Exercising Market Power without Using Prices: Service Time in Online Grocery*

Itai Ater† and Adi Shany§

†Tel Aviv University and CEPR
§Tel Aviv University

June 20, 2022

Abstract

This paper studies how online grocers use service time to respond to local competition and demand conditions when prices are uniformly set at the national level. Using comprehensive data collected twice a week over three years from 180 Israeli local markets, we first show that online grocers set identical prices in all markets where they operate. Next, we exploit regional and temporal variation in entry decisions to conduct difference-in-differences analyses that examine how the incumbent adjusts its service time when new online grocers enter the market. We find that on low-demand days the incumbent's service time decreases shortly before entry. The decrease is greater in monopolistic markets and when the entrant poses a larger competitive threat to the incumbent. By contrast, on high-demand days we find only weak evidence for improvement in service time surrounding entry. Finally, we find evidence for supply-side externalities – showing that service time decreases also in markets that do not experience entry yet are served by a fulfillment center that serves markets facing entry. Overall, our findings show that online grocers exercise their market power by offering worse service. These findings also underscore the importance of competitive and supply-side considerations when analyzing firms' responses, particularly when prices are unresponsive.

JEL: D22; L12; L66

Keywords: online grocery; service time; entry; market power

*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, the Paris Conference on Digital Economics, Tel Aviv University, Hebrew University, Bar Ilan University, Ben Gurion University, and the Bank of Israel for useful comments. Daniel Padon, Adi Omer and Daniel Caspi provided excellent research assistance. Financial support by Eli Hurvitz, Henry Crown, the Falk Institute and the Israeli Science Foundation (Grant No. 568/17) is gratefully acknowledged. E-mails: ater@post.tau.ac.il, adi.shany@tauex.tau.ac.il

1 Introduction

Standard models in economics, management, and marketing show that firms use prices to respond to changing demand and competition conditions. Growing evidence, however, shows that firms' price-setting behavior is often different than what these models describe. In particular, multi-store retailers tend to set similar prices in environments characterized by different demographic and competition conditions (e.g., Cavallo, Neiman, and Rigobon 2014, Cavallo 2017, Adams and Williams 2019, DellaVigna and Gentzkow 2019, Hitsch, Hortaçsu, and Lin 2021). Retailers also do not adjust prices when local demand and competition conditions drastically change (Arcidiacono, Ellickson, Mela, and Singleton 2020, Gagnon and López-Salido 2020, Goldin, Homonoff, and Meckel 2022). These findings, which cast doubts on our understanding how firms operate, motivate our research questions: How do firms respond to changes in demand and competition without changing prices? What are the roles of operational capabilities and capacity constraints in determining these responses?[1]

We propose that firms strategically use service levels to deal with changing competition and demand conditions. Theoretical models show that service levels may deteriorate or improve when competition intensifies or when demand falls (e.g., Spence 1975, Hörner 2002, Dana and Fong 2011, Cachon and Harker 2002). On one hand, firms may offer better service in competitive environments to attract consumers and reduce churn. On other hand, if the provision of service involves economies of scale then strong competition and low sales will result in worse service levels. Indeed, the tension between competition, scale and service quality is an integral part of the recent debate on the effectiveness of competition policy.[2] Despite its importance, and probably due to lack of available data on measures of service that vary across firms, markets and time, the evidence on the relationship between competition, demand and service levels is particularly scarce.

In this paper we focus on service time, perhaps the most valuable measure of service in retail markets, and examine how it varies with demand and competition in the Israeli online grocery market. Notably, prices in this industry are uniformly set at the national level, whereas service and competition levels are determined locally. Our findings indicate that competition improves service time and that the improvement primarily materializes in monopolistic markets and on low-demand days, when grocers arguably have slack resources. On high-demand days – when resources are better utilized – we find only weak evidence for a causal impact of competition on service time.

[1] Different explanations were proposed for why multi-store retailers set uniform pricing. DellaVigna and Gentzkow (2019) suggest that firms set uniform pricing due to large managerial costs; Hitsch, Hortaçsu, and Lin (2021) claim that lack of data at the store level hinders optimal pricing decisions, whereas Ater and Rigbi (2022) point toward fairness and brand-image concerns as the main reason why food retailers adopt uniform pricing. Notably, in this paper we do not attempt to explain these pricing decisions but rather take them as a starting point for the analysis.

[2] See, for instance, https://www.ftc.gov/news-events/press-releases/2022/01/ftc-and-justice-department-seek-to-strengthen-enforcement-against-illegal-mergers.

Studying service time in online grocery offers an excellent opportunity to learn about the relationships between service levels, demand, and competition. First, the importance of service time has grown with the rise of e-commerce and corresponding changes in consumers' time preferences. The success of mega firms such as Amazon, Fedex, Uber, Doordash, and Instacart depends on their ability to serve customers quickly, and before rivals do.[3] Probably due to lack of data, empirical evidence on the relationship between competition, demand and service time is virtually non-existent. We are not aware of empirical studies that examine the impact of competition on service time. Second, sales in the online grocery market had been growing rapidly 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.[4] In many countries, new online grocers are expanding into local markets where established online grocers already operate. Our analysis exploits spatial and intertemporal changes in the competitive landscape of the Israeli online grocery market to examine how the dominant online grocer, with presence in all local markets, adjusts its service time when competition intensifies. Third, demand for online grocery is characterized by high-demand (pre-weekend) and low-demand (beginning of the week) periods. This within-week demand seasonality offers a unique opportunity to examine how incumbents respond to impending entry in distinct demand conditions in the same week and in the same market. Since many staffing and scheduling decisions are determined locally, an analysis that exploits local variation is useful to identify the causal impact of competition on service time in distinct demand conditions. Finally, online grocers in many countries including Israel (Cavallo 2017) set identical prices in all local markets where they offer service. This dichotomy allows us to abstract from the impact of competition and demand on prices, and to focus on the impact of competition and demand on service time.

The main data that we use include bi-weekly service time data for the five online grocery chains that were active between August 2016 and July 2019 in Israel. For this period, we used a web crawler to collect data from 180 home addresses that correspond to distinct local markets across Israel. The crawler was active twice a week, namely, at midnight on Wednesdays and Saturdays; representing high-demand (pre-weekend) and low-demand (post-weekend) conditions, respectively.[5] For each home address, and for each online grocer serving that address, the crawler recorded the

[3]Recent surveys report that 46% of the respondents abandoned their shopping carts online as a result of shipping times that were too long or not provided. See www.mckinsey.com/industries/retail/our-insights/same-day-delivery-ready-for-takeoff, and coresight.com/research/from-quick-commerce-to-instant-needs-exploring-business-models-in-rapid-delivery/.

[4]See www.businessinsider.com/online-grocery-report. and www.statista.com/topics/3144/online-grocery-shopping-in-the-united-kingdom/, respectively. In 2021, the share of online grocery of all grocery sales was 9.5%, and predicted to double by 2025 (https://www.statista.com/study/20820/us-consumers-online-grocery-shopping-statista-dossier/. Following the surge in demand for online food delivery services, several U.S. cities passed orders that cap the maximum fees that delivery-app can receive. Such regulations are likely to shift attention to non-price attributes, such as service time. See https://www.newyorker.com/culture/q-and-a/the-fight-to-rein-in-delivery-apps.

[5]In Israel, weekend days are Friday and Saturday. We use longitudinal customer-level data from an online platform to show that demand is considerably larger on pre-weekend days than on post-weekend days.

online grocer's available service time to the specific address, measured as the elapsed time between order time and promised delivery time. This measure is useful since it captures the information available to consumers when they choose a preferred grocer. The number of online grocers offering service to a particular home address is our measure of competition in the corresponding local market.

We first document the cross-sectional relationships between service time, price, and competition. Panel (a) of Figure 1 displays the relationship between competition and service time for the five online grocers. The figure shows a downward sloping service time curve for each online grocer. The greater is the number of online grocers active in a local market, the shorter is the service time offered by the online grocer. We supplement the crawler data with price data on a representative basket of products sold by each of the five online grocers in the same local markets. Panel (b) of Figure 1 shows that the online grocers set identical prices in all the local markets where they operate, irrespective of the level of local competition. In the next step, we examine how service time and prices vary with demand conditions. Panel (a) of Figure 2 shows that service times are longer on high-demand days than on low-demand days. By contrast, prices are not more expensive on high-demand days than on low-demand days (panel (b)). The patterns shown in Figures 1 and 2 suggest that grocers strategically use service time to cope with changing local demand and competition conditions. However, other explanations are also plausible. For instance, urban areas may attract more online grocers and economies of density in cities also enable shorter service times.

To mitigate such concerns and to rule out alternative explanations, we take advantage of the panel structure of the data to identify the impact of entry by an online grocer on the service time offered by the incumbent.[6] We implement both an event study design that accommodates the possibility of dynamic treatment effects, and a parametric difference-in-differences (DiD) design that exploits variation in the timing of entry of online grocers into new local markets. These analyses compare the service time offered by the incumbent online grocer in markets that experienced entry (treated markets) to the service time offered by the incumbent in markets that did not experience entry yet (untreated markets) while controlling for time-invariant conditions within the same market and for time-variant effects that are fixed across markets. We use the distinction between Wednesdays and Saturdays to examine how service time changes in response to impending entry on high- and low-demand days, respectively. The key assumption is that, conditional on market- and month-fixed effects, the decision and timing of entry are uncorrelated with the incumbent's service time. To test the validity of this assumption, we provide evidence that entry decisions are driven by long-term demographic and regional considerations, and are not linked to entry decisions

[6]The online grocery market changed dramatically over the study period. We observe almost 200 entries to new local markets and a decline of nearly 40% in the number of monopolies, i.e., local markets served only by the dominant online grocer.

in the offline channel. We also verify that the results are unchanged when we use recent staggered DiD estimation methods (Sun and Abraham 2020, Borusyak, Jaravel, and Spiess 2021).

The results show that impending entry drives the incumbent to reduce service time. The improvement is larger and substantial when costs are relatively low or when benefits are high. In particular, service time falls on low-demand days of the week (i.e., when arguably the marginal cost of improving service is low), and upon entry into monopolistic markets (i.e., when the potential losses from not improving service are high). The magnitude of the effect is not trivial. Our estimates show that on low-demand days the incumbent's service time falls by about 13% in monopolistic markets. The effect is 25% larger when we restrict attention to entry by aggressive online grocers, i.e., those who pose a larger threat to the incumbent.[7] The decrease in service time on low-demand days begins two months before actual entry takes place, suggesting that improvements are not driven by demand shifts that may occur after entry.[8] By contrast, on high-demand days – when arguably resources are highly utilized – we find little evidence for service time improvements surrounding market entry. This latter finding is consistent with our interpretation that the marginal cost of service is an important factor that can explain the extent to which the incumbent changes its service time in response to entry. In the final step of the analysis, we explore how increased competition in one local market affects service time in adjacent local markets. We examine how entry into a given local market affects service time in markets that do not experience entry, yet are served by the same fulfillment center as markets that do face entry. Our findings indicate that entry also triggers improvements in adjacent markets, and that these improvements are greater when we restrict the analysis to online grocers that pose a larger threat to the incumbent.

Our findings demonstrate a trade-off between the marginal costs incurred from offering shorter service times and the losses suffered when longer service times push consumers to buy elsewhere. In Appendix A, we present a modified version of the newsvendor problem model (Arrow, Harris, and Marschak 1951) which we can use to interpret our findings and understand this trade-off. We use the model to show that entry by an online grocer leads to larger reductions in service time (i) in more concentrated markets, where the costs from losing consumers to rivals are larger, (ii) on low-demand days when the marginal costs of improving service time are lower, and (iii) when the entrant poses a larger threat to the incumbent.

There exists a large theoretical literature in economics and operations on service time and competition (e.g., Luski 1976, De Vany and Saving 1977, 1983, Allon and Federgruen 2007, 2008, 2009, Kalai, Kamien, and Rubinovitch 1992, Cachon and Harker 2002). By contrast, empirical research is almost nonexistent, and to our knowledge, this is the first study that empirically examines the

[7] To identify online grocers that pose a larger competitive threat to the incumbent, we use the customer-level data from the online grocery platform to document substitution patterns across online grocers.

[8] Post-entry improvements in service time can be driven by either competitive concerns or due to changes in costs that may occur after consumers shift to an entrant's services.

impact of competition on service time. Important related papers include Allon, Federgruen, and Pierson (2011) who use annual measures of waiting times at fast-food restaurants to study their impact on market shares. Lu, Musalem, Olivares, and Schilkrut (2013) show how waiting times at a physical store affect purchasing behavior, and Png and Reitman (1994) examine the relationship between service time and competition among gasoline station but lack actual data on service time. To overcome the lack of data on service time, recent studies used the physical distance between sellers and buyers as a proxy for transaction cost and service time (e.g., for eBay, Einav, Knoepfle, Levin, and Sundaresan 2014, Hortaçsu, Martínez-Jerez, and Douglas 2009, and for Amazon, Houde, Newberry, and Seim 2017, 2021). These studies do not examine how service time changes when competition and demand changes in a market. More generally, our paper contributes to the literature on competition and non-price attributes. The intuition that firms with market power can maximize their profits by degrading the service they offer is often cited but rarely tested empirically. Probably closest to our study is Matsa (2011) who shows that incumbent supermarkets reduce their stock-out rate after Walmart enters. Other studies in this literature include Olivares and Cachon (2009) who study the relationship between competition among car dealers and inventory, and Orhun, Venkataraman, and Chintagunta (2015) who study how incumbents respond to entry in the US movie-exhibition industry. Finally, Mazzeo (2003) show that airlines' on-time performance improves when on-route competition is stronger whereas Prince and Simon (2014) show that airlines facing entry or a threat of entry by Southwest Airlines degrade their on-time performance. A common feature of previous studies is that they rely on quality measures that are observed post-purchase (e.g., a flight's on-time performance) or only upon arriving at the store (e.g., product availability). These studies implicitly assume that consumers can compare quality attributes across retailers and that their choice of retailer is based on quality differences. In our case, service time is observed at the time of purchase and can be compared across different online grocers prior to the purchase decision.

A growing number of papers study online grocery and examine how consumer behavior changes in the online channel, and how the online channel affects traditional food stores (Pozzi 2012, 2013, Chintagunta, Chu, and Cebollada 2012, Gil, Korkmaz, and Sahin 2020, Chintala, Liaukonyte, and Yang 2021). None of these papers explicitly consider the role of service time.

The remainder of the paper is organized as follows. In Section 2 we provide necessary background on the Israeli retail food market, describe the data and present relevant descriptive statistics. In Section 3 we discuss the empirical methodology and present the results. In Section 4 we discuss and conclude.

2 Industry background, data, and descriptive evidence

2.1 The online grocery market in Israel

In a standard online grocery service, consumers do not visit a physical store; instead, they log in to a dedicated online grocer's website, select the items they wish to buy, choose the delivery time, and pay. The ordered items are later delivered to their home address at the promised delivery time.[9] Our analysis focuses on the five supermarket chains that offered online grocery service in Israel between 2016 and 2019: Shufersal, Mega, Rami Levy, Victory, and Yenot Bitan. The joint market share of these supermarket chains in the overall retail food market was 68% in 2014.[10] Sales through the online channel had been growing already before the pandemic. The market share of online grocery sales in Israel during the study period is estimated below 10%. Shufersal is by far the dominant player in the online grocery channel, with market share of about 70%.[11] In the empirical analysis, we refer to Shufersal as the incumbent online grocer, as it was active in all local markets throughout the sample period. According to Shufersal's 2018 annual financial report, 13.6% of its annual sales come from the online channel, up from 4.2% in 2014 and 11.5% in 2017. Shufersal, with 283 physical stores as of 2016, is also the largest player in the traditional offline grocery channel. Rami Levy, the second-largest supermarket chain in terms of overall turnover, has about a 12% market share in the online channel, whereas Victory's market share in the online channel is about 2.5%.[12] In 2019, 7.2% of Rami Levy's sales and 4% of Victory's sales were from the online channel. The figures for Mega and Yenot Bitan, which are not publicly traded, are not available but are lower than those of the other publicly traded chains.[13]

Online grocers set prices and delivery fees at the national level. Prices and fees are identical across all the local markets where the grocers offer service. Each chain operates an online channel that involves a dedicated website (e.g., Shufersal.co.il, www.rami-levy.co.il) where consumers can complete their order, and observe delivery areas and available delivery time slots for each local market. Orders are delivered to the address specified by the customer at the time of purchase. According to Article 18A in the Israeli Consumer Protection Law, a delay of more than two hours

[9] The first online grocery services were introduced in the U.S. in the 1990s. Early ventures failed due to logistical challenges in the "last mile" and in delivering perishable goods in a timely manner to consumers' home address. In an interview,the vice president of Webvan, perhaps the first online grocery service, its VP noted that "mean travel time between delivery stops is the key to success in the home delivery business." See https://www.reuters.com/article/net-us-amazon-webvan/from-the-ashes-of-webvan-amazon-builds-a-grocery-business-idUSBRE95H1CC20130618.

[10] 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.

[11] See https://www.themarker.com/consumer/.premium-1.10616581 and https://www.ynet.co.il/articles/0,7340,L-4907570,00.html.

[12] See https://www.themarker.com/consumer/.premium-1.10616581

[13] Mega filed bankruptcy proceedings in early 2016 and divested many of its stores. In July 2016, Israel's Competition Authority approved a merger between Yenot Bitan and Mega. Yet, the operations of these two chains, and particularly their online services, were kept separate.

in delivery may lead to a NIS 300 fine (about $90). Orders are delivered from fulfillment centers that are typically used also as regular stores. Before retailers enter a new locality, they need to recruit labor (packers/drivers), obtain specialized food delivery trucks, and modify the website and the interior structure of physical stores that are also used as fulfillment centers. Entry is also often accompanied with a local advertising campaign to raise awareness of the new service.

In Israel, supermarkets are closed from early afternoon on Friday to Sunday morning, making demand considerably higher on pre-weekend days than on post-weekend days of the week (Sunday and Monday). According to Storenext (2015), 57.9% of sales in physical stores are on pre-weekend days (19.4% on Wednesday, 22.9% on Thursday, and 15.6% on Friday). As we will later show, this pattern also reflects demand for online grocery. Moreover, since online orders are typically distributed from physical stores, capacity utilization (i.e., labor and capital) is higher on pre-weekend days and lower on post-weekend days.

2.2 Data

We collected service time and competition data on 180 different home addresses between 2016 and 2019. Each address corresponds to a distinct locality. We augment the service time and competition data with information on online grocery prices, the location of physical stores, and demographic information. We also use longitudinal customer-level data from a large online grocery platform. Below we describe each of the data sources that we use.

2.2.1 Service time and competition data

Our main data source is a web crawler that accessed the websites of each of the five supermarket chains named above twice a week between August 2016 and July 2019. The crawler was active at midnight on Wednesdays and Saturdays, which as we later show are a high-demand day and a low-demand day for online grocery service, respectively. 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 so, it also recorded the earliest available home-service time slot offered by each chain for each address. Each address corresponds to a different locality (i.e., an area served by a distinct local or municipal authority) and, except in the largest cities, retailers offer online service to either all addresses in a given locality or to none at all. Accordingly, we consider each address and locality as a separate local market. To avoid over-identifying entries and exits that are driven by the malfunctioning of the crawler, we aggregate the crawler data to the monthly level. We use the crawler data to build the two main variables that we use in the analysis: competition and service time.

Competition. The number of online grocers that offer service to each address serves as our

Table 1: Summary statistics: Service time (in hours) of the incumbent retailer

	Pre-entry monopolistic markets		Pre-entry monopolistic/ duopolistic markets		All markets	
	Markets with entry	Markets w/o entry	Markets with entry	Markets w/o entry	Markets with entry	Markets w/o entry
	(1)	(2)	(3)	(4)	(5)	(6)
Wednesday	48.45	44.25	44.34	43.48	38.46	38.40
	(30.31)	(26.14)	(29.94)	(25.70)	(26.95)	(24.22)
Saturday	35.13	34.26	32.67	32.91	28.77	29.59
	(21.81)	(21.23)	(21.22)	(20.23)	(19.18)	(18.74)
# Markets	55	31	88	38	129	51
# Observations	1,978	1,115	3,162	1,366	4,630	1,832

Notes: The table reports means of the incumbent's service times (standard deviations in parentheses) on Wednesday and Saturday in markets that experienced entry in odd- numbered columns, and markets that did not experience entry (even-numbered columns). Columns (1) and (2) include markets where only one retailer was active before entry. Columns (3) and (4) include markets where only one or two retailers were active before entry and Columns (5) and (6) include all markets.

measure of local competition in a given month. This measure of competition is not subject to concerns about the exact definition of the geographical market since consumers order groceries to their home address. We also use this information to identify entries and the entrants' identity.[14]

Service time. The elapsed time between the crawler's recorded time and the earliest available home-service time slot is our measure for service time in each local market on a given day.[15] The use of the promised delivery time to calculate the service time is useful since consumers observe the promised delivery time when they purchase. Moreover, consumers can choose their preferred retailer based on comparing promised delivery times by different grocers.[16]

Our final sample consists of 180 local markets with information on the number of active online grocers in each market in each month. We also compute the mean service time offered by each grocer in each market on Wednesdays and Saturdays in each month between August 2016 and July 2019. Shufersal, the dominant online grocer, was active in all 180 local markets during the whole sample period. Table 1 provides summary statistics on Shufersal's service time by day and by competition level, distinguishing between markets that experienced entry (odd-numbered columns) and markets that did not experience entry (even-numbered columns). Service times are shorter on Saturdays and in more competitive markets. The differences in service times between markets that experienced entry and those that did not experience it are small and statistically insignificant, except on Wednesdays in monopolistic markets.

[14]Entries are instances in which a retailer begins to offer service in a market for at least three consecutive months.

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

[16]Promised delivery times are a good proxy for actual delivery times. In addition to reputational costs, online grocers might be subject to legal fines if an order is delayed for more than 2 hours (see Section 2.1).

2.2.2 Price data

We use detailed data on the monthly average prices of 52 popular items sold by the five online retailers in all local markets where they operate. We use these prices to calculate the basket price sold by each of the five online grocers at each of the 180 local markets in each month. We also separately compute the basket price on each Sunday and each Thursday in each week in our sample. We obtained these price data from Pricez.co.il, a price comparison platform that collects prices of products sold by food retailers in Israel. The price data are available under Israel's price transparency regulation, which makes prices of all products sold by Israeli supermarket chains in both online and traditional stores available online (Ater and Rigbi 2022). We use the price data to show how online grocers use prices in different demand and markets conditions.

2.2.3 Online grocery shopping data

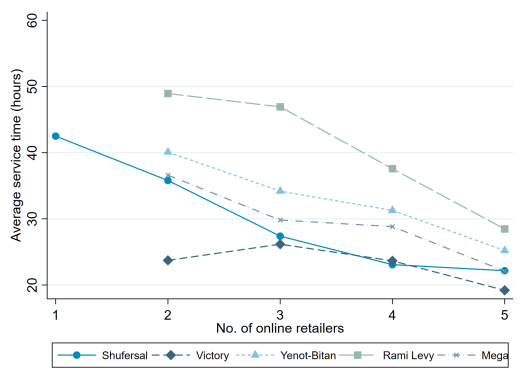
We use proprietary data from MySupermarket.co.il, an online platform that enables users to shop at each of the five online grocers if the retailer offers service in their locality. MySupermarket's users can compare prices and contemporaneously observe available service times offered by each retailer. The data include all orders performed through MySupermarket during the data collection period. These data include the date and the time of each order, the retailer's identity, the number of products, total amount paid, a customer id, and the city where the customer lives. Unfortunately, these data do not include information on service time. These data cover about 700,000 orders by nearly 85,000 customers. About 85% of these customers live in one of the 180 localities that we track. Appendix B provides more details on these data. We use these data to show that demand for online grocery service is considerably larger on pre-weekend days than on post-weekend days, to document switching patterns across online grocers, thereby identifying which retailers pose a greater threat to the incumbent, and finally to show that customers are more likely to switch to a different grocer on high-demand days, i.e. when service times are longer.

2.2.4 Store and demographic data

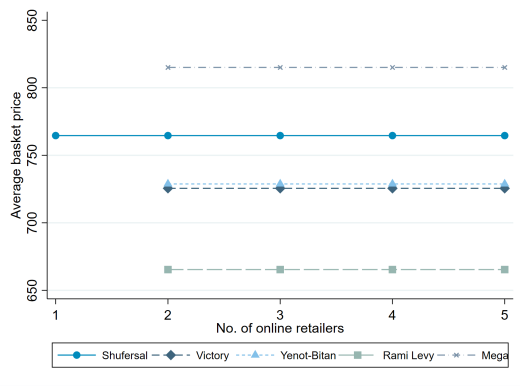
We used chains' annual reports and media coverage to collect data on their physical stores including opening dates of new stores. We also identify the locations of the fulfillment centers that operated during the sample period, and match these centers to the 180 local markets based on the closest driving distance. Figure E1 in Appendix E shows the locations of the 180 local markets in our sample (black dots) and Shufersal's (the incumbent) 34 fulfilment center (red dots) that operated during the sample period. We also use demographic information obtained from the Israeli Central Bureau of Statistics on the 180 local markets. This information includes population size, income per capita, vehicle per capita, and socioeconomic and periphery indices for each of the markets for

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

(a) Mean service time by competition level



(b) Mean basket price by competition level



Notes: Panel (a) plots the average service time for each grocer against the number of active online grocers in each local market. Panel (b) plots the average basket price for each grocer against the number of active online grocers in each local market. Both graphs are based on monthly data from August 2016 to July 2019. Panel (a) shows a clear pattern of downward-sloping curves of service time, where service time is considerably shorter in markets served by more online grocers. For instance, Shufersal's (the largest grocer's) mean service time in monopolistic markets is 42 hours. In markets with five online grocers, its mean service time is 22 hours. Panel (b) shows that grocers choose different price levels, but the price levels (including promotions) are identical across markets characterized by different levels of competition. Finally, looking across the two panels, we observe that pricier online grocers tend to offer shorter service times.

the years 2016, 2017, and 2018.[17]

2.3 Descriptive evidence

2.3.1 Service time, prices and competition

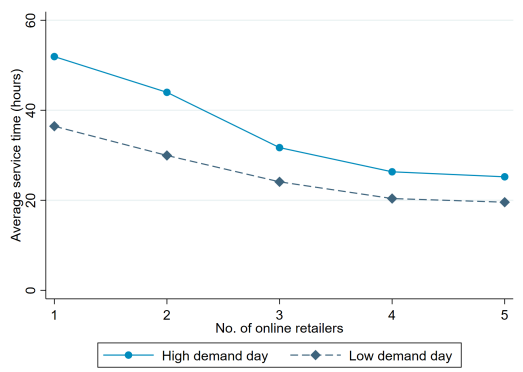
Figure 1 presents the relationship between competition and service time (Panel (a)), and between competition and prices (Panel (b)) separately for each of the five online grocers. Panel (a) plots the mean of the monthly average of service time for each grocer against the number of active online grocers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

In Panel (a) we observe a clear pattern of downward-sloping curves of service time. This pattern holds for each of the five online grocers. Service time is considerably shorter in more competitive markets. For instance, Shufersal's mean service time in markets where it is the only online grocer is 42 hours. In markets where Shufersal competes with four online grocers, its mean service time is only 22 hours. Nevertheless, we cannot interpret these patterns as causal, since they do not take into account other factors that may affect service time such as market density. According to Panel (b) of Figure 1, online grocers set identical prices in all the markets where they operate, irrespective of the level of competition. Also, online grocers choose different price levels and there exists a strong negative relationship between service time and the basket price offered by a given

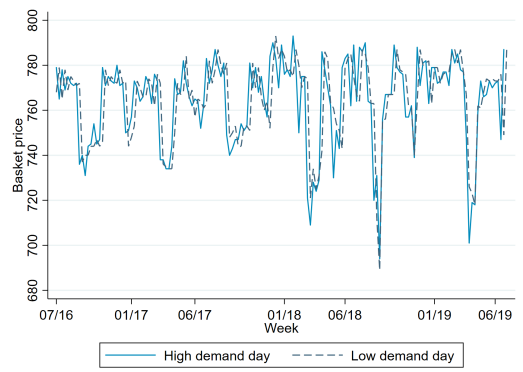
[17] The socioeconomic index for each locality is based on demographic and economic variables. The periphery index is based on the distance between each locality and Tel Aviv.

Figure 2: Service time and prices by competition & demand conditions

(a) Mean service time by demand & competition



(b) Basket price on low- and high- demand days



Notes: Panel (a) shows the average service time of Shufersal (the incumbent) as a function of the number of online grocers in the local market, separately for low- and high- demand days, based on monthly data from August 2016 to July 2019. Panel (b) shows the daily price of a basket of 52 products sold on Shufersal's online channel, separately for Sunday and Thursday – for each week from August 2016 to July 2019. The figure shows that service times on high-demand days are longer than on low-demand days. Service time is shorter and the difference between high- and low- demand days is smaller in more competitive markets. Panel (b) shows that unlike service time, Shufersal's prices (including promotions) 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 low-demand days (Sundays) and on high-demand days (Thursdays). Similar patterns for the other online grocers are shown in the Appendix C.

grocer: pricier retailers offer shorter service times. 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.

2.3.2 Service time, prices, and demand

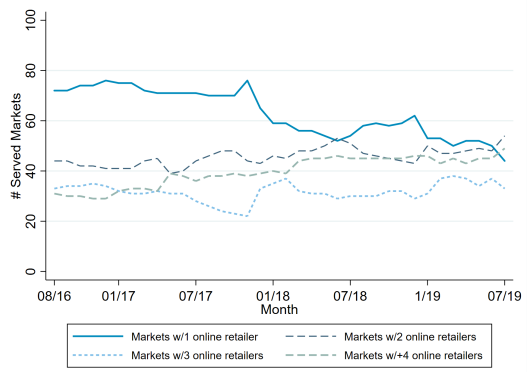
To support the classification of Wednesday as a high-demand day and Saturday as a low-demand day, Figure B3 in Appendix B presents the cumulative percent of orders for online grocery through MySupermarket on Tuesday and Wednesday and on Friday and Saturday. The figure shows that the cumulative percent of orders is about three times larger on Wednesdays than on Saturdays.[18]

Panel (a) of Figure 2 builds on the distinction between low- and high- demand days, and presents Shufesal's service time in markets with different competition levels. The figure shows that for a given competition level, service time is longer on high-demand days than on low-demand days. Furthermore, service time is shorter and the difference in service time between high- and low-demand days becomes 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 five online retailers, the mean service time is 25 hours on Wednesdays and 20 hours on Saturdays. Panel (b) of Figure 2 presents a time series of Shufersal's average basket price on Sunday and on Thursday in each week during the three-year sample period. We chose Sunday and Thursday because these are the days following the crawler's operating time at midnight on

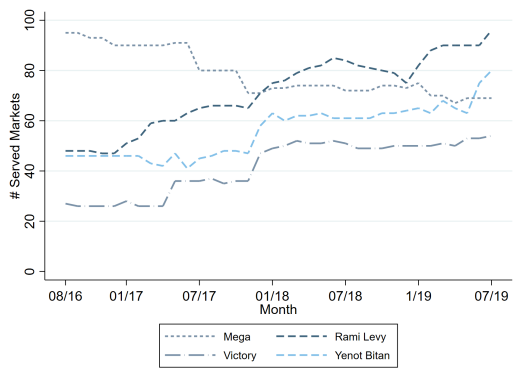
[18]Since service time is determined based on the back-log of orders and average service time is longer than 24 hours, it makes sense to aggregate orders over periods longer than 24 hours, relative to the crawler time at midnight on Wednesday and Saturday. Alternative definitions generate similar patterns.

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

(a) Market structure evolution



(b) Online grocers' expansion



Notes: Panel (a) plots the number of markets served by a different number of online grocers in each month during the sample period. In August 2016, 72 markets were monopolies and in 31 markets at least four online retailers were active. Over the 3 years, competition intensified. In July 2019, the last month in the sample, 44 local markets were monopolies and in 49 markets at least four online retailers were active. Panel (b) displays the number of markets served by each online grocer in each month of the sample period. We exclude Shufersal since it operated in all 180 markets throughout the sample period. Victory, Yenot Bitan, and Rami Levy experienced massive growth in the number of markets they served, growing respectively from 27, 46, and 48 markets in August 2016 to 54, 80, and 96 markets in July 2019. Mega, which faced considerable financial difficulties during the period, exited many of the local markets it served. Overall, at least one entry took place in 129 of the markets in our sample.

Saturday and Wednesday, respectively. As shown in the figure, unlike service times, Shufersal's prices do not vary with demand conditions over the days of the week. That is, there is no discernible difference between the price of the basket on days where demand is low (Sundays) and on days where demand is high (Thursdays). Figure C1 in Appendix C shows similar patterns for the other online grocers.

2.3.3 Entry and market structure evolution

Panel (a) of Figure 3 shows the evolution of available online grocery service over the sample period. In August 2016, 72 markets were served only by Shufersal, and 31 markets were served at least four online retailers. Over the 3 years competition intensified. In July 2019, 44 local markets were served only by Shufersal, and 49 markets were served by at least four online retailers. Panel (b) of Figure 3 shows the expansion patterns of each of the online grocers, except Shufersal, which was active in all 180 markets throughout the sample period. As can be seen in the figure, Victory, Yenot Bitan, and Rami Levy experienced massive growth in the number of markets that they serve, growing respectively from 27, 46, and 48 markets in August 2016 to 54, 80, and 96 markets in July 2019. Overall, we observe 198 entries during the sample period. At least one entry took place in 129 markets, and in 55 of these markets, Shufersal (the incumbent) was a monopoly before entry (see also Table 1).

3 Estimation and Results

The patterns presented in Section 2.3 provide suggestive evidence that competition and demand conditions are important determinants of service time. That is, lower competition and higher demand are associated with shorter service time. However, since these correlations are potentially driven by cross-market differences, in order to make a causal argument we need to examine how service time changes once competition changes in a given market.

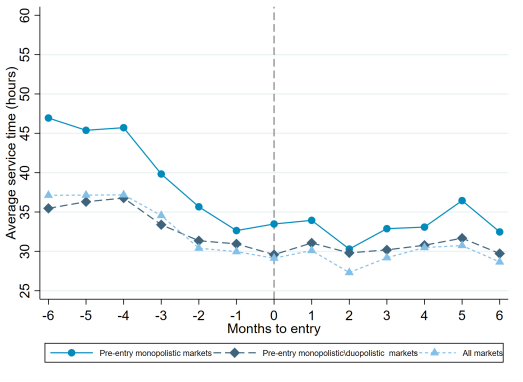
We take advantage of the massive expansion by online grocers into new local markets to identify the impact of impending entry on the incumbent's (Shufersal's) service time. We begin with an event study analysis that accommodates the possibility of dynamic treatment effects on the incumbent's service time before and after a rival enters. This analysis is useful for identifying the timing of the incumbent's response to impending entry. Next, we perform a parametric difference-in-differences (DiD) analysis. In both analyses we distinguish between low- and and high- demand days (Saturdays and Wednesdays, respectively) and between different pre-entry market structures (monopolies, markets with up to two online grocers, and all markets).

The analysis compares the service time offered by the incumbent in markets that experienced entry (treated markets) to the service time offered by the incumbent in markets that did not experience entry (untreated markets). The variation in the timing of the entry allows us to perform the regression analyses while controlling for time-invariant conditions within the same market, and for time-variant effects that are fixed across markets. Markets that experienced at least one entry (129 markets) are treated markets, and markets that did not experience entry (51 markets) are control markets. If there were multiple entries to one of the 129 local markets, we restrict attention to the first entry (70% of markets experienced only one entry during the sample period). To identify a causal effect of competition on service time, we assume the existence of parallel trends. That is, absent entry, the difference in potential service time offered by the incumbent would be the same across all markets and all months, conditional on market and month fixed effects. This requirement is more likely to be satisfied in our setting given that we focus on service time offered by the incumbent (e.g., Goolsbee and Syverson 2008, Matsa 2011). In Section 3.4 we provide further evidence that entry decisions are predominantly driven by the entrant's operational capabilities rather than the incumbent's capabilities. If entrants do time their entry and focus on markets where the incumbent faces stricter capacity constraints, then our estimates are potentially biased downward.

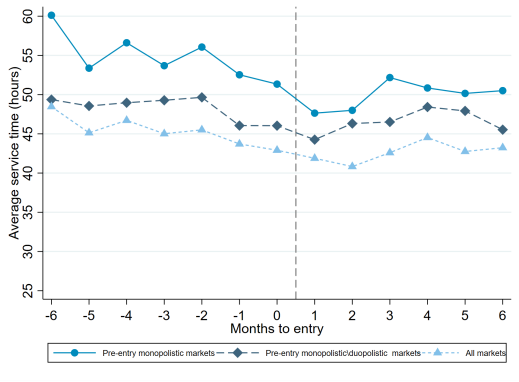
Before turning to the estimation itself, it is useful to examine the raw data. Figure 4 uses the raw service time data to show the mean service time of Shufersal in the 6 months before and the 6 months after entry. In this figure, we restrict attention to entries by Rami Levy and Victory,

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

(a) Low demand day



(b) High demand day



Notes: The figure plots average service times by Shufersal (the incumbent online grocer) in the 129 markets that experienced entry before and after a rival grocer entered the local market. The figure distinguishes between low-demand (Panel (a)) and high-demand (Panel (b)) days, and between different competition levels. Service times are shorter on low-demand days than on high-demand days. Also, service times are shorter in more competitive markets on both low- and high- demand days. We observe a decrease in service times that occurs before entry, and this decrease is more pronounced on low-demand days and in monopolistic markets.

which account for the majority of entries and are considered as aggressive entrants. The figure distinguishes between low- and high- demand days of the week and between different pre-entry market structures (monopolies, duopolies and monopolies, and all markets). According to the figure, service times are shorter on low-demand days and in more competitive markets. More importantly, we observe a decrease in service time that begins a few months before entry. This decrease is more pronounced on low-demand days and in pre-entry monopolistic markets.

3.1 Event study estimation

Our first empirical exercise is a nonparametric estimation of an event study design in the spirit of Goolsbee and Syverson (2008) who examine the impact of Southwest's entry on prices set by incumbent airlines before and after entry takes place. The primary advantage of the event study approach is that it allows us to visually (and flexibly) assess the different trends in service time relative to the entry month, and to identify a pre-entry response by the incumbent. The basic event study specification has the following form:

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

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

of months k before or after entry. Standard errors are clustered at the locality level to account for within-market correlation in the error term. Markets that did not experience entry during the sample period are used as the control group. Since markets in the control group may experience different trends in service time, in the analyses we use either all untreated markets or only not-yet-treated markets (i.e., markets that did not experience entry, and have the same competition level as pre-entry treated markets). We also perform additional robustness tests, using alternative definitions of control groups. All results are qualitatively the same.

The key coefficients of interest are β_k, which capture the change in the dependent variable in a given month k relative to its average value in the excluded period. In the baseline specification, the subscript j is running from 6 months before entry to 6+ months after entry, and the excluded period is more than 6 months before entry. We use six months before and after entry since we want to capture the short-term impact of entry. We estimate Equation (1) separately for low- and high-demand days of the week (Saturday and Wednesday, respectively) and for subsamples that include different pre-entry market structures. Including lags in Equation (1) enables us to identify the timing of the pre-entry response.

Recent econometric literature shows that two-way fixed effects (TWFE) event study coefficients might be biased if there is heterogeneity in treatment effects between groups of units treated at different times (De Chaisemartin and d'Haultfoeuille, 2020, Goodman-Bacon, 2021, Borusyak et al., 2021, Callaway and Sant'Anna, 2020, Sun and Abraham, 2020). In such cases, each event time coefficient may be "contaminated" with effects from other cohorts.[19] In Appendix F, we verify that our findings are not sensitive to using alternative estimators, proposed by Sun and Abraham (2020) and Borusyak et al. (2021), that allow for heterogeneous treatment effects.

3.1.1 Results

Figure 5 presents the results of the event study regression analysis. The figure plots the point estimates and the 90 percent confidence intervals for the β_k coefficients in Equation (1) 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 that were monopolies before entry. Sub-figure (b) focuses on markets that were served by up to two online grocers before entry, and sub-figure (c) reports the results for all markets. Dark-blue circles indicate the coefficients from a sample that uses as a control group all

[19] Goodman-Bacon (2021) and Callaway and Sant'Anna (2020) show that the inclusion of a control group can alleviate this issue as long as the control group is not treated yet. In the presence of heterogeneous treatment effects, the ideal control group include never treated or not-yet-treated markets during the sample period. Accordingly, in our main analysis we report results using either a control group that includes all untreated markets or a control group that includes only untreated markets that have the same competition level as treated markets. In Figure D1 in Appendix D we also report results from an analysis that uses only treated markets.

the markets that did not experience entry during the sample period. Light-blue diamonds indicate the estimated coefficients from a sample that uses as control markets that did not experience entry and have the same competition level as pre-entry treated markets (i.e., for treated monopolistic markets, the untreated markets are markets where Shufersal was a monopoly throughout the sample period).

The results in Panel (a) show that service time in pre-entry monopolistic markets decreased by 10% to 20% on low-demand days. The decrease in service time is statistically significant two months before actual entry took place. The post-entry coefficients are also negative and significant on low-demand days, and have about the same magnitude as the coefficients in the two months preceding entry. Our estimates for service time on high-demand days do not show a significant change in service time, before or after entry. Also, in more competitive markets (Panels (b) and (c)) we find a smaller impact on service time on low-demand days, and an insignificant change in service time on high-demand days. Overall, we observe a decline in the service time offered by the incumbent already before entry, and this decrease is larger in more concentrated markets. Also, the effect is significant only on low-demand days. In Section 3.3 we offer our preferred interpretation for these results.

To test the robustness of the results, Figure D1 in Appendix D shows estimation results when only treated markets are used and Figure D2 in Appendix D shows estimation results from a specification that expands the event window to 12 months before and 12 months after entry. The results shown in these Figures are similar to the results in Figure 5 and strengthen the robustness of our analysis.

3.2 Difference-in-differences estimation

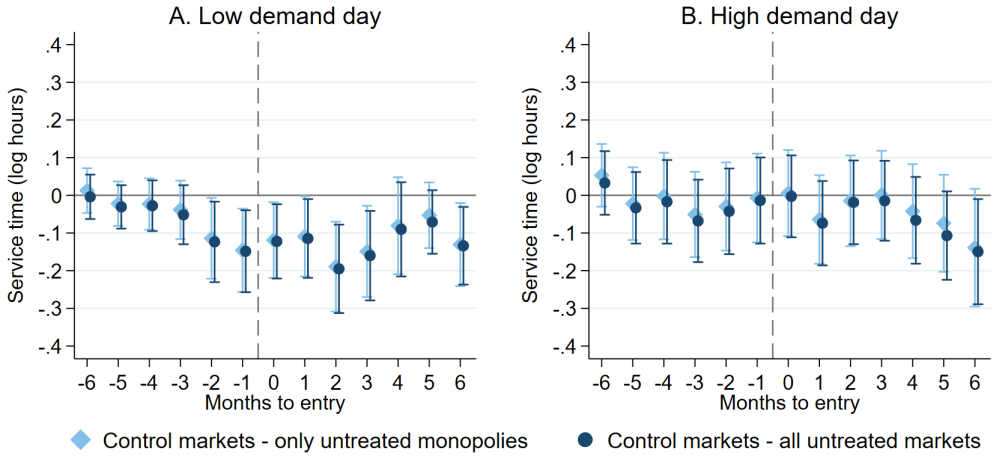
The event study estimation results uncover two short-term responses by the incumbent to impending entry: a significant decrease in service time in the two months preceding entry, and a non-dynamic nature of response following entry. We rely on these patterns and continue the analysis by using a parametric DiD estimation of the static effect of entry. In particular, we estimate the following two-way fixed effects DiD regression:

$$Log(delivery\_time)_{it} = \delta_i + \alpha_t + \rho_1 pre\_entry_{it} + \rho_2 post\_entry_{it} + \lambda X'_{it} + u_i, \tag{2}$$

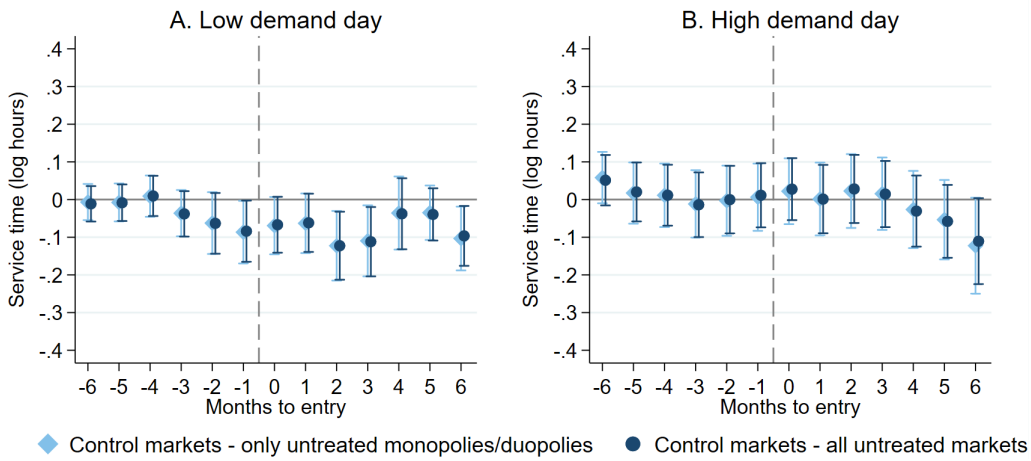
where pre_entry_{it} is a dummy for the 1–2 months preceding entry into the local market and $post\_entry_{it}$ is a dummy for the months after entry into the local market. We also estimate specifications including X'_{it}, which is a vector of time-variant variables. These variables include the number of brick-and-mortar stores operated by rivals in the local market (we use the number

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

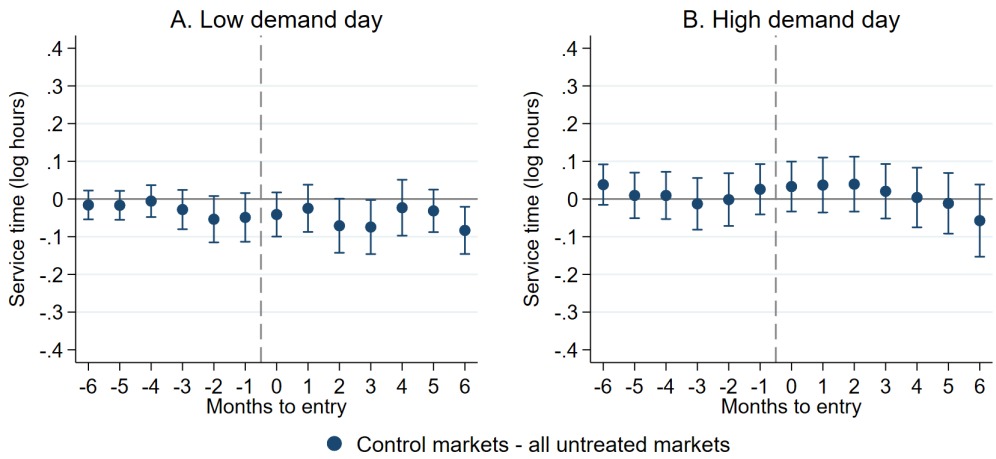
(a) Pre-entry monopolistic markets



(b) Pre-entry monopolistic/duopolistic markets



(c) All markets



Notes: The figures plot the coefficients of β_j for j running from 6 months before entry to 6 months after entry and their 90 percent confidence intervals, from estimating Equation (1) using different subsamples. Standard errors are clustered at the market level. The dependent variable is the incumbent's log service time in the local market, and results are presented separately for low- and high- demand days. Panel (a) reports the estimated effects of entry in pre-entry monopolistic markets. Panel (b) considers duopolistic markets before entry and Panel (c) all other markets. The dark-blue circles indicate the coefficients from a sample that uses the markets that did not experience entry during the sample period as control markets. The light-blue diamonds indicate the estimated coefficients from a sample that uses as control the 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. The results suggest that the incumbent reduces service time when facing entry, but only on low-demand days. The reduction begins shortly before entry and is greater in pre-entry monopolistic markets.

of stores within a 10km radius of the local market but results are similar when we use alternative definitions as shown in Table D1 in Appendix D), and dummies for exits and subsequent entries in the same market to capture potential changes in the number of online retailers beyond the first entry. We also add a specific Shufersal fulfillment center linear time trend to capture any potential time trend in service time. Standard errors are clustered at the locality level to account for within-market correlation in the error term. Similar to the event study estimation, we estimate Equation (2) separately for low- and high- demand days, and for subsamples 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 uncover the effect of entry on service time in adjacent markets that did not experience entry.

3.2.1 Results

Main results. Table 2 presents the estimated results of Equation (2). Columns (1)–(3) focus on low-demand days and Columns (4)–(6) on high-demand days. Panel A reports the estimated effects of entry on the incumbent's service time in pre-entry monopolistic markets. Panel B reports the estimated effects of entry on the incumbent's service time in markets that were served by up to two online grocers before entry, and Panel C reports the estimated effects of entry for all markets. The results shown in Table 2 are based on an analysis that uses all untreated markets as the control group. Similar results are obtained when we use untreated markets with the same pre-entry competition level as the control group, or do not include a control group and exploit only the variation in entry timing for identification (see Table D2 in Appendix D).

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

Response by entrant type. To explore whether the incumbent's response varies with the identity of the entrants, we consider Rami Levy and Victory as aggressive online grocers, and examine how their entry affects the incumbent's service time.[20] Table 3 reports the parametric estimation results when entry is restricted only to entry by aggressive online grocers. The table

[20] To identify aggressive online grocers, we use the longitudinal customer-level data from MySuperMarket to show that Shufersal's loyal customers are likely to switch to Rami Levy and Victory when they choose not to order from Shufersal (36% switch to Rami Levy and 28% switch to Victory). See Appendix B for more details. Figure 1 also shows that Rami Levy offers the cheapest basket and Victory offers the shortest service time.

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

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

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$,

Notes: The table reports estimation results for Equation (2). Standard errors in parentheses are clustered at the market level. The dependent variable in Columns (1)-(3) is Shuferal'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 the 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 was active before entry. The sample in Panel B includes treated markets where Shufersal and another grocer 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 regressions also include market and month fixed-effects. According to the results, on low-demand days and in pre-entry monopolistic markets, a significant 10%-13% decrease in service time is observed two months before entry and in the months after entry. The estimates in more competitive markets are smaller and are not always statistically significant. The estimates on high-demand days of the week are generally negative but statistically insignificant.

shows that on low-demand days the incumbent's service time decreases when one of the aggressive retailers enters the local market. The magnitude of the effect is nearly 25% larger than in the main specification and is significant also for entries into competitive markets. Thus, in pre-entry monopolistic markets (Panel A), the incumbent decreases service time by 16.2% before entry and by 12.2% after entry (Column (3)). According to Panel C, which shows the results for all markets, the incumbent reduces service time by 7.7% and 6.8% before and after entry, respectively. On high-demand days, we find no effect before entry by aggressive grocers, and a marginally negative significant effect on service time post-entry in monopolistic markets.

Response in adjacent markets. We also examine how service time changed in markets that are not entered but are adjacent to markets that experience entry. We use this analysis to explore whether there are spillovers in the production of service time, taking advantage of the fact that several local markets are served by the same fulfillment center. In this analysis, we distinguish

Table 3: The effect of entry of aggressive grocers on service time, by competition & demand levels

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

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$,

Notes: The table reports estimation results for Equation (2). 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 the 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 another grocer were active before entry, and 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 online grocer 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.

between entry into adjacent monopolistic markets and entry into adjacent competitive markets, and also between entries of aggressive online grocers and all online grocers. To conduct the analysis, we classify each of the 180 markets to Shufersal's 34 fulfillment centers, and focus on the 51 local markets that did not experience any change during the entire sample period (these are served by 22 fulfillment centers) and on low-demand days. We repeat the parametric estimation (Equation (2)) where the entry dummy variable refers to entry into a local market which is near these 51 markets. In particular, this indicator receives the value of one for entry that occurred in a nearby local market that is served by the same fulfillment center. Panel A of Table 4 reports the results when entry is by any grocer to these nearby markets, and Panel B reports the results when entry is by an aggressive online grocer. Columns (1) and (2) present the results for all entry events, and Columns (3) and (4) focus on entry into monopolistic markets. The results suggest that when an aggressive grocer enters a nearby local market, the incumbent improves service time by 8%–10%

Table 4: The effect of entry on service time in adjacent markets (low-demand days)

	Entry into nearby markets		Entry into nearby monopolistic markets	
	(1)	(2)	(3)	(4)
Panel A: Entry by all online grocers [N=1,830, markets=51]				
Pre-entry	0.017	0.019	-0.010	-0.011
	(0.025)	(0.026)	(0.033)	(0.034)
Post-entry	-0.021	-0.011	-0.058	-0.053
	(0.041)	(0.039)	(0.035)	(0.036)
Panel B: Entry by aggressive online grocers [N=1,830, markets=51]				
Pre-entry	-0.027	-0.027	-0.031	-0.031
	(0.038)	(0.039)	(0.040)	(0.040)
Post-entry	-0.091*	-0.087	-0.089*	-0.085*
	(0.051)	(0.053)	(0.046)	(0.046)
Panel C: Entry by aggressive online grocers when they are not active in non-entered adjacent markets [N=1,830, markets=51]				
Pre-entry	-0.050	-0.050	-0.037	-0.038
	(0.046)	(0.047)	(0.050)	(0.051)
Post-entry	-0.106*	-0.101*	-0.105*	-0.101*
	(0.059)	(0.060)	(0.055)	(0.054)
Pre-entry+	0.055	0.056	-0.015	-0.013
pre entry*active entrant	(0.048)	(0.046)	(0.045)	(0.044)
Post entry+	-0.033	-0.027	-0.028	-0.020
post entry*active entrant	(0.047)	(0.046)	(0.041)	(0.041)
Additional controls:				
Rivals' offline stores (10km radius)		✓		✓
Exits and additional entries		✓		✓

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

Notes: Panels A and B report estimation results for regression similar to Equation (2) and Panel C 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 is Shufersal's log service time in the local market on Saturday night. *pre_entry* is an indicator for the one or two months before the first entry into an adjacent market served by the same fulfillment center. *post_entry* is an indicator for the month of entry into the adjacent market and for the following months. Entry indicators in Columns (1) and (2) refer to all entries into nearby markets, and in Columns (3) and (4) to entries only into nearby monopolistic markets. Entry indicators in Panel A refer to entries of all grocers, and in Panels B and C only to entries by aggressive grocers. The specification in Panel C also includes an interaction between entry dummies and indicators for markets where the entrant was already active in adjacent markets. All regressions include market and month fixed-effects. The results suggest that when an aggressive grocer enters one local market, the incumbent improves service time also in adjacent markets that are served by the same fulfillment center (on low-demand days). This improvement is larger also post-entry when the entrant is not active in adjacent markets.

in adjacent markets that are served by the same fulfillment center. A possible explanation for this finding is that the entry of aggressive grocer leads to a significant decrease in demand for online service in the nearby market that experiences entry, which frees up resources that are used by the incumbent's fulfillment center to improve service times in adjacent markets that did not experience entry.[21]

An alternative explanation for the decrease in service time in adjacent markets can be pre-

[21] The finding that service time does not change before entry may imply that our results in the main specification are not confounded by spillover effects to the 51 control markets. The negative effect on the control market after entry might suggest that our post-entry estimates in the main specification are a lower bound for the true effect.

emption, where entry into a nearby local market raises the likelihood of entry also into adjacent markets. Thus, the incumbent improves service time in an effort to preempt subsequent entry into adjacent markets. To provide very suggestive evidence that is consistent with a preemptive motive, in Panel C we distinguish between entries of aggressive grocers into markets when the entering aggressive grocer was either already active or not active in the non-entered adjacent market. In particular, we estimate:

$$\begin{aligned} Log(delivery\_time)_{it} = \delta_i + \alpha_t + \tau_1 pre\_entry_{it} + \tau_2 pre\_entry_{it} * active\_entrant_i \\ + \tau_3 post\_entry_{it} + \tau_4 post\_entry_{it} * active\_entrant_i + \lambda X'_{it} + u_i, \end{aligned} \tag{3}$$

where pre_entry_{it} and $post\_entry_{it}$ are dummy variables for the one or two months before entry, and for the months after entry of an aggressive entrant, respectively (as in Panel B of Table 4). $active\_entrant_i$ is an indicator for whether the entrant is active in the adjacent market i. Panel C of Table 4 reports the estimated coefficients of τ_1 and τ_3, which refer to the effect of entry where the entrant was not active in the adjacent non-entered market, and also the estimated linear combination of $\tau_1 + \tau_2$ and $\tau_3 + \tau_4$, which refers to the effect of entry when the entrant was already active in the non-entered adjacent market. The results show that the reduction in service time in adjacent markets occurs only in local markets that are not already served by the aggressive online grocer. In cases where that online grocer already operate in the adjacent market at the time of a nearby entry, we do not find that the incumbent improves service time. This finding may suggest that the incumbent offers better service time to deter subsequent entries into adjacent markets.

3.3 Interpretations

The empirical analysis shows that the incumbent sets a shorter service time when it faces entry. Service time decreases primarily on low-demand days, in concentrated markets or when a stronger rival enters. Our preferred interpretation for these findings is that the incumbent exercises its market power using service time. Using service time is particularly useful when the retailer cannot change prices.

In Appendix A, we present a modified version of the newsvendor problem model (Arrow et al. 1951) that can be used to interpret our findings. In the model, demand for online grocery varies over the days of the week. Demand is high on pre-weekend days and low on post-weekend days of the week. Prices are fixed do not vary across days, and to achieve a certain service time, the online grocer uses labor (e.g., drivers, packers) and capital (e.g., trucks). These inputs are fixed within a week, implying that inputs are better utilized on high-demand days than on low-demand days. This setting generates a trade-off between overage costs and underage costs. The former costs include the lost one-time margin from customers who do not purchase due to long service

times on high-demand days, and the risk that these customers switch to rivals. This risk increases with the number of retailers in the market. Underage costs are incurred on low-demand days and reflect the costs of redundant trucks or unproductive workforce. In line with the predictions generated from this trade-off we show that service time is shorter on more competitive markets, on low-demand days, or when the retailer is high-priced. We also show that entry in concentrated markets, especially by aggressive rivals, and on low-demand days triggers improvements in service time.

Our empirical analysis further shows that the change in service time begins before entry takes place and continues afterwards. The pre-entry improvements reflect efforts by the incumbent to generate loyalty or lock-in among existing customers, making them less likely to switch to the rival after it enters. This loyalty interpretation is similar to what Goolsbee and Syverson (2008) propose as an explanation for why incumbent airlines reduce prices before Southwest enters a route where they operate. Figure B4 in Appendix B offers further suggestive evidence that the decrease in the service time of the incumbent is meant to improve goodwill and retention among customers. Consistent with this interpretation, in Panel (a) of Figure B4 we show that MySupermarket's loyal customers are more likely to buy from an online grocer that is not their regular retailer (i.e., switch) on days characterized by long service times.[22]

Can alternative explanations give rise to the same patterns? One such explanation is that the reduction in service time is a consequence of lower demand for the incumbent's online service. If customers begin using an entrant's services, then the incumbent may have available resources that it can use to offer a shorter service time. To disentangle between our preferred competition-based explanation and this cost-driven explanation, we distinguish between service time changes that occur before and after entry takes place. In particular, cost-driven improvements in service time can materialize only after entry takes place. If, however, service time starts to decrease already before entry then this change is likely due a strategic response of the incumbent to impending entry. Accordingly, our findings that service time improves before entry likely reflect a deliberate attempt to fend off rivals and to improve customers' goodwill. By contrast, post-entry changes in service time can be explained by either competitive-based or cost-driven reasons.

Does the incumbent know that entrants intend to enter before they actually do? While we do not have direct information on this issue, we note that offering online service requires non-trivial investments, such as recruiting and training new in-store workers, hiring specialized trucks, modifying physical stores for distribution, and changing the online grocery website. Also, before

[22] A loyal customer is a customer who used the online grocery platform more than 10 times, and placed at least 60% of his or her orders with the same online grocer. In our data, there are 9,182 loyal customers overall, and among them 2,861 are loyal customers of Shufersal. Panel (b) further shows that when Shufersal's loyal customers switch, they predominantly prefer Rami Levy and Victory, which we consider as aggressive retailers. See Appendix B for more details.

entry grocers sometimes engage in local advertising. Many of these actions are observable, certainly for rivals that operate in the same local market. Accordingly, it is plausible to assume that the incumbent knows that a rival intends to enter a local market few months before actual entry takes place. Indeed, the fact that we observe a change in service time already 2-3 months before entry might strengthen our interpretation that this improvement is costly to implement but at the same time is required to strengthen loyalty among customers. Conversations we had with industry insiders confirm this view.

3.4 Identification concerns

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

Entry decisions. Entry decisions depend on the socio-demographic characteristics of local markets, such as population size, expected population growth, and average income. These factors are unlikely to significantly change during the time period we study, and the market fixed effects that we include likely capture them. Figure C3 in Appendix C plots the number of first entries that we observe in each month for all 129 markets, and for the 55 markets in which the incumbent was a monopoly before entry. The figure shows that the timing of entry into these markets is spread over three years of the sample period with no specific period of massive expansion. Table D3 presents demographic information on all 180 markets, classified according to whether they did or did not experience entry during the sample period. Odd-numbered columns report the demographic characteristics, means, and standard deviations for markets that experienced entry, distinguished by different pre-entry market structures. Even-numbered columns report for each characteristic the mean difference between markets that experienced entry and those that did not experience entry, alongside results of t-tests comparing these characteristics. The patterns suggest that online retailers are more likely to offer service in more populated and dense localities, which are located closer to the center of Israel and have higher socioeconomic status, but we do not observe clear differences between markets that experienced entry and those that did not, in particular for less competitive markets. Figures E2 and E3 in Appendix E describe the expansion of Shufersal's rivals. The maps show for four time points in our sample period what the markets where each retailer offers online services (red dots) and the locations of the retailers' physical stores (blue dots). The patterns shown in the figures suggest that entry decisions are geographically clustered:

between 2016 and 2019 Rami Levy expanded its online service primarily into the north of Israel, whereas Victory into the south of Israel. This implies that retailers tend to offer new online grocery service in regions where they already offer online service, thereby taking advantage of operational efficiencies (Holmes 2011).

Substitution between online and traditional channels. Offering online service in a local market might by related to a prior decision to expand through the traditional channel in the same region. In such a case, the decrease in the incumbent's service time might be driven by reduced demand for its online service, as customers begin to buy at a newly opened physical store. To address this concern, in the regression we flexibly control for the presence of physical stores (including new stores). The estimated results in Section 3.2.1 (Columns (2), (3), (5), and (6)) account for the presence and for the opening of physical stores within a 10km radius of the local market accessed by the crawler. Table D1 in Appendix D shows similar results when we use alternative definitions to account for the offline channel effect: presence of physical stores within a 5km or 15km radius of the crawler address of the market (Columns (1), (2), (5), and (6)) and the distance (in kilometers) to the first or second physical store (Columns (3), (4), (7), and (8)). The results indicate that the effect of entry on the incumbent's service time is not sensitive to the presence of or the distance to a rival store. Figure C2 in Appendix C and Figures E2 and E3 in Appendix E further indicate that the timing of entry does not seem to depend on the opening of a physical store in the local market. Figure C2 in Appendix C plots the increase in the number of physical stores operated by each retailer except Shufersal against the increase in its coverage in the online service. While Rami Levy, Victory, and Yenot Bitan expanded both their online and traditional operations, we do not observe a clear association between the timeline of these expansions. For instance, only four entries by Victory and Yenot Bitan (two each) occurred one month after they opened a store within a 15km radius of the address served by the online service. All other entries we consider took place at least 6 months after the opening of a new store within a 15km radius.

Local infrastructure. Service times offered by the incumbent may improve due to local changes in infrastructure (e.g., roads). If these changes take place at the same time that a rival firm enters, then we may erroneously attribute the service time improvement to the impact of entry. We believe that this concern is unlikely to hold given that we examine more than a hundred entry decisions, and that service time improves more when aggressive rivals enter and in more concentrated markets. These patterns are unlikely to be systematically related to improvements in infrastructure. Also, we do not find that service time improves on high-demand days. Arguably, if infrastructure changes are important then they should also reduce service time on high-demand days. In addition, the estimated results in Section 3.2.1 (Columns (3) and (6)) account for a

specific Shufersal fulfillment center linear time trend to capture any potential time trend in service time (e.g., technological changes).

4 Discussion and Concluding Remarks

Growing evidence shows that concentration levels and mark-ups have increased in recent decades. This evidence suggests that firms may have market power that they exploit at the expense of consumers. Alternatively, large firms may be becoming more efficient at obtaining higher mark-ups without harming consumers. One way that large firms may save costs is by offering lower service quality. In this paper, we explore this possibility by focusing on the relationship between service time and competition in the Israeli online grocery market. Using three years of bi-weekly longitudinal data on service time and prices in 180 local 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 times. Notably, online retailers set identical prices in different local markets, though they face different local competition and demand conditions. The uniform pricing regularity further implies that service time has an important role in explaining how firms compete.

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 online grocers' service time. We find that incumbents improve service time shortly before a rival enters, and that the effect is larger in concentrated markets and on low-demand weekdays. Entry also affects service time in adjacent markets that are served by the same fulfillment center as markets that experience entry. On high-demand days we do not find that service time changes. Overall, these results suggest that firms use service time to exercise their local market power and that operational considerations affect the extent to which they respond. Using a non-price attribute, such as service time, is particularly effective in a setting where firms adopt a uniform pricing strategy. Nevertheless, firms may and probably do use service time also in markets where prices vary with demand and competition levels.

We note that the regression analysis captures the short-term effect of entry on service time. In the short run, firms face high adjustment costs especially on high-demand days where they already utilize their existing resources. Accordingly, in the regression analysis we do not find that incumbents improve service time on the high-demand days. In the long run, firms can adjust, add relevant inputs and change their production technology. This distinction might explain why in the cross-section analysis we find that service time is significantly shorter not only on low-demand days but also on high- demand days. We leave this issue for further research.

Our results also speak to the debate about uniform pricing. Growing evidence shows that

national chains set similar prices in very different markets. These findings cast doubt on the relevancy of standard models of competition that emphasize the role of prices. In that sense, our findings can help explain how firms that set identical prices across markets use service time to exercise their market power. A possible interpretation for our findings is that service time replaces price in the standard models of competition. In particular, according to a Bertrand model with differentiated products and fixed quality, prices are expected to be lower in more competitive markets and in low-cost markets. In the standard model, entry has a greater impact on prices in monopolistic markets and when incumbents face low marginal costs. Remarkably, our findings offer a parallel result for service time in markets with fixed prices. Thus, service time is higher in monopolistic markets and on high-demand days of the week. Also, service time decreases following entry into monopolistic markets, when stronger rivals enter and when costs are lower. Thus, one may conclude that in the absence of prices, service times are used to exercise market power and eventually also facilitate market clearing.

References

Brian Adams and Kevin R Williams. Zone pricing in retail oligopoly. American Economic Journal: Microeconomics, 11(1):124–56, 2019.

Gad Allon and Awi Federgruen. Competition in service industries. Operations Research, 55(1): 37–55, 2007.

Gad Allon and Awi Federgruen. Service competition with general queueing facilities. Operations Research, 56(4):827–849, 2008.

Gad Allon and Awi Federgruen. Competition in service industries with segmented markets. Management Science, 55(4):619–634, 2009.

Gad Allon, Awi Federgruen, and Margaret Pierson. How much is a reduction of your customers' wait worth? an empirical study of the fast-food drive-thru industry based on structural estimation methods. Manufacturing & Service Operations Management, 13(4):489–507, 2011.

Peter Arcidiacono, Paul B Ellickson, Carl F Mela, and John D Singleton. The competitive effects of entry: Evidence from supercenter expansion. American Economic Journal: Applied Economics, 12(3):175–206, 2020.

Kenneth J Arrow, Theodore Harris, and Jacob Marschak. Optimal inventory policy. Econometrica: Journal of the Econometric Society, pages 250–272, 1951.

Itai Ater and Oren Rigbi. Price transparency, media and informative advertising. Working paper, 2022.

Kirill Borusyak, Xavier Jaravel, and Jann Spiess. Revisiting event study designs: Robust and efficient estimation. Unpublished working paper, version May, 19:2021, 2021.

Timothy F Bresnahan and Peter C Reiss. Entry and competition in concentrated markets. Journal of Political Economy, 99(5):977–1009, 1991.

Gérard P Cachon and Patrick T Harker. Competition and outsourcing with scale economies. Management Science, 48(10):1314–1333, 2002.

Brantly Callaway and Pedro HC Sant'Anna. Difference-in-differences with multiple time periods. Journal of Econometrics, 2020.

Alberto Cavallo. Are online and offline prices similar? evidence from large multi-channel retailers. American Economic Review, 107(1):283–303, 2017.

Alberto Cavallo, Brent Neiman, and Roberto Rigobon. Currency unions, product introductions, and the real exchange rate. The Quarterly Journal of Economics, 129(2):529–595, 2014.

Pradeep K Chintagunta, Junhong Chu, and Javier Cebollada. Quantifying transaction costs in online/off-line grocery channel choice. Marketing Science, 31(1):96–114, 2012.

Sai Chand Chintala, Jura Liaukonyte, and Nathan Yang. Browsing the aisles or browsing the app? how online grocery shopping is changing what we buy. How Online Grocery Shopping is Changing What We Buy (December 23, 2021), 2021.

James D Dana and Yuk-Fai Fong. Product quality, reputation, and market structure. International Economic Review, 52(4):1059–1076, 2011.

Clément De Chaisemartin and Xavier d'Haultfoeuille. Two-way fixed effects estimators with heterogeneous treatment effects. American Economic Review, 110(9):2964–96, 2020.

Arthur S De Vany and Thomas R Saving. Product quality, uncertainty, and regulation: The trucking industry. The American Economic Review, 67(4):583–594, 1977.

Arthur S De Vany and Thomas R Saving. The economics of quality. Journal of Political Economy, 91(6):979–1000, 1983.

Stefano DellaVigna and Matthew Gentzkow. Uniform pricing in us retail chains. The Quarterly Journal of Economics, 134(4):2011–2084, 2019.

Liran Einav, Dan Knoepfle, Jonathan Levin, and Neel Sundaresan. Sales taxes and internet commerce. American Economic Review, 104(1):1–26, 2014.

Etienne Gagnon and David López-Salido. Small price responses to large demand shocks. Journal of the European Economic Association, 18(2):792–828, 2020.

Ricard Gil, Evsen Korkmaz, and Ozge Sahin. Can free-shipping hurt online retailers? Quantitative Marketing and Economics, 18(3):305–342, 2020.

Jacob Goldin, Tatiana Homonoff, and Katherine Meckel. Issuance and incidence: Snap benefit cycles and grocery prices. American Economic Journal - Economic Policy, 14(1):152–178, 2022.

Andrew Goodman-Bacon. Difference-in-differences with variation in treatment timing. Journal of Econometrics, 2021.

Austan Goolsbee and Chad Syverson. How do incumbents respond to the threat of entry? evidence from the major airlines. The Quarterly Journal of Economics, 123(4):1611–1633, 2008.

Günter J Hitsch, Ali Hortaçsu, and Xiliang Lin. Prices and promotions in us retail markets. Quantitative Marketing and Economics, pages 1–80, 2021.

Thomas J Holmes. The diffusion of wal-mart and economies of density. Econometrica, 79(1): 253–302, 2011.

Johannes Hörner. Reputation and competition. American economic review, 92(3):644–663, 2002.

Ali Hortaçsu, F Martínez-Jerez, and Jason Douglas. The geography of trade in online transactions: Evidence from ebay and mercadolibre. American Economic Journal: Microeconomics, 1(1):53–74, 2009.

Jean-François Houde, Peter Newberry, and Katja Seim. Economies of density in e-commerce: A study of amazon's fulfillment center network. National Bureau of Economic Research, 2017.

Jean-François Houde, Peter Newberry, and Katja Seim. The impact of distance and taxes on amazon. working paper, 2021.

Ehud Kalai, Morton I Kamien, and Michael Rubinovitch. Optimal service speeds in a competitive environment. Management Science, 38(8):1154–1163, 1992.

Yina Lu, Andrés Musalem, Marcelo Olivares, and Ariel Schilkrut. Measuring the effect of queues on customer purchases. Management Science, 59(8):1743–1763, 2013.

Israel Luski. On partial equilibrium in a queuing system with two servers. The Review of Economic Studies, 43(3):519–525, 1976.

David A Matsa. Competition and product quality in the supermarket industry. The Quarterly Journal of Economics, 126(3):1539–1591, 2011.

Michael J Mazzeo. Competition and service quality in the us airline industry. Review of Industrial Organization, 22(4):275–296, 2003.

Marcelo Olivares and Gérard P Cachon. Competing retailers and inventory: An empirical investigation of general motors' dealerships in isolated us markets. Management science, 55(9): 1586–1604, 2009.

A Yeşim Orhun, Sriram Venkataraman, and Pradeep K Chintagunta. Impact of competition on product decisions: Movie choices of exhibitors. Marketing Science, 35(1):73–92, 2015.

Ivan PL Png and David Reitman. Service time competition. The Rand Journal of Economics, pages 619–634, 1994.

Andrea Pozzi. Shopping cost and brand exploration in online grocery. American Economic Journal: Microeconomics, 4(3):96–120, 2012.

Andrea Pozzi. The effect of internet distribution on brick-and-mortar sales. The RAND Journal of Economics, 44(3):569–583, 2013.

Jeffrey T Prince and Daniel H Simon. Do incumbents improve service quality in response to entry? evidence from airlines' on-time performance. Management Science, 61(2):372–390, 2014.

A Michael Spence. Monopoly, quality, and regulation. The Bell Journal of Economics, pages 417–429, 1975.

Storenext. Summary of 2015, main trends in the israeli consumer product market. Technical report, StoreNext, 2015.

Liyang Sun and Sarah Abraham. Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. Journal of Econometrics, 2020.

Appendix A A Model of Service Time in Online Grocery

We use a modified version of the newsvendor problem model (Arrow et al. 1951) to interpret the empirical patterns discussed in the main text. The model is useful for three main reasons. First, the model examines how service times vary on low- and high- demand days. Second, prices in the model do not vary with the competition and demand levels. Third, the model captures the trade-off that operations officers and regional managers confront when making decisions about inputs and service time in online grocery service.

A grocer faces uncertain demand for the online grocery service, and chooses the optimal amount of resources required for offering service time, denoted by S. Service time is negatively associated with the amount of resources and is positively associated with demand. Demand is distributed with a continuous cdf $F(\cdot)$ and it varies across days of the week. Let c be the marginal cost of service time based on these resources, where the same resources are used on both low- and high-demand days in the same week, and c is lower on low-demand days than on high-demand days. We denote by R the price of each order that is fixed, and by γ the costs associated with the risk that customers switch to a rival when they are dissatisfied with the service time they get. The risk of switching is increasing in the number of grocers in the market. Assume that S^* denotes the service time offered by the grocer when all resources are used efficiently and exactly meet the demand on that day, denoted by $x(S^*)$. Subsequent customers will not be offered service by the grocer on that day. The grocer then maximizes the following profits:

$$Max_{S^*} \int_0^{S^*} (Rx - cx(S^*))dF(x) + \int_{S^*}^{\infty} (Rx(S^*) - \gamma(x - x(S^*)) - cx(S^*))dF(x)$$

The solution to this maximization problem gives the following characterization of optimal service time and the trade-off between overage and underage costs:

$$F(S^*) = 1 - \frac{c}{R + \gamma.} \tag{4}$$

The trade-off underscores the importance of three factors: 1) the marginal cost of service time (c); 2) the price (R), and 3) the risk of switching (γ). Changes in c, R, and γ affect both service time S^* and S as follows. First, when the marginal cost of service is high, retailers prefer to avoid under-utilization of resources leading to longer service time ($\frac{\partial S}{\partial c} > 0$). Second, a high-priced retailer (R) is more concerned about losing customers and will offer short service times ($\frac{\partial S}{\partial R} < 0$). Third, when the risk of switching (γ) is high, retailers set short service times ($\frac{\partial S}{\partial \gamma} < 0$). These predictions are consistent with the descriptive evidence presented in Section 2.3. Next, we derive predictions that concern incumbents' service time response to the entry of a rival into the same

market.

A.1 Predictions about the effects of entry on service times

Impending entry by a rival increases the level of competition and the risk that customers will switch to a rival's grocery service. In the model, γ captures this risk and the incumbents offer shorter service times when γ rises ($\frac{\partial S}{\partial \gamma} < 0$). The magnitude of this response, however, depends on the respective costs and benefits of improving the service time. When the benefits are high (or the costs are low), the incumbents improve service times more than otherwise.

Pre-entry competition level. In more competitive markets, the marginal effect of a competitor on the incumbents' service times diminishes. Formally, this prediction is captured by $\frac{\partial^2 S}{\partial \gamma \partial \gamma} > 0$. This prediction is a standard prediction also in models that consider the impact of entry on prices, and empirical evidence (e.g., Bresnahan and Reiss 1991) supports it.

High- vs. low- demand levels. Changes in service time also depend on the costs required to adjust service time. When the retailer has available resources, such as trucks and labor, improving service time is less costly. By contrast, when resources are already used then such improvements are costly. Formally, this prediction is captured by $\frac{\partial^2 S}{\partial \gamma \partial c} > 0$. While we do not have direct information on costs or input utilization, we assume that these costs are higher on high-demand days than on low-demand days.

Entrant type. Changes in service time following entry also depend on the entrant's identity. If an entrant poses a larger competitive threat to the incumbent, then incumbents are likely to respond more aggressively by improving service time. We consider entrants that are more likely to poach customers from incumbents as a larger threat.

The results in Sections 3.1.1 and 3.2.1 support the above predictions and show that service time is more responsive to entry in concentrated markets than in competitive markets, and on low-demand/low-utilization days. Also, the impact of entry of aggressive grocers on service time is larger, as expected. In this case, the incumbent is more concerned about consumers switching, and chooses to improve service time more than when a non-aggressive retailer enters.

Appendix B 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 grocers. MySupermarket's users can compare prices and contemporaneously observe available service times offered by each grocer. Figures B1 and B2 below show examples of screenhots observed by users. After compiling a list of items that they want to buy, and the retailer they want to buy from the users transfer the list to the website of a particular grocer 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. 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. Also users of MySupermarket.co.il are likely not representative of all online consumers. They are probably less loyal to a particular grocer and live in localities where more than one online grocer offers service. Nevertheless, we think that these individuals are helpful because online grocers are concerned that these individuals will switch once a new rival enters into the local market.

We use the data from MySupermarket for three purposes: 1) to examine how the number of online grocery orders changes over days of the week (Figure B3); 2) to explore how the daily demand level is related to users' decision to switch, i.e. order from a grocer other than their "regular grocer" (Panel (a) of Figure B4), and 3) to examine consumers' substitution patterns across grocers, and accordingly characterize which grocers are more aggressive entrants (Panel (b) of Figure B4).

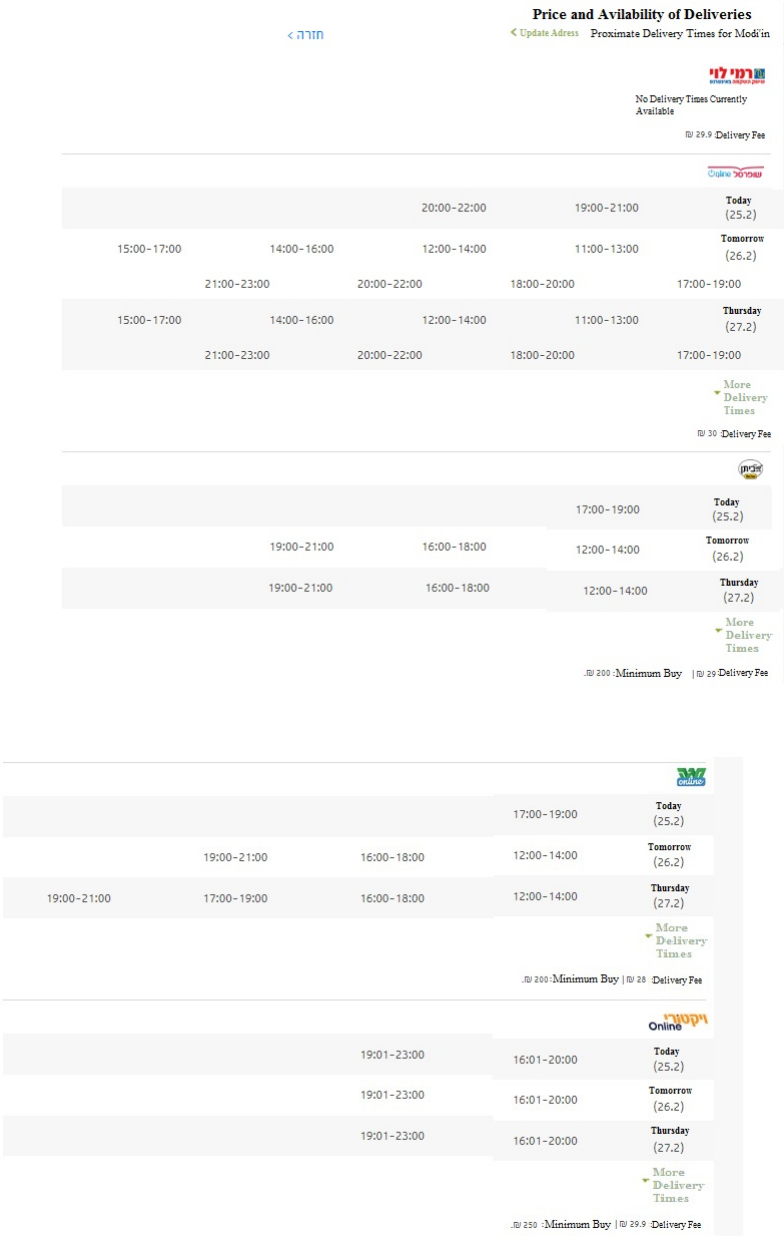
Figure B3 presents the cumulative percent of orders for online grocery on Tuesday and Wednesday, and on Friday and Saturday (i.e., 48 hours before the crawler was active at midnight on Wednesdays and Saturdays). The figure shows that the cumulative percent of orders is about three times larger on Wednesdays than on Saturdays. Figure B4 shows switching patterns of loyal customers. A loyal customer is defined as an individual who used MySupermarket more than 10 times during the sample period, and at least 60 percent of times bought from the same online grocer. There are 9,182 loyal customers in the sample, and among them 2,861 are Shufersal's loyal customers. Panel (a) shows the percentage of orders made by loyal customers and examine on which days these customers do not purchase from their regular retailer. More than 17 percent of switches by loyal customers occur on Thursday, compared to about 12.5 percent of switches to a non-regular vendor on Saturday and on Sunday. These differences are statistically significant. According to the figure, on days characterized with long service time (e.g., Thursday) loyal cus-

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

Figure B1: Online shopping platform - basket price

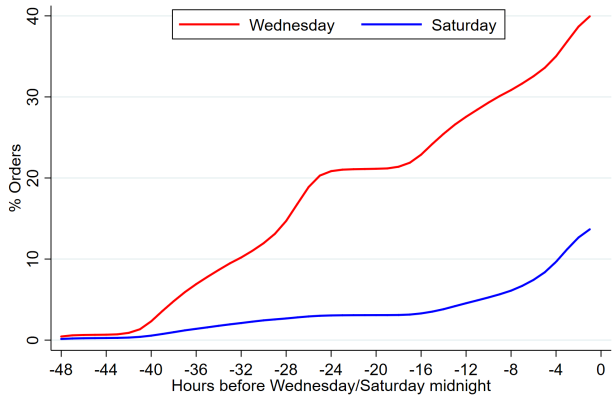
Notes: The figure shows a screenshot from MySupermarket.co.il webpage where consumers observe the basket price offered by each of the online grocers that offer service to their address, and can choose the retailer they want to order from. For instance, Rami Levy, offers the cheapest price for this basket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

Figure B2: Online shopping platform - service time



Notes: The figure shows a screenshot from MySupermarket.co.il where customers observe available delivery time slots offered by the online grocers that offer service to their home address.

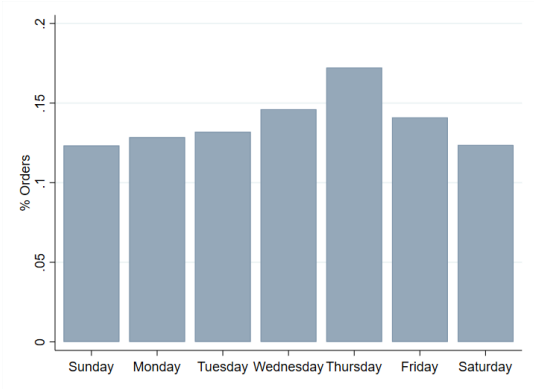
Figure B3: Cumulative number of orders before the crawler time on Wednesday & Saturday



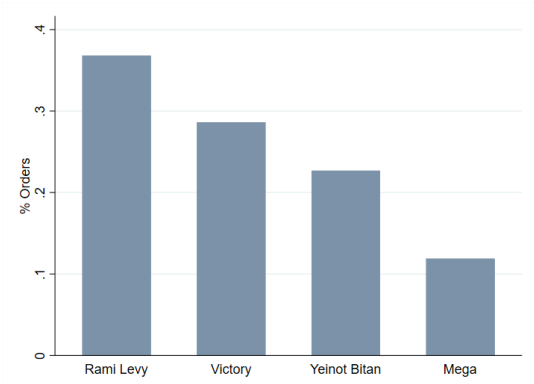
Notes: The figure shows a normalized measure of the share of orders through MySupermarket in the 48 hours that precede the crawler time (at midnight on Saturdays and Wednesdays). The figure demonstrates that demand is considerably higher (about three times more) on pre-weekend days (Tuesday and Wednesday) compared to demand for online grocery service on weekends (Friday and Saturday).

Figure B4: Customers' switching patterns at MySupermarket

(a) Switching patterns across days of the week



(b) Switching patterns across online grocers



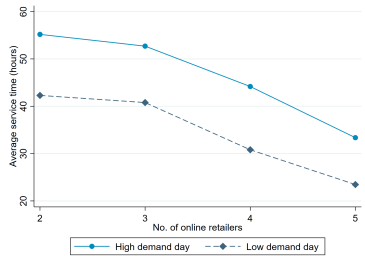
Notes: The figures show switching patterns by loyal online grocery customers. A loyal customer is defined as an individual who used MySupermarket more than 10 times during the sample period, and at least 60 percent of times bought from the same online grocer. There are 9,182 loyal customers in the sample, amd among them 2,861 are Shufersal's loyal customers. Panel (a) shows the percentage of orders by all 9,182 loyal customers which are not from their regular grocer, by day of the week. According to Panel (a), on days characterized with long service time (e.g., Thursday) loyal customers are more likely to switch to an alternate grocer: more than 17 percent of switches occur on Thursday, compared to about 12.5 percent of switches to a non-regular vendor on Saturday and on Sunday. These differences are statistically significant. Arguably, the rise in the number of switches on these days arise because customers are unsatisfied with the service time offered by their regular grocer. Panel (b) focuses on Shufersal's loyal customers and shows the percentage of orders by these customers at alternate grocers. According to Panel (b), most of the switches by Shuferasl's loyal customers are to Rami Levy and to Victory, which we consider as aggressive entrants.

Appendix C Entrants' Service Times, Prices and Stores

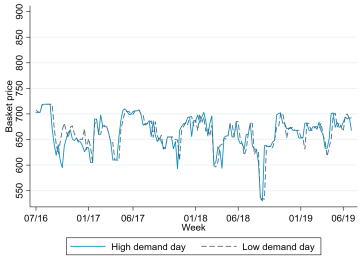
Figure C1: Service time and prices as a function of competition & demand (entrants)

A. Rami Levy

(a) Service time

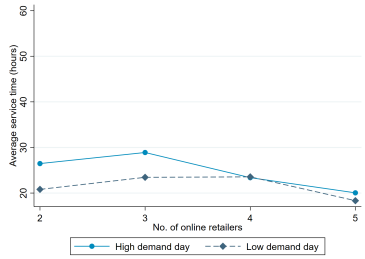


(b) Basket price

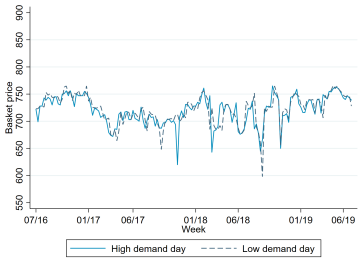


B. Victory

(a) Service time

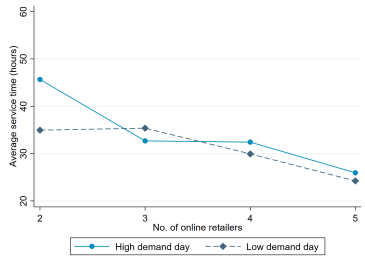


(b) Basket price

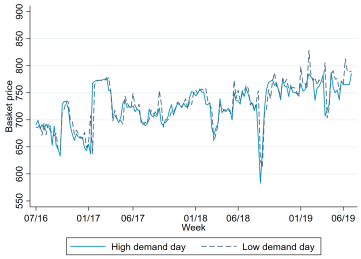


C. Yenot-Bitan

(a) Service time

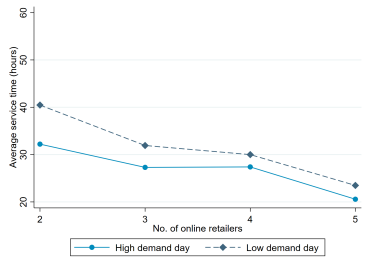


(b) Basket price

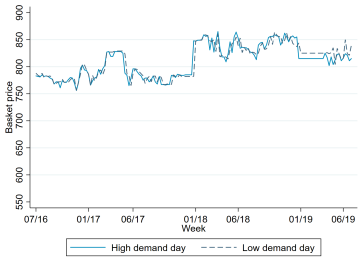


D. Mega

(a) Service time

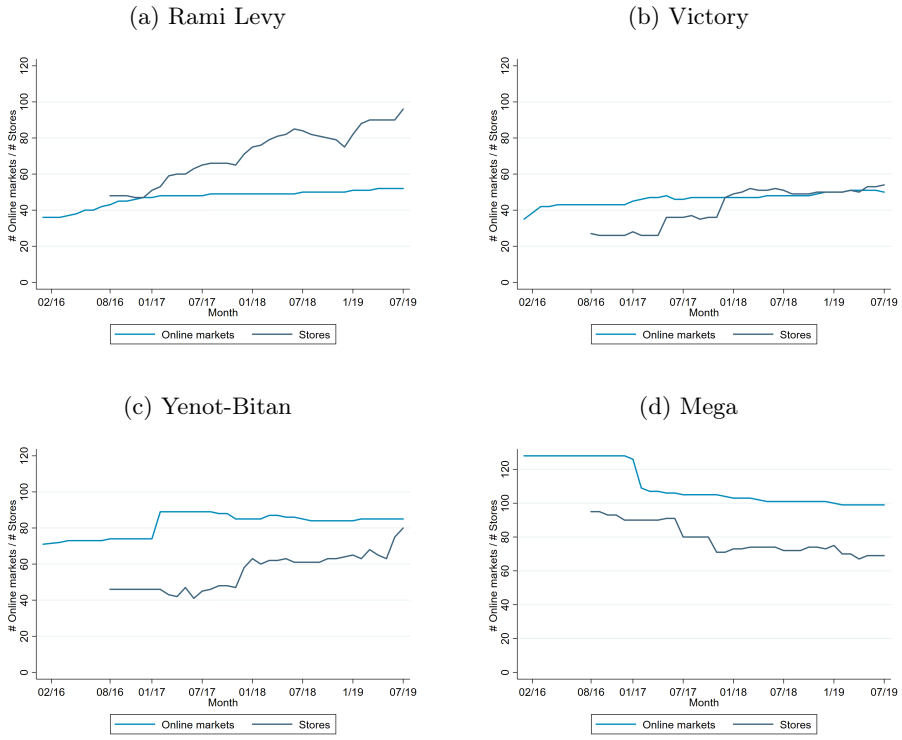


(b) Basket price



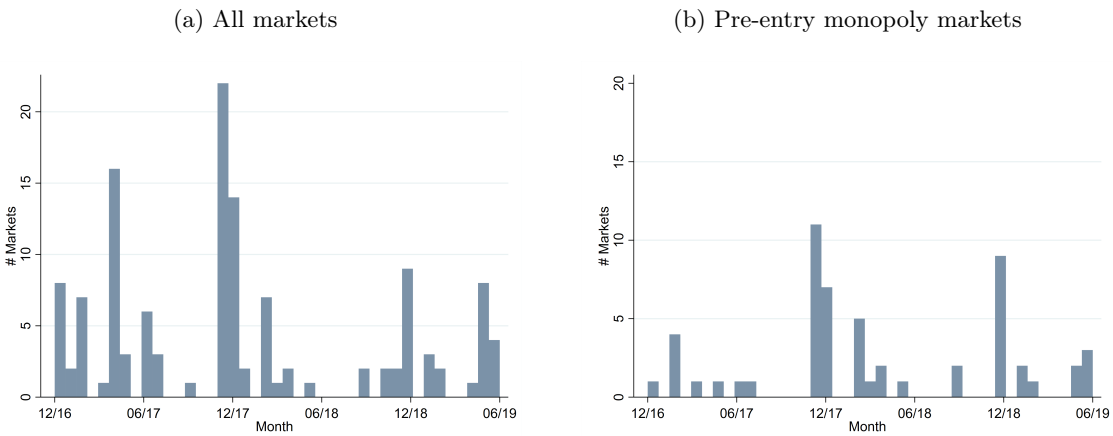
Notes: Panels (a) show the average service time offered by each of grocers (except Shufersal) as a function of the number of active online grocers in the local market, separately for low- and high- demand days. Panels (b) shows the daily price of a basket of 52 products sold by each of the online grocers, separately for Sundays and Thursdays (low- and high- demand days, respectively). Both panels use data between August 2016 and July 2019. The figures show that service time falls with the number of competing online grocers. On the other hand, prices are fixed across local markets, and are also not higher on high-demand days.

Figure C2: The number of physical stores operated by a grocer vs. online expansion by the grocer



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

Figure C3: The distribution of timing of first entry

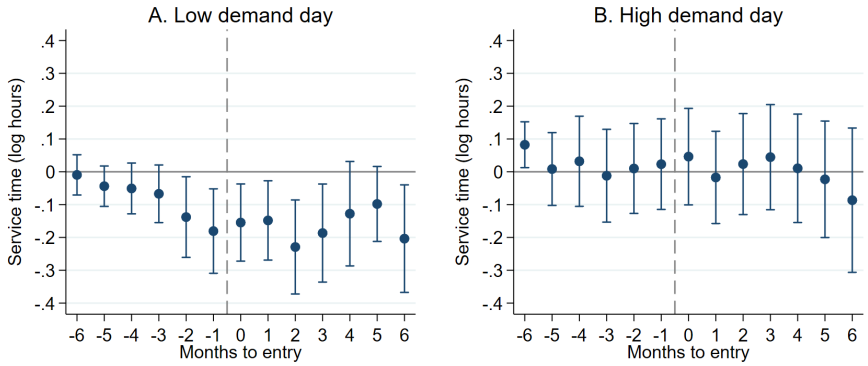


Notes: Panel (a) shows the number of markets that experienced entry in each month during the sample period. Panel (b) shows the number of monopolistic markets that experienced entry in each month during the sample period. The patterns of timing of entry do not reveal a pattern of strategic timing of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

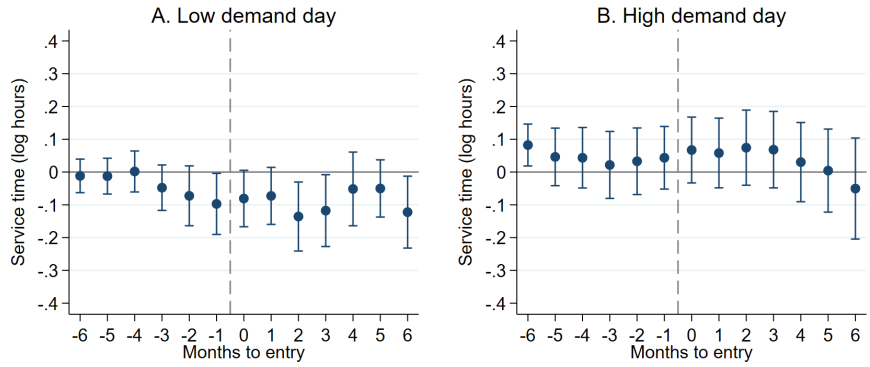
Appendix D Robustness Checks

Figure D1: The effect of entry on the incumbent's service time using treated markets only

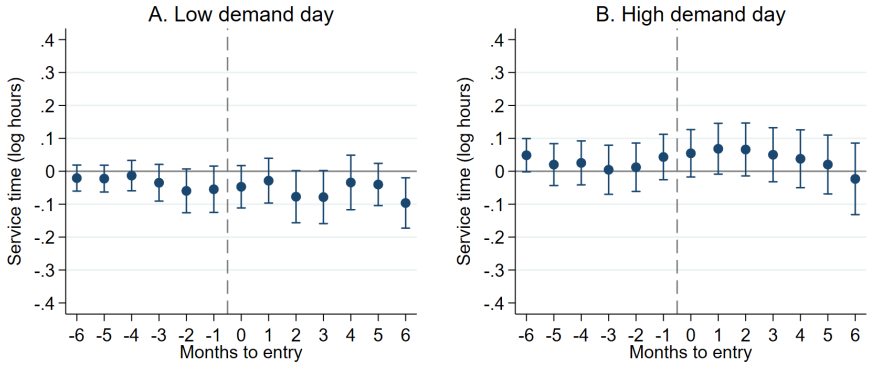
(a) Pre-entry monopolistic markets



(b) Pre-entry monopolistic/ duopolistic markets



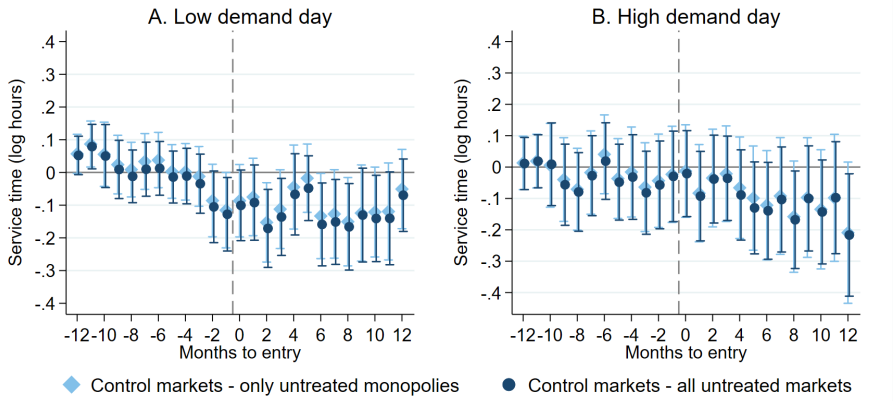
(c) All markets



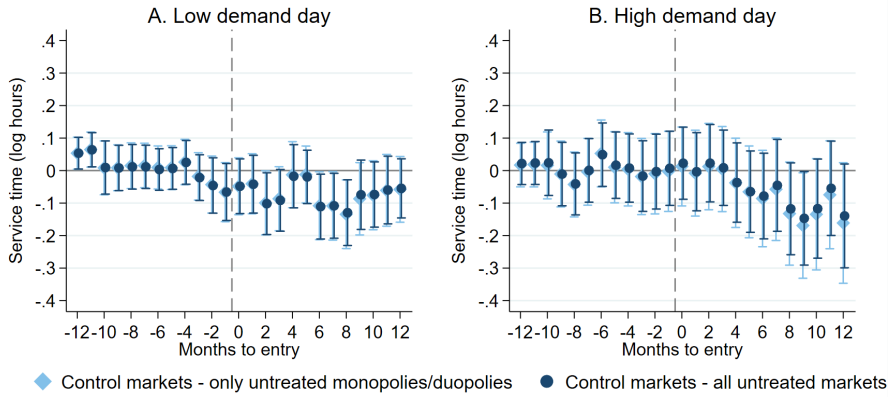
Notes: The figures plot the coefficients of β_j for j running from -6 to 6 and their 90-percent confidence intervals from a regression of Equation (1) for different sub-samples includes only treated markets (markets that experienced an entry during the sample period). Standard errors are clustered at 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.

Figure D2: The effect of entry on the incumbent's service time using a 12-months window

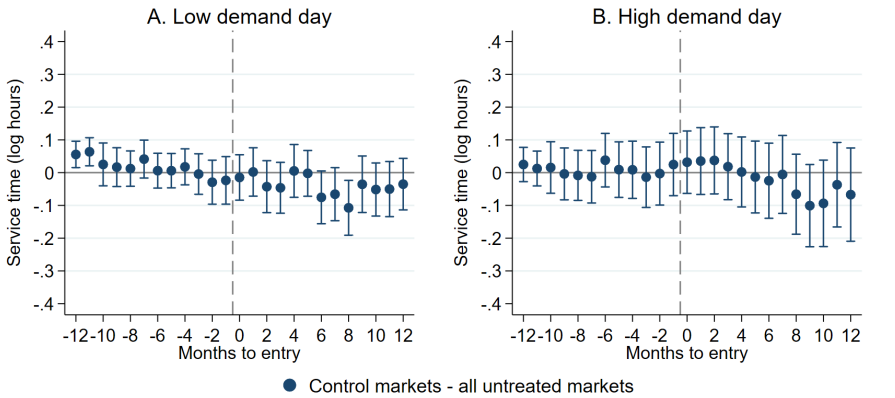
(a) Pre-entry monopolistic markets



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

Table D1: The effect of entry on the incumbent's service time accounting for competition from physical stores

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

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Notes: The table reports estimation results for Equation (2). Standard errors in parentheses are clustered at the market level. The dependent variable in columns 1-4 is Shuseral's log service time in the local market on Saturday night. The dependent variable in columns 5-8 is Shufersal's log service time in the local market on Wednesday night. *pre_entry* is an indicator for one or two months before entry. *post_entry* is an indicator for the month when entry takes place and for the following months. The sample in Panel A includes treated markets where only Shufersal was active before the entry. The sample in Panel B includes treated markets where Shufersal and another grocer were active before entry, and in Panel C the sample includes all treated markets. In all specifications, we use untreated markets (i.e. markets without entries) as the control group and include market and month fixed effects. The results suggest that the effect of an online grocer's entry on the incumbent's service time are not sensitive to the presence of a nearby traditional store.

Table D2: The effect of entry on the incumbent's service time using alternate control markets

	Low-demand day		High-demand day	
	(1)	(2)	(3)	(4)
Panel A: Pre-entry monopolistic markets				
Pre-entry	-0.139**	-0.129**	0.027	0.004
	(0.057)	(0.055)	(0.052)	(0.045)
Post-entry	-0.136**	-0.101**	0.023	-0.004
	(0.060)	(0.050)	(0.058)	(0.043)
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*	0.029	0.016
	(0.041)	(0.040)	(0.036)	(0.034)
Post-entry	-0.062	-0.062*	0.033	0.005
	(0.038)	(0.034)	(0.041)	(0.038)
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*	0.015	0.004
	(0.032)	(0.031)	(0.029)	(0.028)
Post entry	-0.042	-0.046*	0.022	-0.002
	(0.029)	(0.025)	(0.030)	(0.029)
Markets	129	180	129	180
Markets with entry	129	129	129	129
N	4,630	6,462	4,630	6,462
Additional controls:				
No. of rivals' offline stores (10km radius)	✓	✓	✓	✓
Exits and additional entries indicators	✓	✓	✓	✓
Fulfilment center linear time trend	✓	✓	✓	✓

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

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

Table D3: Market demographic characteristics, by entry and competition level

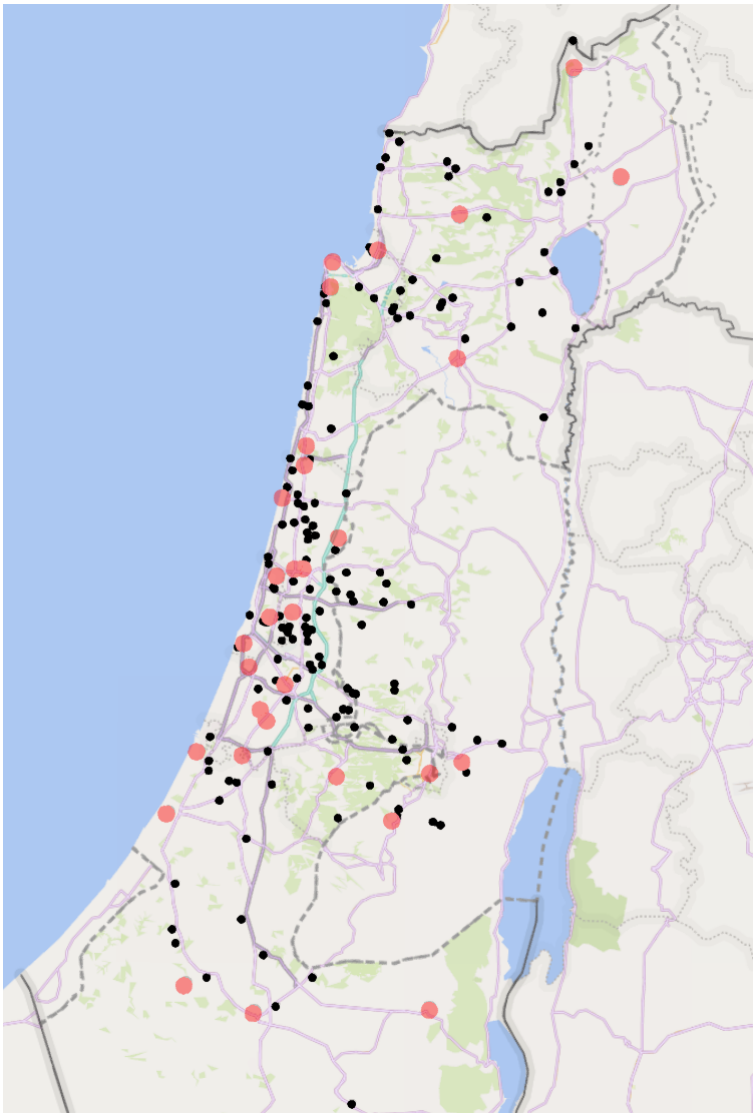
	Pre-entry monopolistic markets		Pre-entry monopolistic/ duopolistic markets		All markets	
	Markets with entry	ΔMarkets w/o entry	Markets with entry	ΔMarkets w/o entry	Markets with entry	ΔMarkets w/o entry
	(1)	(2)	(3)	(4)	(5)	(6)
Population (K)	29.62	-2.840	41.83	-13.41	59.62	-23.33
	(20.68)	[4.358]	(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 means of characteristics (standard deviations in parentheses) in markets that experienced entry alongside mean differences as compared with markets that did not experience entry (t-test standard errors in brackets). Column (1) includes 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 another retailer were active before another rival entered during the sample period. Column (4) includes the same markets as column (2) and markets where Shufersal and another retailer were active during the whole sample period. Column (5) includes all markets that faced entry during the sample period. Column 6 includes all markets whose number of online grocers did not change during the sample period. The socio-demographic characteristics show that markets that had more active firms before entry were more densely populated and are 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.

Appendix E Maps

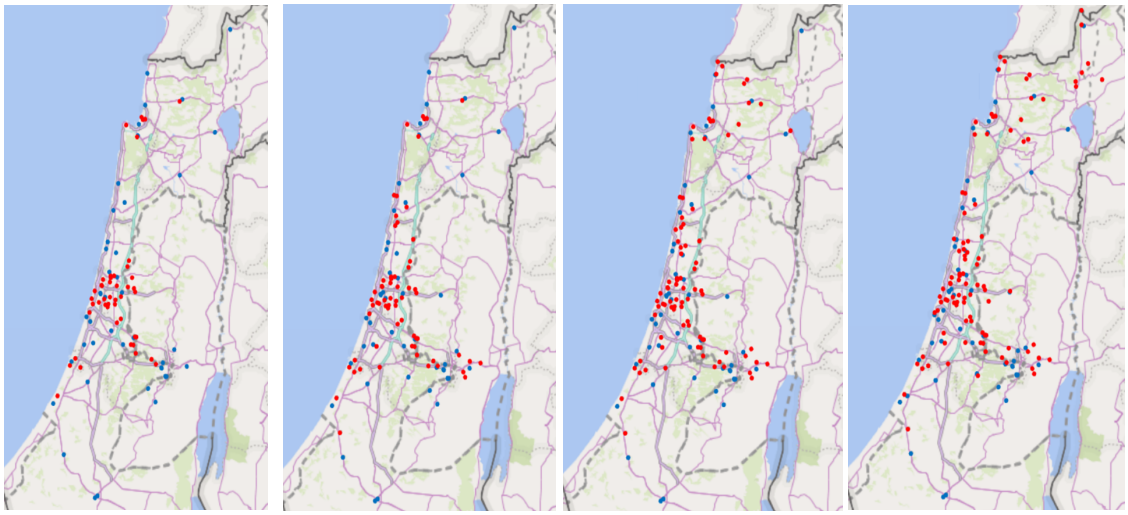
Figure E1: Online local markets (black) and Shufersal's fulfillment centers (red)



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.

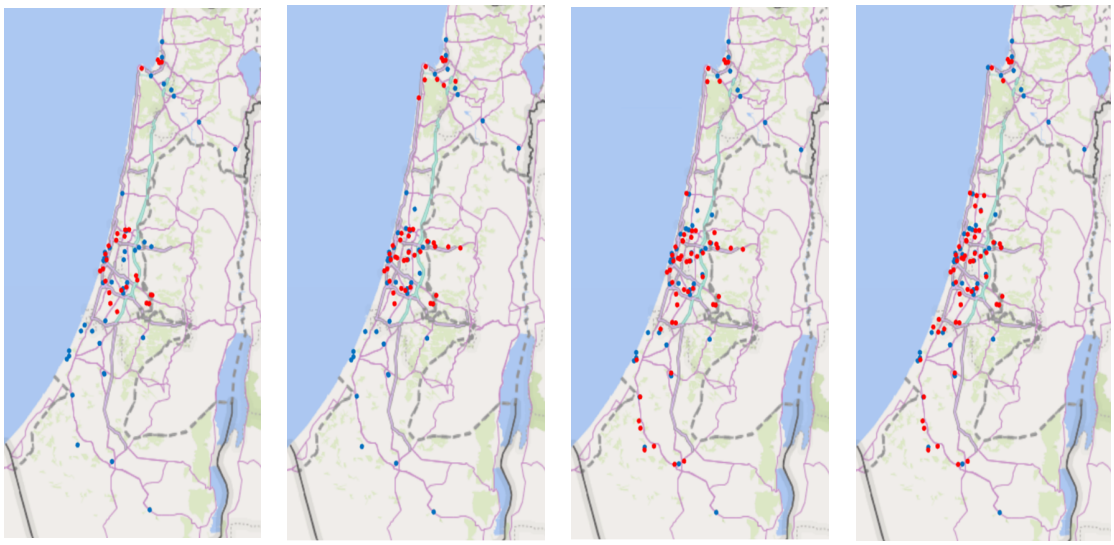
Figure E2: Chains' online service coverage (red) and location of traditional stores (blue)

I. Rami Levy



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

II. Victory

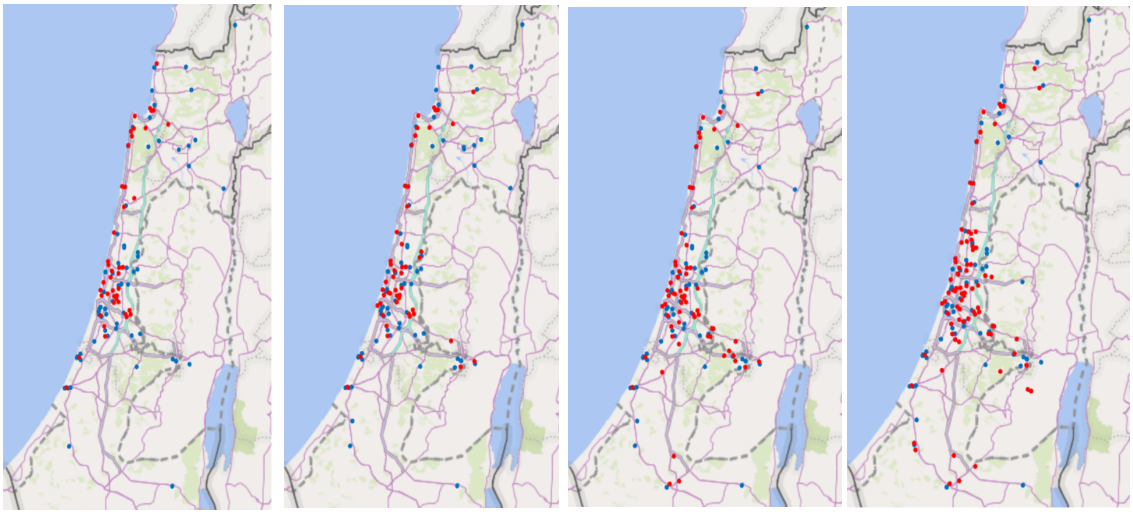


Aug. 2016 Jul. 2017 Jul. 2018 Jul. 2019

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

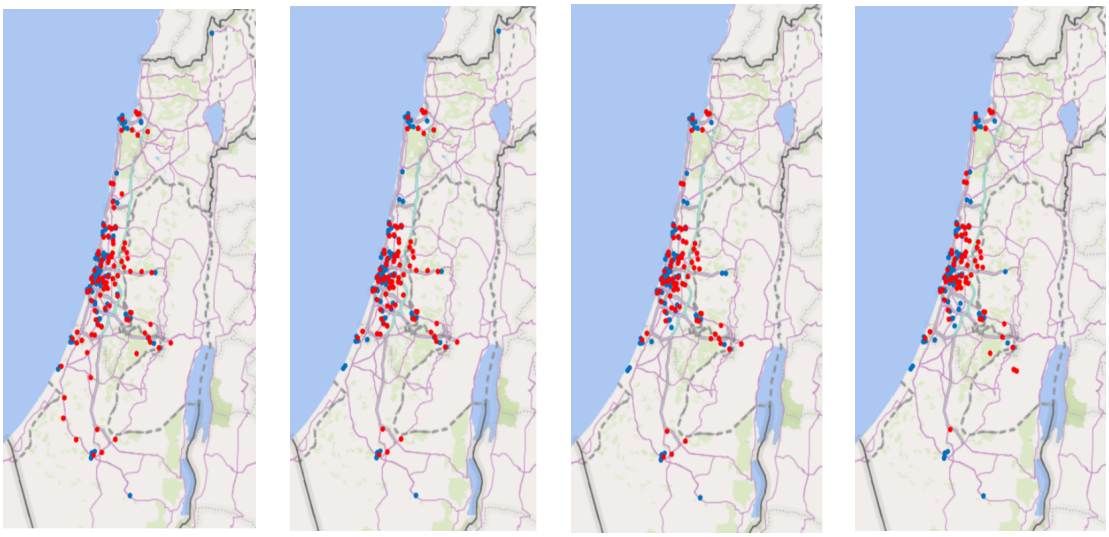
Figure E3: Chains' online service coverage (red) and location of traditional stores (blue)

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

Appendix F Alternative Estimators for TWFE DiD

As mentioned in Section 3.1, the event study coefficients might be biased if there is heterogeneity in treatment effects between groups of units treated at different times. Recent advances in econometric theory suggest that event-study coefficients under staggered treatments represent a weighted average of cohort-specific average treatment effects from units treated at different times (Sun and Abraham, 2020; De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021; Borusyak et al., 2021 and Callaway and Sant'Anna, 2020). The presence of heterogeneous treatment effects and negative weights could generate biased results. Here, we provide evidence for the validity of our estimates by using alternative estimators proposed by Sun and Abraham (2020) and Borusyak et al. (2021). Sun and Abraham (2020) 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. They use either never-treated as controls or "last cohort treated" if no never-treated.[23] Specifically, each event time coefficient from this estimation is a weighted average of the cohort-specific average treatment effect, where the weights are given by the share of cohorts that experienced at least t periods relative to treatment and normalized by the total event time periods we are estimating. Figure F1 shows estimation results using Sun and Abraham (2020) approach. The dark signs are the estimated coefficients from an estimation that uses never-treated markets as the control group, i.e. markets that did not experience entry and have the same competition level as treated markets before entry. Light signs are the estimated coefficients from an estimation that uses "last cohort treated" (markets with entry at the last month of the sample) as control group.[24] 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 3.4, the anticipation in the two months before entry might bias the results. Accordingly, we also use Borusyak et al. (2021) estimator to verify that our results are unchanged.

Borusyak et al. (2021) provide an imputation estimator which is constructed in three steps. First, unit and period fixed effects are fitted by regression on untreated observations only. Second, they are used to impute 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. Borusyak et al. (2021) require that

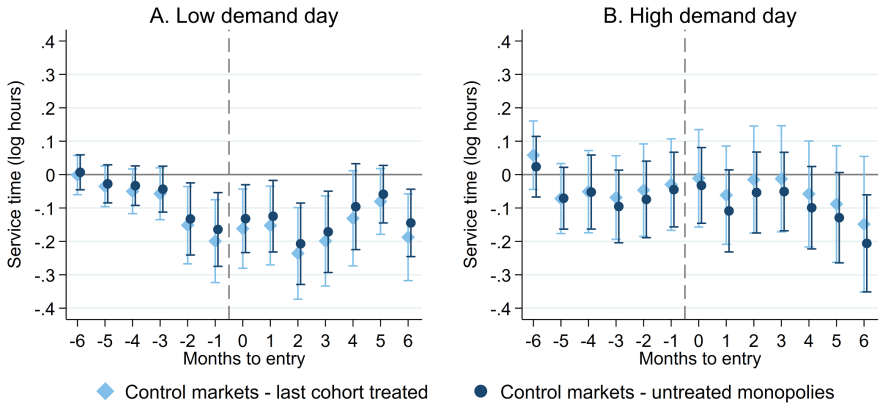
[23] Sun and Abraham (2020) can be considered as a specific case of Callaway and Sant'Anna (2020) estimator. Callaway and Sant'Anna (2020) propose a group-time average treatment effect based on calendar time while Sun and Abraham (2020) propose a regression-based estimator of cohort-specific average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

[24] We do not use all untreated markets as control since according to Sun and Abraham (2020) always treated units should be dropped.

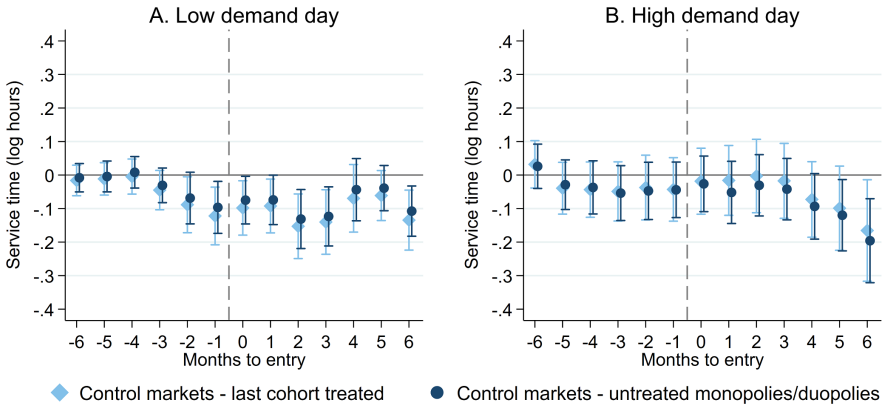
the parallel trend assumption based on a linear function of unit and time fixed effects holds, and allows for a shift in the treatment period when there is known pre-treatment anticipation. Hence, we able to allow for two months anticipation in the Borusyak et al. (2021) estimation method. Figure F2 shows estimation results using Borusyak et al. (2021) approach, assuming a two-months shift in treatment effect, i.e. in $t-2$, and using all untreated markets (dark signs) or only untreated markets that have the same competition level as treated market pre-entry (light signs). The results show similar patterns to the results presented in Figure 5, suggesting that our two-way fixed effects estimates are free of contaminated effects from other periods, and heterogeneity treatment effects.

Figure F1: Sun and Abraham (2020) estimator for the effect of entry on incumbent's service time

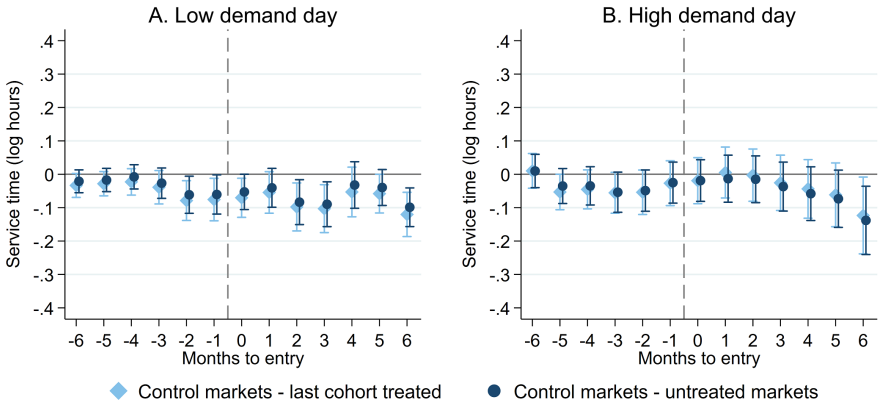
(a) Pre-entry monopoly markets



(b) Pre-entry monopoly / duopoly markets



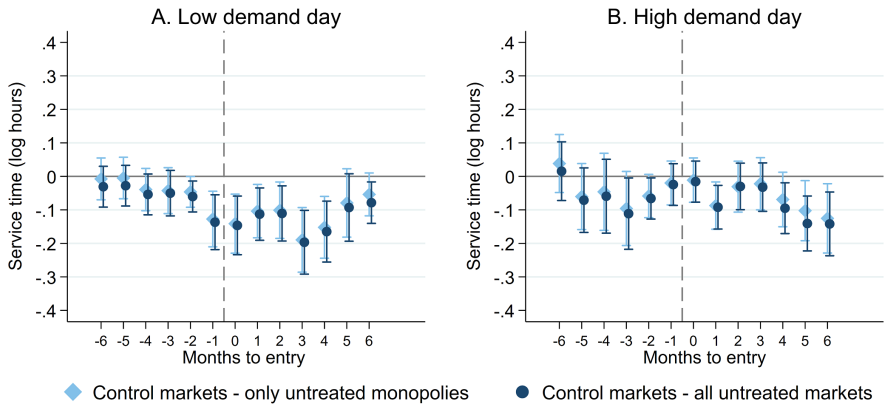
(c) All markets



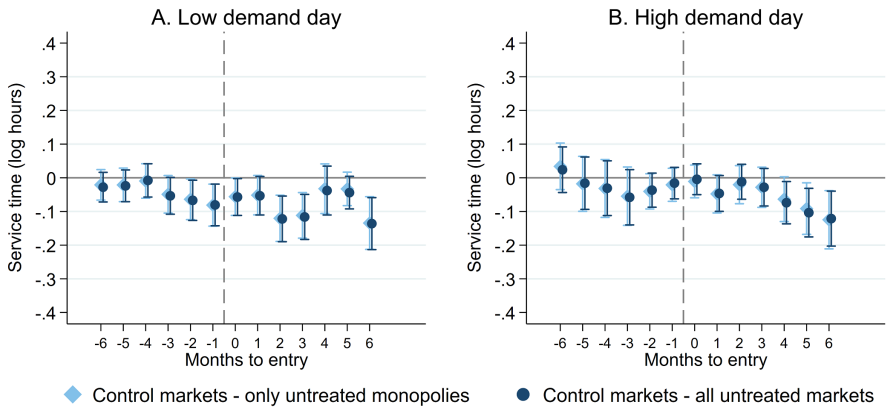
Notes: The figures plot the coefficients of β_j for j running from -6 to 6 and their 90-percent confidence intervals from a regression of Equation (1) for different sub-samples using Sun and Abraham (2020) estimation method. Standard errors are clustered at the market level. The dependent variable is Shufersal's (the incumbent's) log service time in the local market. Estimated results are shown separately for low-demand days and for high-demand days. Panel (a) reports the estimated effects of entry in markets which were monopolies before entry. Panel (b) reports the estimated effects of entry in markets that were served by up to 2 online retailers, and Panel (c) reports the results for all markets. Dark signs are the estimated coefficients from an estimation using never-treated markets as control group, i.e. markets that did not experience entry and have the same competition level as treated markets before entry (we do not use all untreated markets as control since according to Sun and Abraham (2020) always treated units should be dropped). Hence, in Panel A never-treated markets are markets where Shufersal is a monopoly during the all sample period. In Panel B never-treated markets are markets where Shufersal is a monopoly or share the markets with only one additional retailer during the all sample period and in Panel C never-treated markets are all markets without entry, excluding markets where all the 5 retailers are active. Light signs are the estimated coefficients from an estimation using "last cohort treated" (markets with entry at the last month of the sample) as control group. All specifications include market and month fixed effects. Results are qualitatively similar to the two-way fixed effects specification in the main text.

Figure F2: Borusyak et al. (2021) estimator for the effect of entry on incumbent's service time

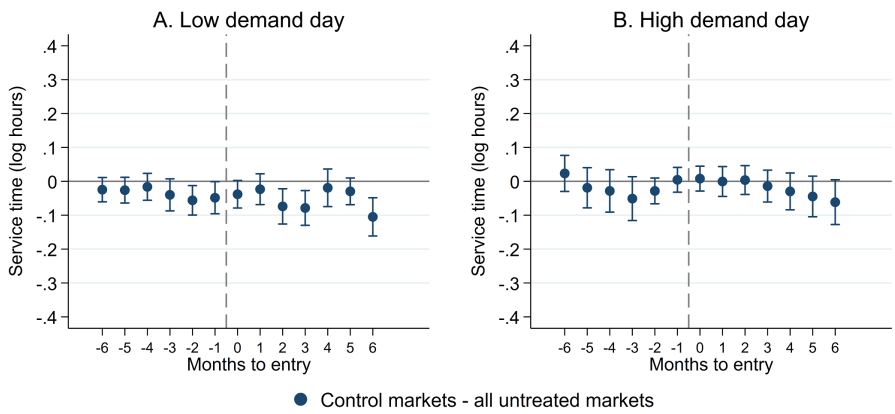
(a) Pre-entry monopoly markets



(b) Pre-entry monopoly / duopoly markets



(c) All markets



Notes: The figures plot the coefficients of β_j for j running from -6 to 6 and their 90-percent confidence intervals from a regression of Equation (1) for different sub-samples using Borusyak et al. (2021) estimation method and assuming 2 months of shift in treatment period ($t-2$). Standard errors are clustered at the market level. The dependent variable is Shufersal's (the incumbent's) log service time in the local market. Estimated results are shown separately for low-demand days and for high-demand days. Panel (a) reports the estimated effects of entry in markets which were monopolies before entry. Panel (b) reports the estimated effects of entry in markets that were served by up to 2 online retailers, and Panel (c) reports the results for all markets. Dark signs are the coefficients from a sample that include all markets that did not experience any entry during the sample period as control group. Light signs are the estimated coefficients from a sample that includes as control only markets that did not experience entry and have the same competition level as treated markets before entry. All specifications include market and month fixed effects. Results are qualitatively similar to the two-way fixed effects specification in the main text.