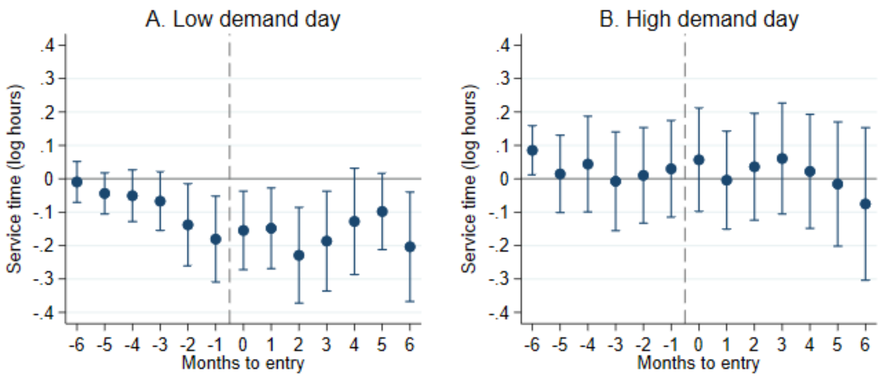
(c) All markets



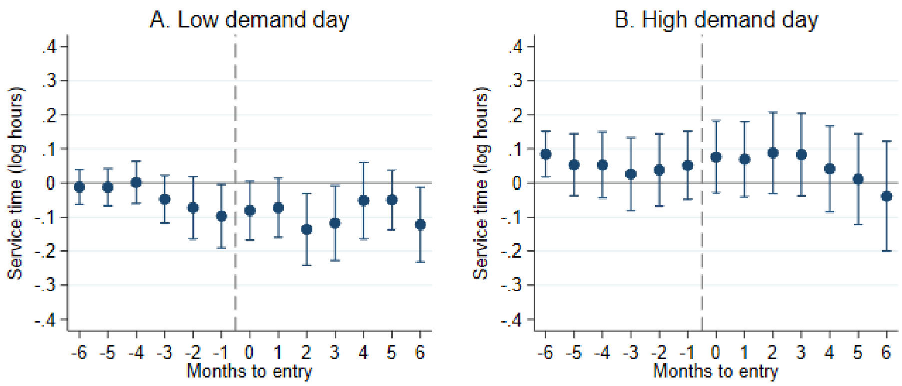
Notes: The figures plot the coefficients of β_j for j running from -12 to 12 and their 90-percent confidence intervals from a regression of equation 2 for different sub-samples. Standard errors are clustered at the market level. The dependent variable is Shufersal's (the incumbent's) log service time in the local market. Estimated results are shown separately for low-damned 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.

Figure B3: The effect of entry on incumbent service time using treated markets only

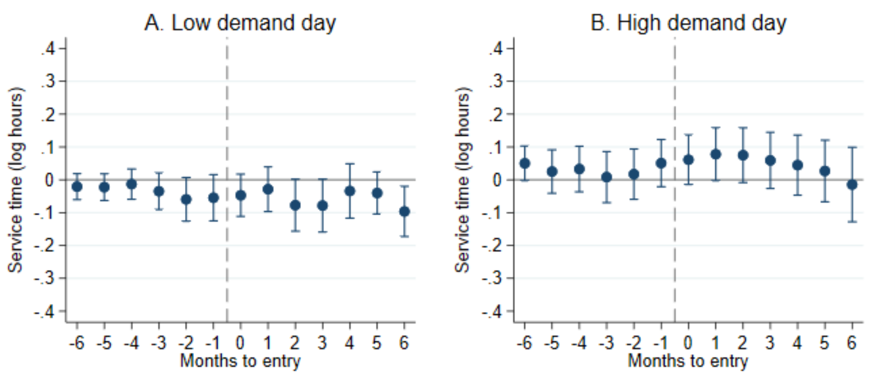
(a) Pre-entry monopolistic markets



(b) Pre-entry monopolistic / duopolistic markets



(c) All markets



Notes: The figures plot the coefficients of β_j for j running from -6 to 6 and their 90-percent confidence intervals from a regression of equation 2 for different sub-samples includes 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-damned 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.

Table B1: The effect of online grocers' entry on service time, by competition from traditional stores

	Low-demand day				High-demand day			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: pre-entry monopolistic markets								
pre_entry	-0.128**	-0.128**	-0.129**	-0.129**	-0.004	-0.007	-0.005	-0.006
	(0.055)	(0.055)	(0.055)	(0.055)	(0.050)	(0.049)	(0.051)	(0.050)
post_entry	-0.092*	-0.093*	-0.089*	-0.091*	-0.016	-0.013	-0.024	-0.021
	(0.049)	(0.048)	(0.048)	(0.049)	(0.044)	(0.044)	(0.044)	(0.044)
Markets	106							
Markets with entry	55							
N	3,804							
Panel B: pre-entry monopolistic / duopolistic markets								
pre_entry	-0.068*	-0.066*	-0.067*	-0.069*	0.022	0.017	0.019	0.019
	(0.039)	(0.039)	(0.039)	(0.039)	(0.036)	(0.035)	(0.036)	(0.036)
post_entry	-0.057*	-0.056*	-0.056*	-0.059*	0.010	0.007	0.007	0.003
	(0.033)	(0.033)	(0.033)	(0.033)	(0.038)	(0.037)	(0.038)	(0.038)
Markets	139							
Markets with entry	88							
N	4,988							
Panel C: all markets								
pre_entry	-0.053*	-0.050*	-0.052*	-0.053*	0.006	0.004	0.004	0.004
	(0.031)	(0.030)	(0.031)	(0.031)	(0.029)	(0.029)	(0.029)	(0.029)
post_entry	-0.047*	-0.045*	-0.046*	-0.048*	-0.001	-0.004	-0.004	-0.007
	(0.026)	(0.025)	(0.025)	(0.026)	(0.030)	(0.030)	(0.030)	(0.030)
Markets	180							
Markets with entry	129							
N	6,456							
rivals' offline stores (5km)	✓				✓			
rivals' offline stores (15km)		✓				✓		
distance to first store			✓				✓	
distance to second 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 1-3 is Shuseral'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 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 B2: The effect of entry on an incumbent's service time with alternate definitions of control markets

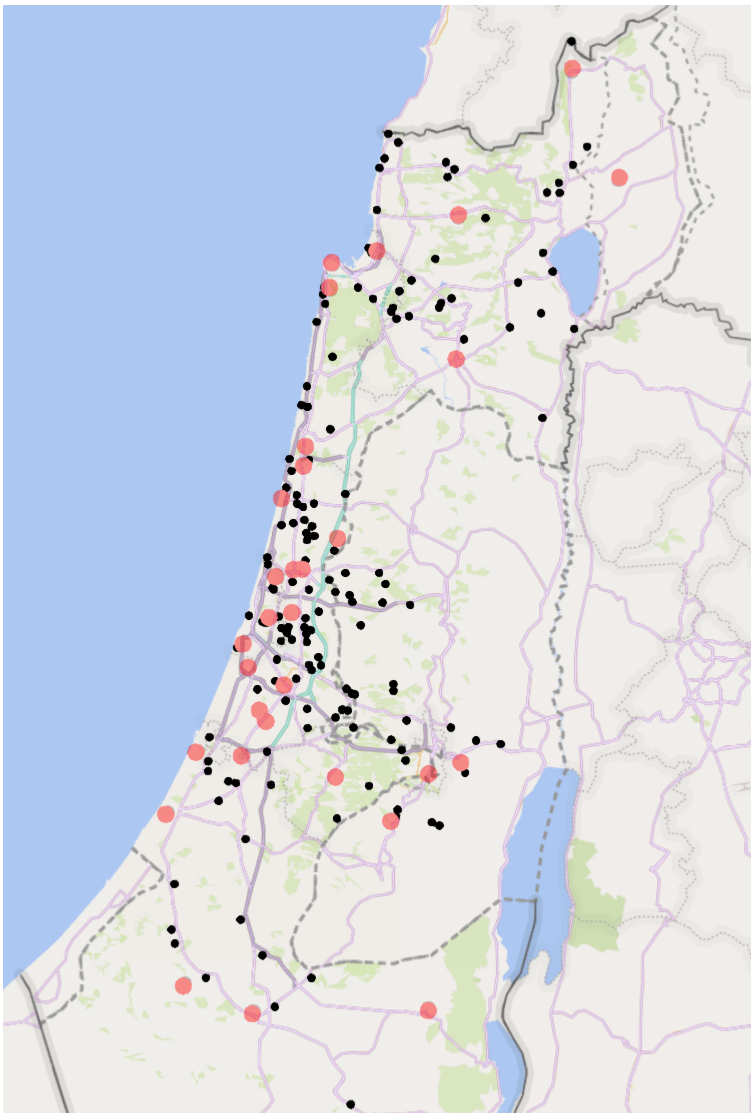
	Low-demand day		High-demand day	
	(1)	(2)	(3)	(4)
Panel A: pre-entry monopolistic markets				
pre_entry	-0.139**	-0.129**	0.029	0.003
	(0.057)	(0.055)	(0.055)	(0.048)
post_entry	-0.136**	-0.101**	0.034	0.0004
	(0.060)	(0.050)	(0.061)	(0.046)
Markets	55	86	55	86
Markets with entry	55	55	55	55
N	1,978	3,093	1,978	3,093
Panel B: pre-entry monopolistic / duopolistic markets				
pre_entry	-0.069*	-0.071*	0.033	0.017
	(0.041)	(0.040)	(0.038)	(0.036)
post_entry	-0.062	-0.062*	0.041	0.008
	(0.038)	(0.034)	(0.043)	(0.040)
Markets	88	126	88	126
Markets with entry	88	88	88	88
N	3,162	4,528	3,162	4,528
Panel C: all markets				
pre_entry	-0.049	-0.052*	0.018	0.005
	(0.032)	(0.031)	(0.030)	(0.029)
post_entry	-0.042	-0.046*	0.027	-0.003
	(0.029)	(0.025)	(0.031)	(0.030)
Markets	129	180	129	180
Markets with entry	129	129	129	129
N	4,630	6,462	4,630	6,462
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 Shuseral'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 columns 1 and 3 the sample includes only treated markets and in columns 2 and 4 we as control 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 C Maps

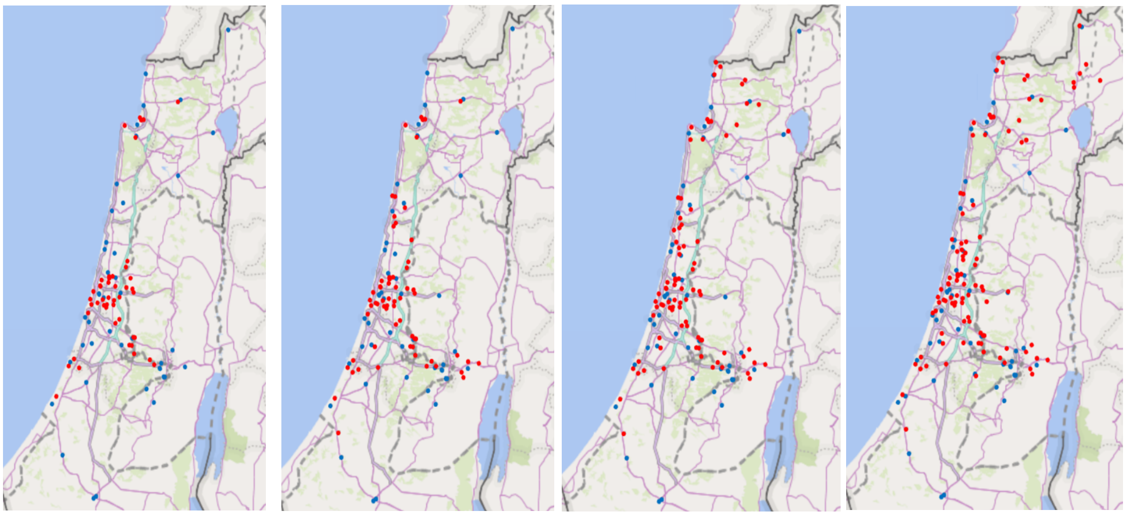
Figure C1: Online local markets (black) and Shufersal's fulfillment centers (red)



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.

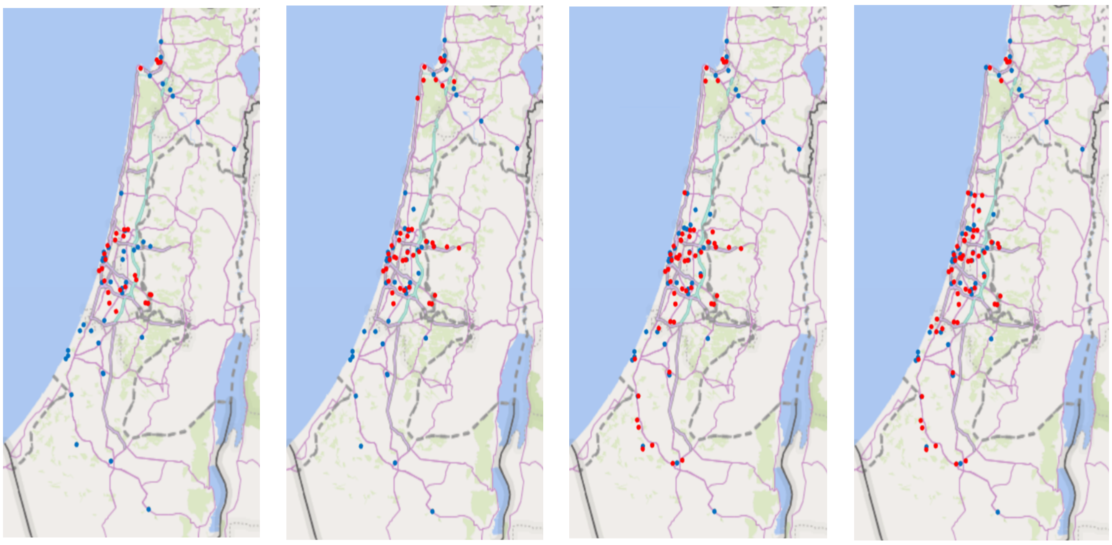
Figure C2: Chains' online service coverage (red) and location of traditional stores (blue)

I. Rami Levy



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

II. Victory

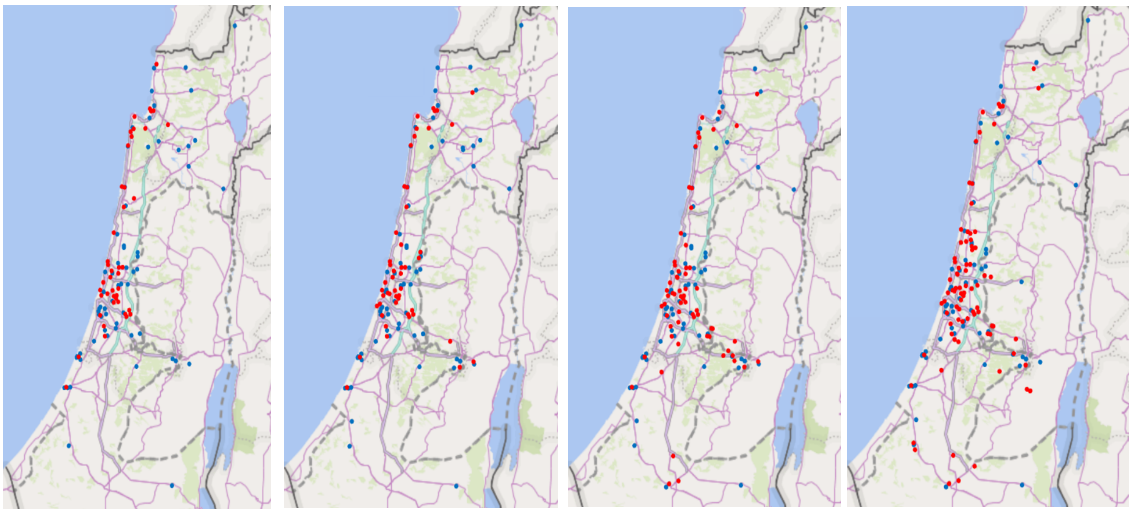


Aug. 2016 | Jul. 2017 | Jul. 2018 | Jul. 2019

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

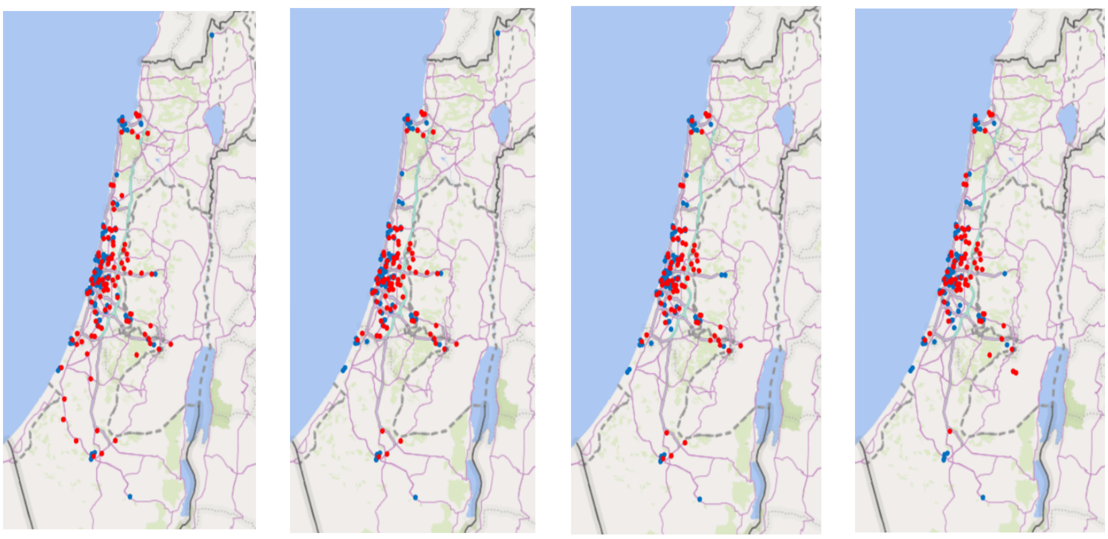
Figure C3: Chains' online service coverage (red) and location of traditional stores (blue)

III. Yeinot Bitan



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

IV. Mega



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

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

Appendix D Alternative estimators for TWFE DiD

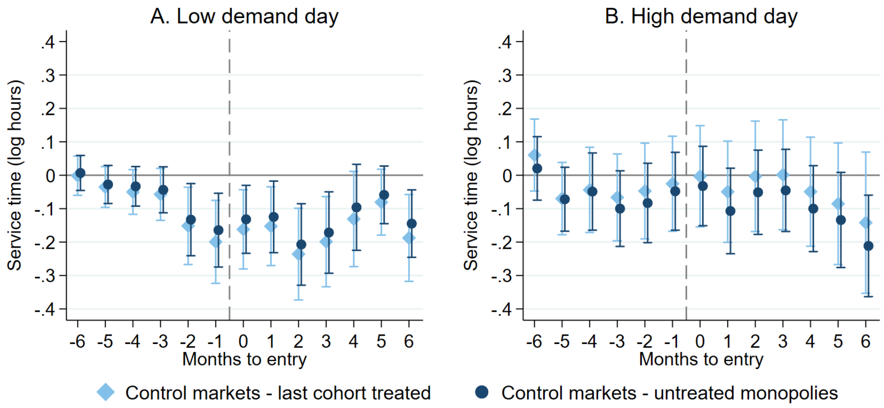
We use two alternative estimation methods (Sun and Abraham (2020) and Borusyak et al. (2021)) that enable us to obtain unbiased estimates under heterogeneity treatment effect. Sun and Abraham (2020) method estimates the dynamic effect for each treatment cohort, and then calculates the weighted average 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.[23] 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 effect estimates is taken with weights, corresponding to the estimation target.

Figure D1 below shows estimation results using Sun and Abraham (2020) method. The results are qualitatively similar to the results in the main text. 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 5.1, the anticipation in the two months before entry might bias the results. Accordingly, we also use Borusyak et al. (2021) to verify that our results are unchanged. Notably, Borusyak et al. (2021) requires 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. Figure D2 shows estimation results using Borusyak et al. (2021) method, assuming a two-months shift in treatment effect. The results show similar patterns to the results presented in Figure 5, suggesting that our TWFE DiD estimates are free of contaminated effects from other periods, and heterogeneity treatment effects.

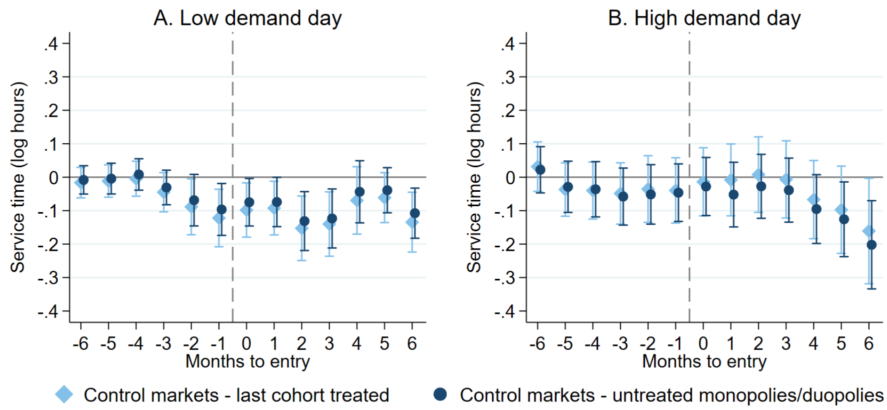
[23] Sun and Abraham (2020) can be considered as a specific case of Callaway and Sant'Anna (2020) estimator. Callaway and Sant'Anna (2020) propose a group-time average treatment effect based on calendar time while Sun and Abraham (2020) propose a regression-based estimator of cohort-specific average 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.

Figure D1: Sun and Abraham (2020) estimator for the effect of entry on incumbent service time

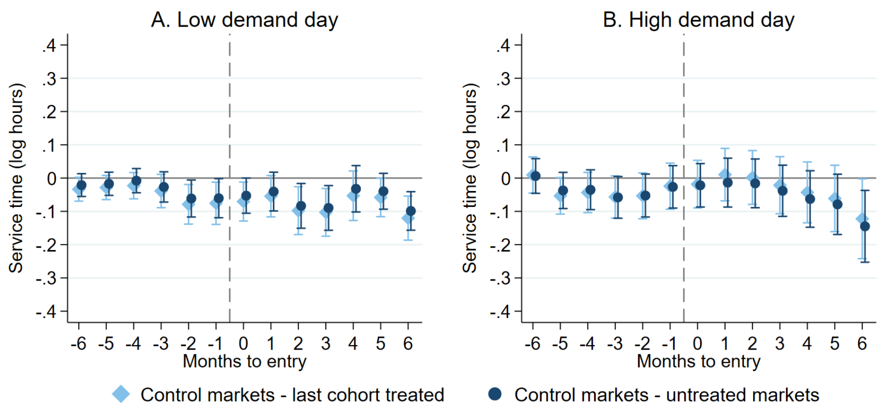
(a) Pre-entry monopolistic markets



(b) Pre-entry monopolistic / duopolistic markets



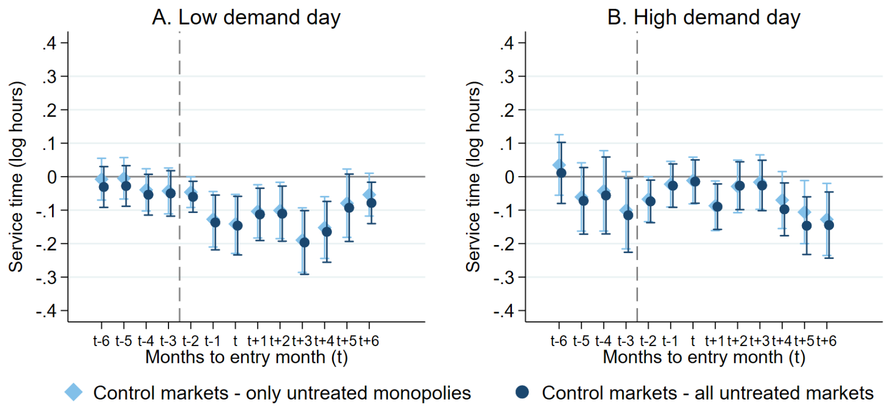
(c) All markets



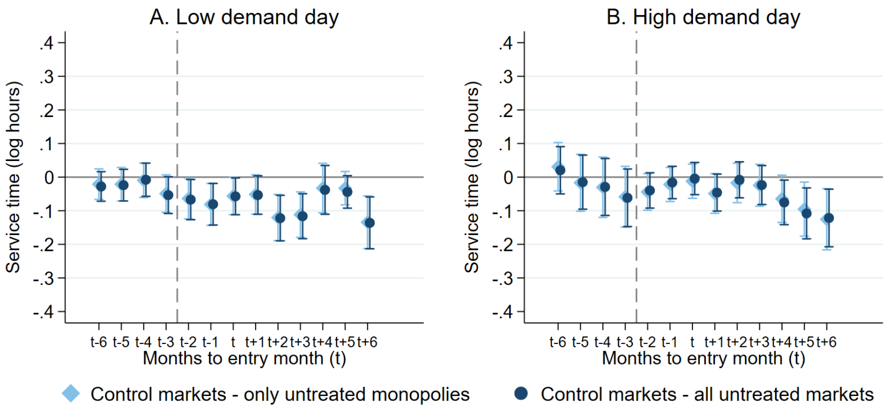
Notes: The figures plot the coefficients of β_j for j running from -6 to 6 and their 90-percent confidence intervals from a regression of equation 2 for different sub-samples using Sun and Abraham (2020) estimation method. Standard errors are clustered at the market level. The dependent variable is Shufersal's (the incumbent's) log service time in the local market. Estimated results are shown separately for low-damned 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 with out 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 TWFE specification in the main text.

Figure D2: Borusyak et al. (2021) estimator for the effect of entry on incumbent service time

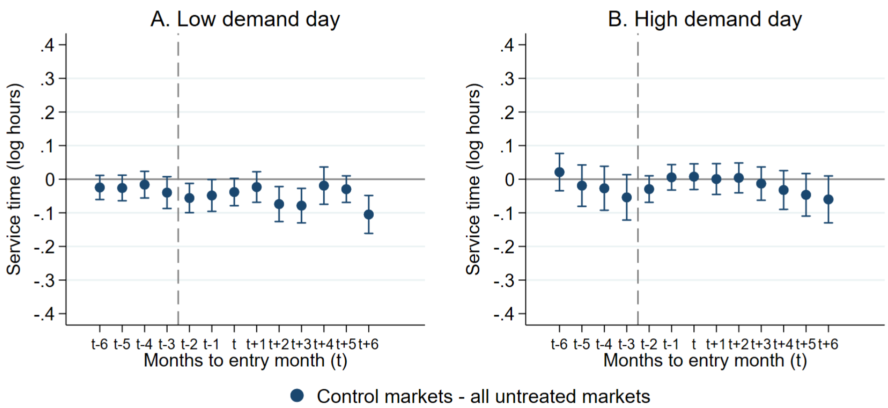
(a) Pre-entry monopolistic markets



(b) Pre-entry monopolistic / duopolistic markets



(c) All markets



Notes: The figures plot the coefficients of β_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. 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-damned 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 TWFE specification in the main text.