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

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November 7, 2023

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 172 Israeli local markets, we show that an online grocer sets identical prices in all markets. By contrast, service time is shorter in more competitive markets and on low-demand days. Next, we exploit regional and temporal variation in entry decisions to examine how the incumbent adjusts its service time when new online grocers enter the market. The incumbent's service time falls significantly on low-demand days and in monopolistic markets. This decrease begins shortly before entry and is greater when the entrant poses a larger competitive threat. On high-demand days and in competitive markets we do not find a significant change in service time in the months surrounding entry. Our findings suggest that firms use service time to exercise their local market power when prices are unresponsive and that operational considerations affect the extent to which they respond.

JEL: D22; L12; L66

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

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1 Introduction

Standard models in economics, management, and marketing show that firms use prices to respond to changing demand and competition conditions. There is growing evidence, however, that firms' price-setting behavior is often different from what these models describe. For instance, 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, Ater and Rigbi 2023). 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 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 the one hand, firms may offer better service in competitive environments to attract consumers and reduce churn. On the other hand, if the provision of service involves economies of scale then competition or weak demand may result in lower service levels.[2] Probably due to lack of data, evidence on the relationship between competition, demand, and service levels is particularly scarce. In this paper, we focus on service time, perhaps the most important 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 but that this improvement mainly materializes in monopolistic markets and on low-demand days, when grocers arguably have slack resources. On high-demand days and in competitive markets – when resources are better utilized – we do not find that service time improves in the months surrounding entry.

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] Nevertheless, empirical evidence on the relationship between competition, demand, and service time is virtually non-

[1] Different explanations have been proposed as to 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 (2023) point to fairness and brand-image concerns as the reason why food retailers adopt uniform pricing. In this paper, we do not attempt to explain these pricing decisions but rather take them as a starting point for the analysis.

[2] Indeed, the tension between competition, scale, and service quality is an integral part of a recent debate on the effectiveness of competition policy. See, for instance, https://www.ftc.gov/news-events/press-releases/2022/01/ftc-and-justice-department-seek-to-strengthen-enforcement-against-illegal-mergers.

[3] 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/.

existent. We are not aware of any empirical studies that examine the impact of competition on service time. The prevalence of service time in retail online markets makes our study relevant for consumers, firms, and policymakers alike. For instance, service time can be relatively easily collected, measured, and used by regulators to assess the level of competition and market power in such markets.

Studying service time in the online grocery market offers an excellent opportunity to learn about the relationships between service levels, demand, and competition. First, sales in the online grocery market were growing rapidly already before the pandemic, and in many countries, new online grocers are expanding into local markets where established online grocers already operate.[4] Our analysis exploits spatial and intertemporal changes in the competitive landscape of the Israeli online grocery market to examine how the dominant online grocer, which operates in all local markets, adjusts its service time when competition intensifies. Second, demand for online grocery is characterized by high-demand (pre-weekend) and low-demand (beginning of the week) periods. This within-week demand variation 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 for identifying 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 regularity 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. More generally, economists traditionally propose that prices should be used to save time and improve resource allocation (e.g., congestion pricing). We explore whether competition can serve as a substitute for prices, and induce shorter service time presumably through better resource allocation.

The main data that we use include 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 172 home addresses that correspond to distinct local markets across Israel. The crawler was active twice a week, at 10 pm 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 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.

[4] 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 (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 is 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 apps 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.

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, showing a downward-sloping service time curve for each online grocer. The greater the number of online grocers active in a local market, the shorter 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 online grocers set identical prices in all the local markets where they operate, irrespective of the level of local competition. Next, 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 use service time to cope with changing local demand and competition conditions. However, other explanations are also plausible. For instance, more online grocers operate in urban areas, and economies of density in cities may enable them to offer shorter service times.

To mitigate such concerns and to rule out alternative explanations, we take advantage of the panel structure of our data to identify the impact of an online grocer's entry on the incumbent's service time.[6] In Appendix A, we present a modified version of the newsvendor problem model (Arrow et al. 1951) that motivates the empirical analysis and provides testable predictions. According to the model, entry by an online grocer leads to larger reductions in the incumbent's service time (i) in more concentrated markets, where the costs of losing consumers to rivals are larger, (ii) on low-demand days when the marginal costs of improving service time are lower, or (iii) when the entrant poses a larger threat to the incumbent. We implement both an event study design, to accommodate the possibility of dynamic treatment effects, and a parametric difference-in-differences (DiD) design. These analyses exploit the variation in the timing of entry of online grocers into new local markets in order to estimate the changes in service time offered by the incumbent in these markets. Markets that did not experience entry serve as control markets to account for time-variant effects that are fixed across markets. We use pre-entry market structure differences and the distinction between high- and low-demand days to examine how this response depends on the potential costs and benefits of changing service time. 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 in the traditional, physical store channel. We also verify that the results are unchanged when we use recent staggered DiD estimation methods (Sun and Abraham 2021, Borusyak, Jaravel, and Spiess 2022) or when we use alternative control markets.

The results show that impending entry drives the incumbent to reduce service time on low-demand days of the week (when arguably the marginal cost of improving service time is low), and when rivals enter

[6] The online grocery market changed dramatically over the study period. We observe about 150 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.

monopolistic markets (when the potential cost of not improving service time is 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 10% to 16% in monopolistic markets, increasing the probability of same-day deliveries by 8% to 11%. This effect increases by more than 25% when we restrict attention to entry by aggressive online grocers, i.e., those who pose a larger threat to the incumbent. Interestingly, the improvement in service time begins two months before actual entry takes place. By contrast, on high-demand days and in competitive markets – when arguably resources are better utilized and the costs of losing consumers to rivals are lower, respectively – we find little evidence of service time improvements. Our preferred interpretation of these findings is that when prices are inflexible, incumbents use service time to exercise their market power.

Our findings reflect the trade-off, highlighted by the newsvendor problem model, between the marginal costs incurred from offering shorter service times and the losses suffered when longer service times push consumers to buy elsewhere. The incumbent is likely to improve service time when the costs of improving service are sufficiently low or when the benefits of better service are high. While customers' decision to start using the entrant's services may also explain why the incumbent's service time declined, it is less plausible as an explanation for the pre-entry patterns we document. In the paper, we provide qualitative evidence that the incumbent anticipates entry, supporting our interpretation of a pre-entry strategic response by the incumbent. We also apply an alternative identification strategy that exploits cross-sectional variation in the threat of entry and obtain similar qualitative results.

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 impact of competition and/or demand conditions 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) who show how waiting times at a physical store affect purchasing behavior, and Png and Reitman (1994) who examine the relationship between service time and competition among gasoline stations but lack actual data on service time. To overcome the lack of data on service time, recent studies used 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, however, examine how service time changes when competition and demand vary in a given market.

Our paper also adds to the empirical literature that examines the impact of competition on non-price attributes, such as popular movies (Orhun et al. 2015), airline delays (Mazzeo 2003; Prince and Simon 2015), self-reported customer satisfaction surveys at retail stores (Busso and Galiani 2019), service offerings in the mobile service industry (Economides, Seim, and Viard 2008), and auto dealers' inventory levels (Olivares and Cachon 2009). Most studies find a positive association between competition and quality.[7] Probably closest to our study is Matsa (2011) who shows that incumbent supermarkets reduce their stock-out rate after Walmart enters a local market. Our study offers a more nuanced response, providing causal evidence that competition can improve service time, but that this response depends on the level of demand and market conditions. Our setting considers the impact of entry into a local market on low- and high-demand days and at different pre-entry competition levels. It thus allows us to examine the interrelations between service quality, demand, and competition, something that previous studies have failed to do. Indeed, the theoretical literature shows that service level depends on demand and capacity conditions (e.g., De Vany and Saving 1983), but thus far this insight has received little attention in the empirical literature. Moreover, existing studies typically focus on quality attributes that are observed by consumers 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 adequately compare quality attributes across retailers. In our case, service time is observed at the time of purchase, and can therefore be easily compared across different online grocers prior to the purchase decision. Finally, 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 2022). Yet, none of these papers explicitly considers the role of service time.

The remainder of the paper is organized as follows. In Section 2 we provide the necessary background on the Israeli retail food market, describe the data, and present relevant descriptive statistics. In Section 3 we present the empirical methodology and report the results. In Section 4 we address identification concerns and Section 5 concludes.

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.[8] 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.[9] The market share of online grocery sales in

[7]A few studies find that competition improves quality, but may also reduce welfare, by harming accuracy/reliability of credit ratings (Becker and Milbourn 2011) or through greater inspection leniency in vehicle emission tests (Bennett, Pierce, Snyder, and Toffel 2013).

[8]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.

[9]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. A third channel,

Israel during the study period is estimated below 10%, and 'Shufersal' is by far the dominant player in the online grocery channel, with a market share of about 70%.[10] In the empirical analysis, we refer to Shufersal as the incumbent online grocer, as it was active in all the local markets that we observe 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 physical store 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%.[11] 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.[12]

Online grocers set prices and delivery fees at the national level. Prices and fees are identical across all the local markets where online 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 in delivery may lead to a NIS 300 fine (about $80). 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 and 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 Friday afternoon 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 the demand for online grocery service. 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 172 different home addresses for the period between 2016 and 2019. Each address corresponds to a distinct locality. We augment the service time and com-

sometimes referred to as click-and-collect, was not commonly available in Israel during the relevant time period.

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

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

[12] 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. Towards the end of 2018, a few small players, such as Quik, began offering online grocery service in large dense urban areas.

petition 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 10 pm on Wednesdays and Saturdays, which as we later show are high- and low-demand days 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 172 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 all addresses in a given locality or 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 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 deliveries to their home address. We also use this information to identify entries and the entrants' identity.[13]

Service time. The elapsed time between the crawler's recorded time and the starting time of the earliest available home-service time slot is our measure for service time in each local market on a given day.[14] 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 by comparing promised delivery times across different grocers.[15]

Our final sample consists of 172 local markets with information on the number of active online grocers in each market each month. We also compute the monthly mean service time offered by each grocer in each market on Wednesdays and Saturdays between August 2016 and July 2019. Table 1 provides summary statistics for the service time offered by Shufersal, which was active in all 172 local markets during the whole sample period, by day and by pre-entry competition level, distinguishing between markets that experienced entry (odd-numbered columns) and markets that did not (even-numbered columns). Panel A reports service time in hours, Panel B reports service time in days based on 24-hour intervals, and

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

[14]In Israel, supermarkets and grocery deliveries are unavailable on Friday evening and Saturday. To account for this, we subtract 24 hours 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.

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

Table 1: Summary statistics: Service time of the incumbent retailer

	Monopolistic markets		Duopolistic markets		Competitive 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)
Panel A: Service time in hours						
Wednesday	52.62	48.00	37.53	43.07	24.78	22.84
	(35.65)	(31.44)	(32.08)	(29.24)	(14.50)	(10.90)
Saturday	33.14	32.16	25.79	24.76	17.71	17.84
	(21.21)	(20.64)	(19.26)	(13.33)	(8.735)	(7.361)
Panel B: Service time in days						
Wednesday	2.487	2.299	1.911	2.105	1.377	1.302
	(1.463)	(1.298)	(1.324)	(1.239)	(0.611)	(0.470)
Saturday	1.696	1.657	1.433	1.358	1.115	1.099
	(0.830)	(0.819)	(0.776)	(0.554)	(0.338)	(0.281)
Panel C: Same-day delivery						
Wednesday	0.442	0.476	0.645	0.554	0.759	0.784
	(0.445)	(0.442)	(0.412)	(0.433)	(0.331)	(0.317)
Saturday	0.525	0.545	0.737	0.716	0.920	0.929
	(0.472)	(0.471)	(0.412)	(0.409)	(0.209)	(0.180)
# Markets	54	31	32	7	34	14
# Observations	1,944	1,116	1,152	251	1,224	504

Notes: The table reports the means of the incumbent's service times (standard deviations in parentheses) on Wednesday and Saturday in markets that experienced entry (odd-numbered columns), and markets that did not experience entry (even-numbered columns). Panel A reports the means and standard deviations of service times in hours, Panel B reports means and standard deviations for service times in days, and Panel C reports the means and standard deviations of the percentages of same-day deliveries. Columns (1) and (2) include markets where only one retailer was active before entry. Columns (3) and (4) include markets where only two retailers were active before entry, and Columns (5) and (6) include markets where more than two retailers were active before entry.

Panel C reports the percentage of same-day deliveries. The table shows that service times are shorter on Saturdays and in more competitive markets. For example, Column (1) shows that the average delivery time in pre-entry monopolies markets is 53 hours (2.5 days) on Wednesdays and 33 hours (1.7 days) on Saturdays.[16] The differences in service times on Saturday between markets that experienced entry and those that did not experience it are small and statistically insignificant. The differences on Wednesdays between markets that experienced entry and those that did not are larger but with no consistent pattern.

2.2.2 Price data

We use detailed data on the monthly average prices of 52 same-barcode popular items sold by the five online retailers in all local markets where they operate. We use these prices to calculate the basket price charged by each of the five online grocers at each of the 172 local markets 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

[16]This means that a delivery ordered at 10 pm on Wednesday would be expected to be delivered on Sunday evening (53 hours + 24 hours after the adjustment of no deliveries on weekends or one-and-a-half days to Friday noon and an additional day for Sunday) and delivery ordered at 10 pm on Saturday would be expected to be delivered on Tuesday noon.

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 2023). We use the price data to show how online grocers use prices in different demand and market 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 simultaneously observe available service times offered by each retailer. The data include all orders placed through MySupermarket during the data collection period. The data include the date and the time of each order, the retailer's identity, the number of products, the total amount paid, a customer id, and the city where the customer lives. Unfortunately, these data do not include information on service time. The data cover about 700,000 orders by nearly 85,000 customers. About 70% of these customers reside in one of the 172 localities we track, and mainly in localities in which more than two online grocers operate. Appendix B provides more details on these data, which we use to show that 1) demand for online grocery service is considerably larger on pre-weekend days than on post-weekend days, 2) switching patterns across online grocers thereby identifying which retailers pose a greater threat to the incumbent, 3) 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 use supermarket chains' annual reports and media coverage to collect data on their physical stores including the 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 172 local markets based on the closest driving distance. Figure C1 in Appendix C shows the locations of the 172 local markets in our sample (black dots) and Shufersal's (i.e. the incumbent's) 32 fulfillment centers (red dots) that operated during the sample period. We also use demographic information obtained from the Israeli Central Bureau of Statistics on the 172 local markets. This information includes population size, income per capita, vehicles per capita, and socioeconomic and periphery indices for each of the markets for the years 2016, 2017, 2018, and 2019.[17]

2.3 Descriptive evidence

2.3.1 Service time, prices and competition

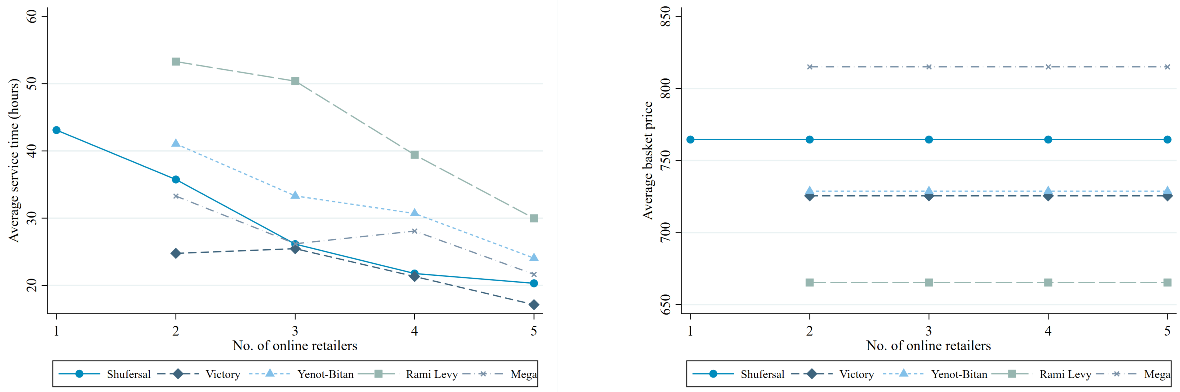
Figure 1 presents the relationship between competition and service time (Panel (a)), and between competition and prices (Panel (b)) separately for each of the five online grocers. Panel (a) plots the mean

[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 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 43 hours. In markets with five online grocers, its mean service time is 20 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.

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.

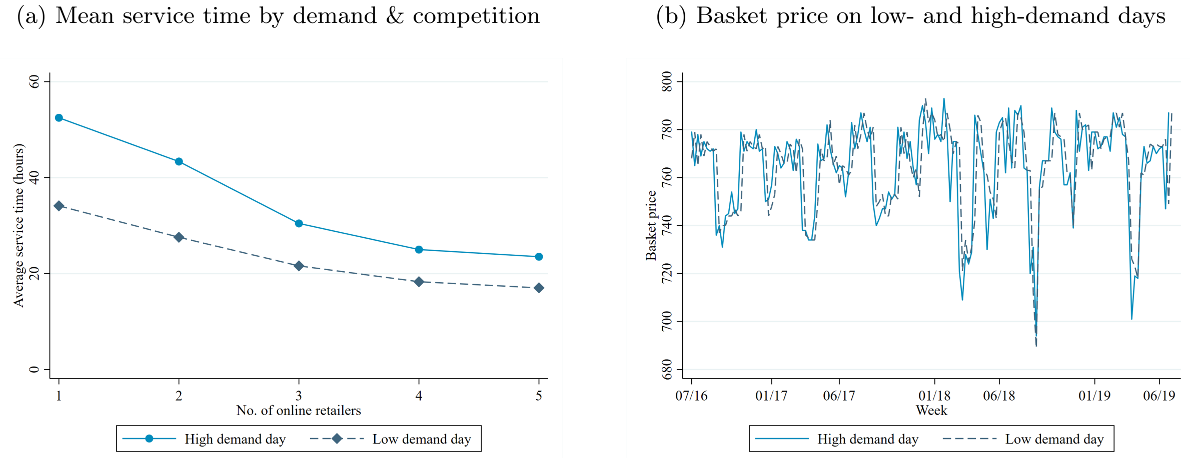
In Panel (a) we observe a clear pattern of downward-sloping curves of service time. This pattern holds for each of the five online grocers. Service time is considerably shorter in more competitive markets. For instance, Shufersal's mean service time in markets where it is the only online grocer is 43 hours. In markets where Shufersal competes with four online grocers, its mean service time is only 20 hours.[18] 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. While online grocers choose different price levels, there exists a strong negative relationship between the average service time and the basket price offered by a given 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 percentage of orders for online grocery through MySupermarket on Tuesday and Wednesday and on Friday and Saturday. The figure shows that the cumulative

[18] See also Figure C2 in Appendix C for grouped box-and-whisker plots showing the distribution of service times by online grocers in different market conditions.

Figure 2: Service time and prices, by competition and demand levels



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 time on high-demand days is 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 Appendix C.

percentage of orders is about three times larger on Wednesdays than on Saturdays.[19]

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. 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 monopoly markets is 52 hours on Wednesdays and 34 hours on Saturdays. In markets with five online retailers, the mean service time is 23 hours on Wednesdays and 17 hours on Saturdays.[20]

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 on Saturday and Wednesday, respectively. As shown in the figure, unlike service times, Shufersal's prices do not vary with demand conditions over the days of the week. That is, while the price of the basket changes over the week, there is no evidence for low prices on days when demand is low (Sundays) and high prices on days when demand is high (Thursdays). Figure C5 in Appendix C shows similar patterns for the relationships between service time and demand and for prices and demand for the other online grocers.[21][22]

[19] 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 10 pm on Wednesday and Saturday. Alternative definitions generate similar patterns.

[20] Figures C3 and C4 in Appendix C provide further evidence regarding the distribution of the incumbent's service times, which are shorter in competitive markets and on low-demand days. Figure C3 shows grouped box-and-whisker plots of the incumbent's service times by competition and demand levels, and C4 shows the distribution of service times by hours and days offered by the incumbent at different market competition levels and different demand levels.

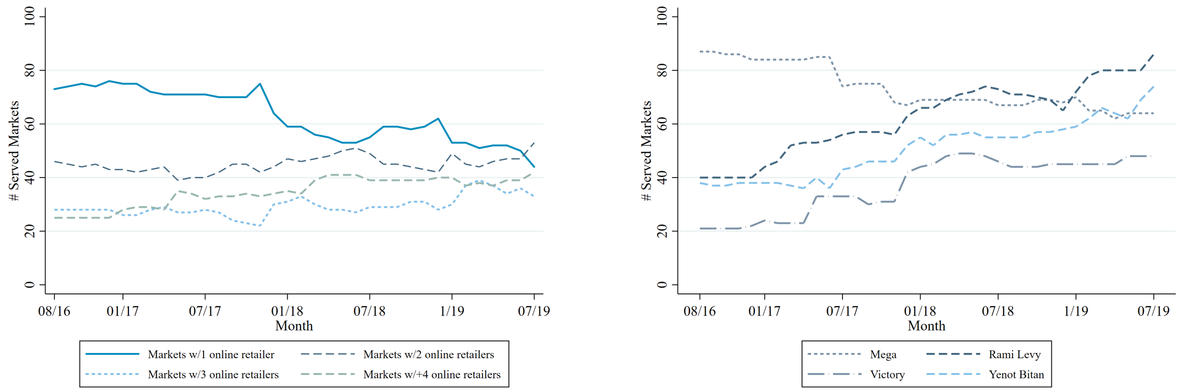
[21] See also Figure C6 in Appendix C for grouped box-and-whisker plots showing the distribution of service times for each online grocer in different market conditions and at different demand levels.

[22] Figure C7 in Appendix C plots the difference between prices on Sunday and on Thursday in each week separately for each online grocer in order to provide further evidence that prices are not correlated with demand.

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, 73 markets were monopolies, and in 25 markets at least four online retailers were active. Over the three years, competition intensified. In July 2019, the last month in the sample, 44 local markets were monopolies, and in 42 markets at least four online retailers were active. Panel (b) plots the number of markets served by each online grocer in each month of the sample period. We exclude Shufersal since it operated in all 172 markets throughout the sample period. Victory, Yenot Bitan, and Rami Levy experienced massive growth in the number of markets they served, growing respectively from 21, 38, and 40 markets in August 2016 to 48, 74, and 86 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 120 of the markets in our sample.

2.3.3 Entry and market structure evolution

Panel (a) of Figure 3 shows the evolution of available online grocery services over the sample period. In August 2016, 73 markets were served only by Shufersal, and 25 markets were served by at least four online retailers. Over the three years competition intensified. In July 2019, 44 local markets were served only by Shufersal, and 42 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 172 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 21, 38, and 40 markets in August 2016 to 48, 86, and 74 markets in July 2019. Overall, we observe 154 entries during the sample period. At least one entry took place in 120 markets, and in 54 of these markets, Shufersal (the incumbent) was a monopoly before entry (see also Table 1).

Figure C8 in Appendix C illustrates the variation in the timing of entry by Shufersal's rivals. Panel A of Figure C8 plots all entries observed each month, distinguishing between entries that are the first to be observed in each market and for first entries in markets in which the incumbent was a monopoly. Panels B, C, D, and E of Figure C8 plot the same but focus separately on entries by Rami Levy, Victory, Yenot Bitan, and Mega, respectively. The figures show that the timing of entry into markets is spread over the three years of the sample period with a mass expansion toward the end of 2017. Figure C9 in Appendix C plots the number of physical stores of the four retailers in each month. Rami Levy and Victory increased the number of their stores by 9 and 7, respectively, and Yenot Bitan increased the number of its stores at the expense of Mega (see footnote 12). However, we do not observe a clear association between the timing of online service and physical store expansion. In Section 4.2 we formally test this.

3 Empirical strategy, estimation, and results

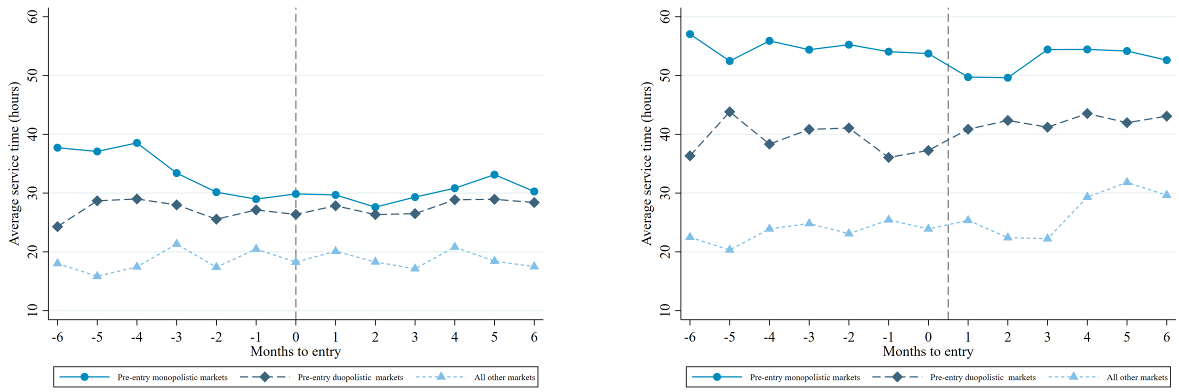
The patterns presented in Section 2.3 provide suggestive evidence that competition and demand conditions are important determinants of service time. That is, weaker competition and higher demand are associated with longer service times. However, since these correlations are potentially driven by cross-market differences, 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.

To motivate the analysis, in Appendix A, we present a modified version of the classic newsvendor problem model (Arrow et al. 1951). In the model, demand for online grocery service varies over the days of the week. Prices are fixed and do not vary across days, and to achieve a certain service time, the online grocer uses labor (drivers and packers) and capital (trucks). These inputs are fixed within a week, implying that inputs are better utilized on high-demand days than on low-demand days. The model's solution to the online grocer problem generates a trade-off between overage costs and underage costs. Overage costs include the lost one-time margin from customers who do not purchase from the grocer due to long service times on high-demand days and the risk that these customers switch to the grocer's rivals. Underage costs are incurred on low-demand days and reflect the costs of redundant trucks or an unproductive workforce. The predictions of this trade-off are in line with the descriptive evidence presented in Section 2.3. Moreover, this trade-off provides predictions regarding the response of the incumbent to entry. This response depends on the respective costs and benefits of adjusting service time. When the benefits are high (e.g., in more concentrated markets) or the costs are low (on low-demand days), the incumbent improves service times more than otherwise. In the empirical analysis, we rely on these predictions and distinguish between low- and high-demand days (Saturdays and Wednesdays, respectively), and between different pre-entry market structures (monopolies, duopolies, and competitive markets).

The analysis exploits variation in the timing of entry of online grocers into new local markets to estimate the changes in service time offered by the incumbent in these markets, while controlling for time-invariant effects in the same market, and for time-variant effects that are fixed across markets. Markets that experienced at least one entry (120 markets) are treated markets, and markets that did not experience any entry (52 markets) are control markets. If there were multiple entries into one of the 120 local markets, we restrict attention to the first entry (as shown in Figure C8, most markets experienced only one entry during the sample period). We analyze the change in the incumbent's service time in response to entry separately for high- and low-demand days and for pre-entry monopolistic, duopolistic,

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 120 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.

and competitive markets. To identify a causal effect of entry 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. In Section 4 we provide evidence that supports this assumption.

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. The figure distinguishes between low- and high-demand days of the week and between different pre-entry market structures (monopolies, duopolies, and competitive markets). According to the figure, service times are shorter on low-demand days and in more competitive markets. However, we also observe a clear decrease in service time that begins a few months before entry on low-demand days and in pre-entry monopolistic markets.[23] In competitive markets and on high-demand days, we do not observe such patterns.

3.1 Event study estimation

Our first empirical exercise is a nonparametric estimation of an event study design, which enables us to visually and flexibly assess different trends in service time relative to the entry month. Motivated by Figure 4, we conjecture that the incumbent may respond to the upcoming entry before entry takes place.[24]. Hence, our basic event study specification has the following form:

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

[23]After the sample period of our study, Shufersal offered consumers in competitive markets same-day delivery if they purchased on early weekdays. We are unaware of such or other promotions during the sample period. If such offers existed they would make it more difficult to find an effect on service time on low-demand days.

[24]Note that our treatment is the entry and not the threat of entry. In Section 4.4 we discuss why the assumption that entry is known in advance is reasonable, and provide evidence to support this assumption.

where the dependent variable, $Log(service\_time)_{it}$, 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 and service time. Month–year fixed effects account for seasonal and other trends at the national level. The variable $entry_i$ is the month of entry into 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.

The key coefficients of interest are β_k, which capture the change in the dependent variable in k months relative to its average value in the excluded period. The excluded period is set to more than j months before entry in order to identify both pre-entry and post-entry responses. Markets that did not experience entry during the sample period are used as the control group. We use the estimates of β_k from $k = -j$ to $k = -1$ to test for parallel trends and to identify the timing of a pre-entry response if it exists. The estimates of β_k for $k \geq 0$ capture the change in the incumbent's service time following entry. In Section 3.3 we discuss how to interpret the estimated change in service time both before and after 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.

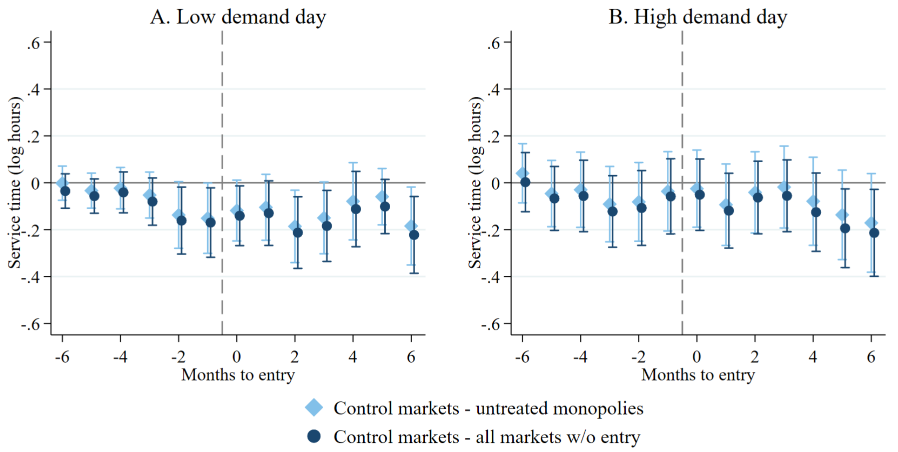
Recent econometric literature has shown that two-way fixed effects (TWFE) event study coefficients might be biased if there is heterogeneity in treatment effects between groups of units treated at different times (De Chaisemartin and d'Haultfoeuille, 2020, Goodman-Bacon, 2021, Borusyak, Jaravel, and Spiess, 2022, Callaway and Sant'Anna, 2021, Sun and Abraham, 2021). In such cases, each event time coefficient may be "contaminated" with effects from other cohorts. Goodman-Bacon (2021) and Callaway and Sant'Anna (2021) show that the inclusion of a control group alleviates this issue as long as the control group is not treated yet. In the presence of heterogeneous treatment effects, the ideal control group includes never-treated or not-yet-treated markets during the sample period. Accordingly, in the analyses, we use either all untreated markets (i.e., markets that did not experience entry and have at least the same competition level as pre-entry-treated 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, and estimators proposed by Sun and Abraham (2021) and Borusyak, Jaravel, and Spiess (2022) that allow for heterogeneous treatment effects (see Appendix D). All results are qualitatively the same.

3.1.1 Results

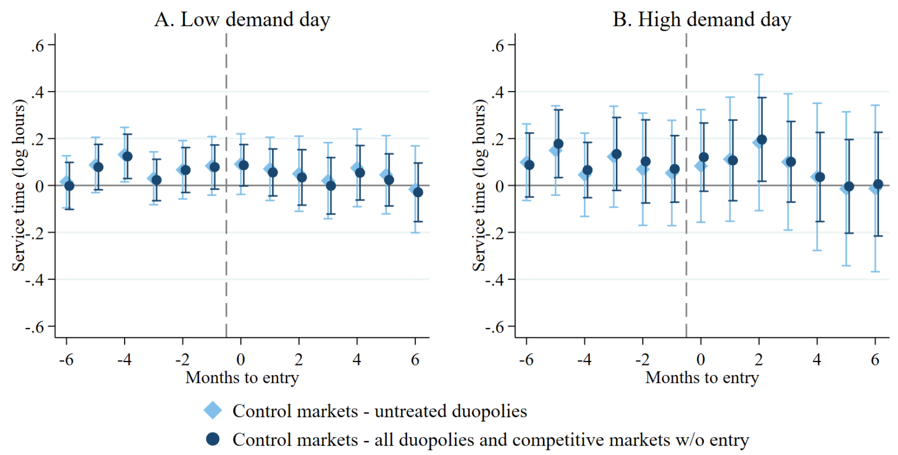
We first estimate Equation (1) where the excluded period is more than 6 months before entry ($j = 6$) and include the full set of relative indicator variables. Figure 5 plots the point estimates and the 95 percent confidence intervals for the β_k coefficients in Equation (1) for $k = -6$ to $k = 6$. Estimation results are shown separately for low- and high-demand days of the week. The figure reports the estimated effects of entry on the incumbent's service time in markets that were monopolies before entry (sub-figure (a)),

Figure 5: The effect of entry on service time, by competition and demand levels
Excluded period: More than 6 months before entry

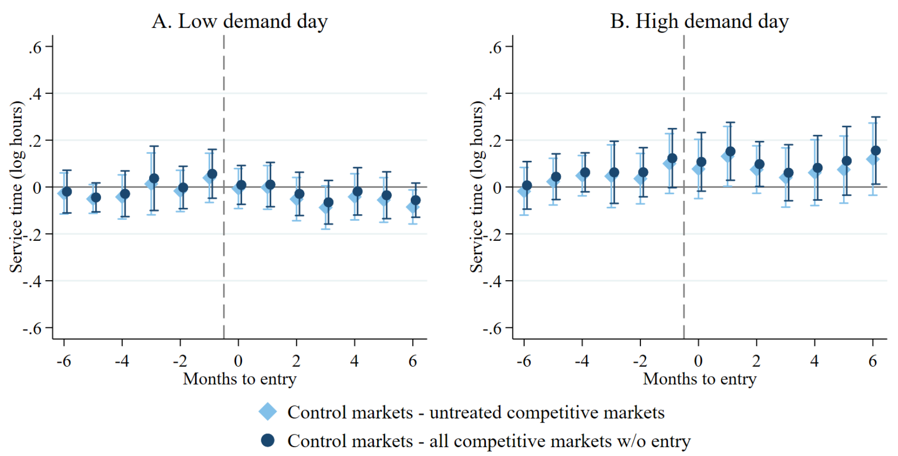
(a) Pre-entry monopolistic markets



(b) Pre-entry duopolistic markets



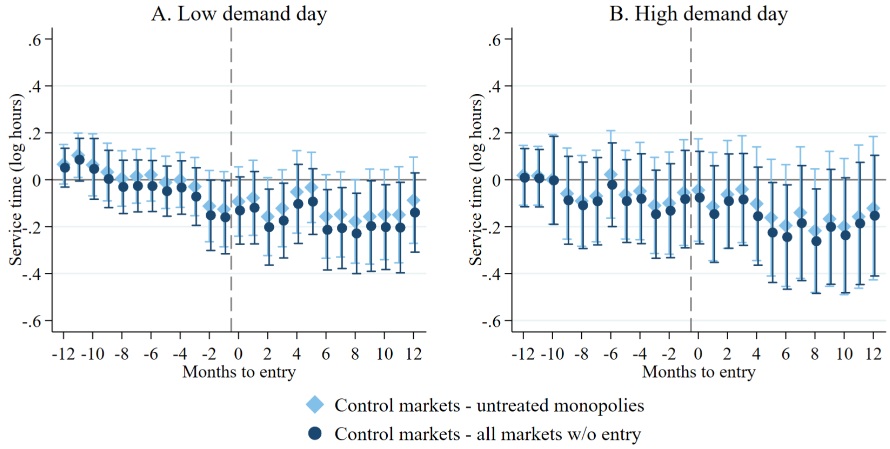
(c) Pre-entry competitive markets



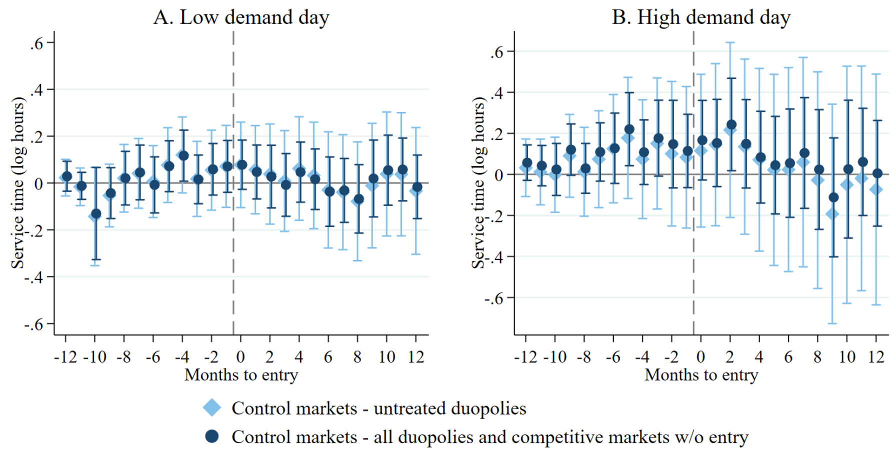
Notes: The figure plots the coefficients of β_k for j ranging from -6 to 6 and their 95-percent confidence intervals. The coefficients are obtained from estimating Equation (1), with a full set of relative indicator variables for $k \geq -6$, using different subsamples. The excluded period is set to more than 6 months before entry. Standard errors are clustered at the market level. The dependent variable is the incumbent's log service time in the local market, and the results are presented separately for low- and high-demand days. Sub-figure (a) reports the estimated effects of entry on the incumbent's service time into monopolistic markets, sub-figure (b) focuses on duopolistic markets, and sub-figure (c) on all other markets. The light-blue diamonds indicate the estimated coefficients from a sample that uses as the control group all the markets that did not experience entry and have the same competition level as treated markets. The dark-blue circles indicate the coefficients from a sample that uses as the control group the markets that did not experience entry and have at least 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 in monopolistic markets and that on low-demand days the reduction begins shortly before entry.

Figure 6: The effect of entry on service time, by competition and demand levels
Excluded period: more than 12 months before entry

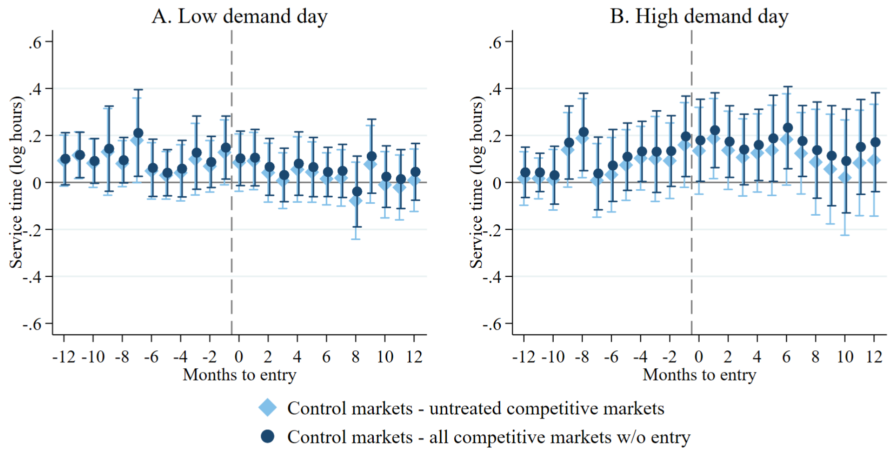
(a) Pre-entry monopolistic markets



(b) Pre-entry duopolistic markets



(c) Pre-entry competitive markets



Notes: The figure plots the coefficients of β_k for j ranging from -12 to 12 and their 95 percent confidence intervals. The coefficients are obtained from estimating Equation (1), with a full set of relative indicator variables for $k \geq -12$, using different subsamples. The excluded period is more than 12 months before entry. 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. The figure reports the estimated effects of entry into monopolistic markets (sub-figure (a)), duopolistic markets (sub-figure (b)), and all other markets (sub-figure (c)). The light-blue diamonds indicate the estimated coefficients from a sample that uses as the control group all the markets that did not experience entry and have the same competition level as treated markets. The dark-blue circles indicate the coefficients from a sample that uses as the control group the markets that did not experience entry and have at least 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 in pre-entry monopolistic markets, and that on low-demand days the reduction begins shortly before entry.

markets that were served by two online grocers before entry (sub-figure (b)), and competitive markets (at least three online grocers before entry, sub-figure (c)). Light-blue diamonds indicate the estimated coefficients from a sample that uses as the control group all 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 those in which Shufersal was a monopoly throughout the sample period, and for treated competitive markets, the untreated markets are those with three or four online grocers throughout the sample period). Dark-blue circles indicate the coefficients from a sample that uses as the control group all markets that did not experience entry during the sample period and have the same or higher competition level.

The results in sub-figure (a) show that the incumbent's service time in pre-entry monopolistic markets decreased by 10% to 20% on low-demand days both before and after a rival enters. 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. On high-demand days we find no significant change before entry and a marginally significant decrease in service time only five months after entry. In more competitive markets (sub-figures (b) and (c)) our estimates, both on low-demand days and high-demand days, are generally statistically insignificant. Moreover, the fact that most of the coefficients in the pre-entry period are statistically insignificant provides evidence for parallel trends, whereas sub-figure (a) shows parallel trends three months and more before entry. Figure 6 plots the point estimates and the 95 percent confidence intervals for the β_k coefficients in Equation (1) for $k = -12$ to $k = 12$ to allow for a 12-month pre-entry time horizon ($j = 12$). The results in Figure 6 are qualitatively similar to those in Figure 5 and provide further support for the parallel trends assumption.[25]

Overall, we find robust evidence for a decline in the service time offered by the incumbent after a rival enters a monopolistic market. On low-demand days, the decline in service time begins two months before entry, a pre-entry decline that we do not observe on high-demand days and in more competitive markets. In Section 3.3 we discuss our preferred interpretation of these results and address the concern about pre-trends in service time.

3.2 Difference-in-differences estimation

We rely on the patterns uncovered in the event study estimation results and continue the analysis by using a parametric DiD estimation of the static effect of entry. In particular, we estimate the following

[25]In Appendix E we present results from alternative specifications that support the results presented in Figures 5 and 6. Figure E1 shows estimation results of Equation (1) with month fixed effects interacted with quantiles for market growth to allow for more flexible time trends and including a vector of time-variant variables (i.e., the number of nearby physical stores operated by rivals in the local market, dummies for exits and subsequent entries, and a specific Shufersal fulfillment center linear time trend). Figure E2 shows estimation results from a specification that restricts the sample to observations in the 12 months before and the 12 months after entry, using $k = -12$ as the reference period. Figure E3 shows estimation results when only treated markets are used, and Figure E4 shows estimation results without holidays. The results from these alternative specifications are consistent with the results shown in Figures 5 and 6, and provide robust support for the patterns observed in sub-figure (a).

two-way fixed effects DiD specification:

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

where pre_entry_{it} is a dummy for the one or two 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 in which we replace the month fixed effects with month fixed effects interacted with quantiles for market growth to allow for more flexible time trends, and specifications that include X'_{it}, a vector of time-variant variables (i.e., the number of physical stores operated by rivals in the local market, dummies for exits from and subsequent entries into the same market).[26] We also include Shufersal fulfillment center linear time trend to capture potential different time trends in service time.[27] 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.

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. The table reports the estimated effects of entry on the incumbent's service time in pre-entry monopolistic markets (Panel A), pre-entry duopolistic markets (Panel B), and all other markets (Panel C). The results shown in Table 2 are based on an analysis that uses as the control group all untreated markets with the same or a higher pre-entry competition level. Similar results are obtained when we use as the control group only untreated markets with the same pre-entry competition level, when we use as the control group only untreated markets with a higher pre-entry competition level, or when we do not include a control group and only exploit the variation in entry timing for identification (see Table E2 in Appendix E).

The results in Table 2 are consistent with the event study results. On low-demand days and in pre-entry monopolistic markets, a significant 14% to 16% decrease in service time is observed two months before entry. This decrease continues also in the months after entry, though to a somewhat lesser degree. The estimated effects are not sensitive to the opening of nearby physical stores operated by rivals, to subsequent changes in the number of online grocers, or to the inclusion of a specific Shufersal fulfillment center linear time trend. Moreover, they are not sensitive to replacing the time-variant fixed effects with time-period fixed effects interacted with quantiles for market growth, suggesting that these results are not driven by time-variant unobserved variables at the market level.

The estimates in competitive markets on low-demand days are smaller, and mostly statistically in-

[26] We use the number of stores within a 10 km radius of the local market but the results are similar when we use alternative definitions for the number of physical stores operated by rivals in the local market (Table E1 in Appendix E).

[27] Figure E5 in Appendix E presents evidence of different time trends for different fulfillment centers. The figure plots the coefficients from regressing the log of service time on the time trend for each fulfillment center while controlling for market and time fixed effects, separately for low- and high-demand days. The figure shows that some centers improved their service times during the sample period, primarily on high-demand days.

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						
Pre-entry	-0.143**	-0.150**	-0.159**	-0.0441	-0.026	-0.039
	(0.067)	(0.063)	(0.064)	(0.065)	(0.056)	(0.056)
Post-entry	-0.141**	-0.107**	-0.109**	-0.130**	-0.035	-0.051
	(0.061)	(0.052)	(0.052)	(0.065)	(0.050)	(0.047)
Markets		106			106	
Markets with entry		54			54	
N		3,804			3,809	
Panel B: Pre-entry duopolistic markets						
Pre-entry	0.065	0.029	0.040	0.071	0.024	0.044
	(0.040)	(0.037)	(0.039)	(0.060)	(0.059)	(0.059)
Post-entry	-0.009	-0.047	-0.018	-0.006	0.0003	0.032
	(0.039)	(0.038)	(0.036)	(0.072)	(0.063)	(0.060)
Markets		53			53	
Markets with entry		32			32	
N		1,901			1,901	
Panel C: Pre-entry competitive markets						
Pre-entry	0.051	-0.001	-0.008	0.083*	0.007	0.035
	(0.034)	(0.036)	(0.038)	(0.044)	(0.034)	(0.041)
Post-entry	-0.022	-0.082**	-0.088**	0.079*	-0.035	-0.010
	(0.033)	(0.037)	(0.037)	(0.046)	(0.051)	(0.047)
Markets		48			48	
Markets with entry		34			34	
N		1,723			1,718	
Controls:						
Market FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓		✓	✓	
Time FE # market growth (quantiles)			✓			✓
No. of rivals' physical stores (10 km radius)		✓	✓		✓	✓
Exits and additional entries		✓	✓		✓	✓
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 entry. *post_entry* is an indicator for the month when entry takes place and for the following months. The table reports the estimated effects of entry on the incumbent's service time in pre-entry monopolistic markets (Panel A), pre-entry duopolistic markets (Panel B), and all other markets (Panel C). In all panels, the control markets are markets that did not experience entry and have at least the same competition level as treated markets. All specifications include market and month fixed effects, in Columns (2) and (5) they also include controls for the number of physical stores within a 10 km radius operated by rivals, dummies for exits from and subsequent entries into the same market, and a specific Shufersal fulfillment center linear time trend. The specifications in Columns (3) and (6) include month fixed effects interacted with quantiles for market growth instead of month fixed effects only. The results show that on low-demand days and in pre-entry monopolistic markets, a significant 11%–16% decrease in service time is observed two months before entry and in the months after entry. The estimates in competitive markets and on high-demand days are smaller or positive and are mostly statistically insignificant.

significant. We find only an 8% decrease in service time after entry with the inclusion of time-variant variables (consistent with the results in Panel (c) in Figures D2 and E1). The estimates on high-demand days are small and statistically insignificant when we control for time-variant variables.

Same-day deliveries. We find that in monopolistic markets on low-demand days the incumbent offered shorter service time in the face of entry. However, the marginal value of shorter service time for

Table 3: The effect of entry on same-day deliveries, by competition and demand levels

	Low-demand day		High-demand day			
	Same-day delivery		Same-day delivery		Delivery before the weekend	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Pre-entry monopolistic markets						
Pre-entry	0.110**	0.116***	0.008	0.012	-0.004	0.005
	(0.042)	(0.043)	(0.036)	(0.036)	(0.035)	(0.035)
Post-entry	0.085**	0.084**	0.037	0.048	-0.028	-0.015
	(0.037)	(0.038)	(0.032)	(0.031)	(0.032)	(0.030)
Markets	106		106			
Markets with entry	54		54			
N	3,804		3,809			
Panel B: Pre-entry duopolistic markets						
Pre-entry	0.008	0.0004	-0.004	-0.012	-0.021	-0.029
	(0.024)	(0.027)	(0.043)	(0.046)	(0.019)	(0.024)
Post-entry	0.044*	0.014	0.005	-0.005	-0.014	-0.025
	(0.026)	(0.026)	(0.040)	(0.039)	(0.028)	(0.027)
Markets	53		53			
Markets with entry	32		32			
N	1,901		1,901			
Panel C: P re-entry competitive markets						
Pre-entry	-0.017	-0.007	-0.046	-0.065*	-0.013	-0.019
	(0.029)	(0.031)	(0.030)	(0.035)	(0.020)	(0.025)
Post-entry	0.015	0.019	-0.012	-0.036	0.028	0.015
	(0.021)	(0.023)	(0.040)	(0.043)	(0.030)	(0.029)
Markets	48		48			
Markets with entry	34		34			
N	1,723		1,718			
Controls:						
Market FE	✓	✓	✓	✓	✓	✓
Time FE	✓		✓		✓	
Time FE # market growth (quantiles)		✓		✓		✓
No. of rivals' physical stores (10 km radius)	✓	✓	✓	✓	✓	✓
Exits and additional entries	✓	✓	✓	✓	✓	✓
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)–(2) is the monthly percentage of Shufersal's same-day deliveries in the local market for orders on Saturday. The dependent variable in Columns (3)–(4) is the monthly percentage of Shufersal's same-day deliveries in the local market for orders on Wednesday. The dependent variable in Columns (5)–(6) is the monthly percentage of Shufersal's deliveries arriving before the weekend. *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 table reports the estimated effects of entry into monopolistic markets (Panel A), duopolistic markets (Panel B), and all other markets (Panel C). In all panels, the control markets are markets that did not experience entry and have at least the same competition level as treated markets. All specifications include market and month fixed effects, in Columns (1), (3), and (5) they also include controls for the number of stores within a 10 km radius operated by rivals, dummies for exits from and subsequent entries into the same market and a specific Shufersal fulfillment center linear time trend. The specifications in Columns (2), (4), and (6) include month fixed effects interacted with quantiles for market growth instead of month fixed effects only. The results show that on low-demand days and in pre-entry monopolistic markets, a significant 8%–11% increase in the likelihood of same-day delivery is observed two months before entry and in the months after entry. The estimates in competitive markets or on high-demand days are smaller and mostly statistically insignificant.

consumers may vary depending on how long the service time was to begin with. While a shortening of service time from the evening to the afternoon on the same day may not make much of a difference to consumers, a shortening of service time from next-day to same-day delivery does. As Figure C4

Table 4: The effect of entry of aggressive grocers 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						
Pre-entry	-0.173**	-0.191**	-0.203**	-0.033	-0.025	-0.040
	(0.085)	(0.081)	(0.084)	(0.072)	(0.064)	(0.063)
Post-entry	-0.180**	-0.140**	-0.144**	-0.173**	-0.061	-0.090*
	(0.074)	(0.064)	(0.066)	(0.075)	(0.056)	(0.052)
Markets		93			93	
Markets with entry		41			41	
N		3,339			3,342	
Panel B: Pre-entry duopolistic markets						
Pre-entry	0.059	0.004	0.028	0.141*	0.075	0.098
	(0.052)	(0.045)	(0.046)	(0.082)	(0.077)	(0.070)
Post-entry	-0.043	-0.096*	-0.050	-0.008	0.019	0.034
	(0.053)	(0.050)	(0.045)	(0.097)	(0.075)	(0.065)
Markets		42			42	
Markets with entry		21			21	
N		1,507			1,505	
Panel C: Pre-entry competitive markets						
Pre-entry	0.021	-0.036	-0.046	0.125**	0.021	0.021
	(0.051)	(0.048)	(0.052)	(0.057)	(0.041)	(0.058)
Post-entry	-0.031	-0.092**	-0.107**	0.073	-0.050	-0.063
	(0.049)	(0.043)	(0.041)	(0.074)	(0.070)	(0.059)
Markets		35			35	
Markets with entry		21			21	
N		1,257			1,252	
Controls:						
Market FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓		✓	✓	
Time FE # market growth (quantiles)			✓			✓
No. of rivals' physical stores (10 km radius)		✓	✓		✓	✓
Exits and additional entries		✓	✓		✓	✓
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 when entry takes place and for the following months. The table reports the estimated effects of entry on the incumbent's service time in pre-entry monopolistic markets (Panel A), duopolistic markets (Panel B), and all other markets (Panel C). In all panels, the control markets are markets that did not experience entry and have at least the same competition level as treated markets. All specifications include market and month fixed effects, and in Columns (2) and (5) they include also controls for the number of physical stores within a 10 km radius operated by rivals, dummies for exits from and subsequent entries into the same market, and a specific Shufersal fulfillment center linear time trend. The specifications in Columns (3) and (6) include month fixed effects interacted with quantiles for market growth instead of month fixed effects only. The results show that on low-demand days the incumbent improves service time in response to an entry by an aggressive rival in all pre-entry market conditions, where the effect diminishes with the level of competition. In pre-entry monopolistic markets, the improvement begins before entry takes place and its magnitude is about 25% larger than in the main specification. We also find that on high-demand days, the effect of entry on service time into monopolistic markets is negative and marginally significant, after entry takes place.

in Appendix C shows, most deliveries in monopolistic markets on low-demand days take place within two days of the order. To investigate whether improvements in service times translate into increased probability of same-day deliveries, Columns (1)–(4) in Table 3 report the parametric estimation results where the outcome variable is the monthly percentage of same-day deliveries (i.e. deliveries within 24 hours). The results show that on low-demand days and in pre-entry monopolistic markets, the incumbent increases the percentage of same-day deliveries by about 11% in the two months before a rival enters, and by about 8% after the rival enters. We do not find a significant effect on the monthly percentage of same-day deliveries on high-demand days and in competitive markets. Moreover, Columns (5) and (6) in Table 3, which report the parametric estimation results for high-demand days using the monthly percentage of deliveries arriving before the weekend as the dependent variable, show no effect of entry on the percentage of deliveries before Friday afternoon, irrespective of the level of competition.

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. We define Rami Levy and Victory as aggressive online grocers since Rami Levy offers the cheapest basket and Victory offers the shortest service time (see Figure 1). Moreover, our longitudinal customer-level data show that Shufersal's loyal customers are more 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).[28] Table 4 reports the parametric estimation results when entry is restricted to entry by aggressive online grocers (i.e., Rami Levy and Victory only). The table 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 monopolistic markets (Panel A), the incumbent decreases service time by about 20% before entry and by 14% after entry (Column (3)). According to Panel C, which shows the results for competitive markets, the incumbent reduces service time by about 10% after entry. On high-demand days, we find a significant negative effect on service time after entry in monopolistic markets, and a significant positive effect on service time before entry in competitive markets, which disappears when we control for time-variant variables.

3.3 Interpretations

Our findings show that the incumbent firm offers shorter service time when it faces entry. In particular, the incumbent reduces service time, before and after entry, on low-demand days, in concentrated markets, and when the entrant poses a larger competitive threat. Our preferred interpretation of these findings is that when prices are inflexible, in concentrated markets, the incumbent sets long service times, thereby exercising their market power. As competition intensifies, the incumbent offers shorter service time, when the relevant costs of improving service time are not too high. In particular, on high-demand days, the incumbent's resources are better utilized before entry and therefore it is more costly to improve service time. Our findings are consistent with the predictions generated by the model in Appendix A, where the magnitude of the improvement in the incumbent's service time depends on the respective costs and benefits. When the benefits are high (in pre-entry concentrated markets) and the costs are low (on low-demand days), the incumbent improves service time more than otherwise. Shorter service time can

[28]See Panel (b) of Figure B4 in Appendix B for more details.

also be 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 shorter service times. Thus, post-entry changes in service time can be explained by the model, indicating a deliberate attempt to enhance customers' loyalty, or by a change in demand following the entry of a new rival. Unlike post-entry changes in service time, pre-entry changes are unlikely to reflect improvements to service time due to reduced demand, leaving the strategic-loyalty response a more likely explanation.[29]

Our interpretation relies on two main assumptions: the timing of entry decisions is not correlated with the incumbent's service time in the local market and the incumbent knows in advance that a rival intends to enter a local market. While we lack data to test these assumptions directly, in the next section we provide several pieces of evidence that explain why we think that these assumptions are plausible and also discuss why alternative explanations for our findings are less likely to hold.

4 Identification concerns

4.1 Entry decisions

Figure F1 in Appendix F describes the geographical expansion, both online and traditional, of the incumbent's rivals. The maps show for four distinct dates during the sample period the following information: (1) the 172 markets in our sample (light-red dots), (2) markets where each retailer offers online service (red dots), (3) the locations of the retailers' physical stores (light-blue dots), and (4) the locations of the retailer's physical stores with online service (dark-blue dots; available only for Rami Levy and Victory). The patterns in the figures suggest that entry decisions are geographically clustered. In particular, Rami Levy expanded its online service primarily into the north of Israel, whereas Victory expanded into the center and the south of Israel. Retailers also tend to offer new online grocery services in regions where they already have physical stores, thereby taking advantage of their operational efficiencies (Holmes 2011). These patterns suggest that entry decisions are predominantly driven by the entrant's geographical presence and operational capabilities rather than the incumbent's capabilities.

Entry decisions may also depend on the sociodemographic characteristics of local markets, such as population size, expected population growth, and average income. These factors are unlikely to have changed significantly during the sample period, and the market fixed effects, or the interaction between the month fixed effects and the market-growth quantiles that we include likely capture them. Table F1 in Appendix F presents demographic information on all 172 markets, classified by competition level and according to whether they did or did not experience entry during the sample period. Odd-numbered columns report the means and standard deviations of the demographic characteristics for markets that experienced entry, distinguished by different pre-entry market structures. Even-numbered columns report

[29] Panel (a) of Figure B4 in Appendix B provides suggestive evidence for the importance of service time in retaining customers. The figure shows 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 (see Appendix B for more details). 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.

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 table shows, as expected, that competition is higher in more populated localities, higher population growth, higher socioeconomic status, and closer to the center of Israel. However, in less competitive markets there is no discernible difference in these characteristics, except for population size, between markets that experienced entry during the sample period and markets that did not experience entry. Moreover, these characteristics were almost unchanged within markets during the sample period.

Another potential concern is that demand shocks at the market level drive both the entrant's decision to enter a market and the incumbent's decision to improve its capabilities. We first note that this concern means that we should also observe improvements in service time on high-demand days, a finding that we do not have. Moreover, we use information on online searches to gauge increased interest in online grocery service in the months surrounding entry. While the available data is not of high quality, the analysis does not indicate increased demand for online service in the months surrounding entry.[30]

4.2 Substitution between online and traditional channels

Offering online service in a local market might be 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, we use a similar specification to our event study specification (Equation (1)) to estimate the association between entry by an online grocer into a local market and the opening of a physical nearby store by the same grocer. Hence, for each rival, we regress the distance traveled between the local market and the rival's first or second store on dummy indicators for the months relative to the month of the rival's entry into the local market. The excluded period is more than 12 months before entry. Figure F2 in Appendix F plots the point estimates and the 95 percent confidence intervals from estimating this specification separately for each rival (except Mega due to lack of variation in entries). We do not find evidence of a significant change in the distance traveled between the local market and the rival's first or second closest stores in the months leading up to entry. These results suggest that offering an online service was not preceded by changes in the traditional channel. Moreover, in our main DiD estimation, we flexibly control for the presence of physical stores and show 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.[31]

[30] To learn about local trends we use data from Semrush, a research company that provides search engine optimization information on keyword search and internet traffic, to calculate monthly market-level traffic based on traffic from keywords containing names of the relevant localities in addition to words related to online grocery service. We were able to construct monthly traffic only for 59 local markets in our sample, in 10 of which Shufesal was a monopoly. We use this sample to estimate the relationship between entry and online traffic related to online grocery service (based on an event-study specification similar to Equation (1)) and find small and insignificant coefficients for increased online interest (the results are available upon request). While this analysis supports our interpretation, we note that the sample that we use may be selective and not sufficient to provide convincing evidence on online traffic.

[31] 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 10 km radius of the local market accessed by the crawler. Table E1 in Appendix E shows similar results when we use alternative definitions to account for the traditional channel effect: the presence of physical stores within a 5 km or 15 km 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)).

4.3 The role of local infrastructure

Service times offered by the incumbent may also improve due to local changes in infrastructure (e.g., roads). If these changes take place at the same time that a rival 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).

4.4 The anticipation effect

An important finding from our analysis is the pre-entry decline in the incumbent's service time. We claim that this change reflects the incumbent's deliberate response to the upcoming entry to improve customer loyalty. While we do not have direct information that the incumbent knows that rivals intend to enter before they actually do, we provide qualitative evidence about this aspect. We also offer an alternative identification strategy that leans more on the threat of entry rather than on the entry itself. The findings from this latter approach further strengthen our preferred interpretation regarding the incumbent's response to entry.

4.4.1 Evidence on the incumbent's anticipation

Offering online service requires nontrivial investments, such as recruiting and training new in-store workers, purchasing specialized trucks, modifying physical stores for distribution purposes, and changing the online grocery website. Many of these actions take place long before entry and are observable, certainly for rivals that operate in the same local market. Hence, it is more likely that the incumbent improves service time shortly before actual entry to strengthen customer loyalty rather than to deter entry. Moreover, Shufersal's rivals announced in their financial reports that they intend to expand their online services using existing stores. Victory launched an online website in January 2017 and Yenot Bitan launched an online website in May 2017. Indeed, Figure C8 in Appendix C shows that entries by Victory were mainly during 2017 and entries by Yenot Bitan started in May 2017.

We collected data on all Shufersal's ad campaigns from 2015 to 2019 from Yifat, a leading business information company, to provide suggestive evidence that Shufersal anticipated these massive entries during 2017. Figure F3 in Appendix F shows the percentage of Shufersal's advertising expenses allocated to the online channel by month of launch from January 2015 to December 2019 out of total Shufersal's advertising expenses.[32] Comparing Figure F3 with Figure C8 shows that Shufersal invested more in the online channel in the months preceding the aforementioned massive entries. Most of the costs of the campaigns launched in December 2016 and November 2017 (70% and 80%, respectively) were allocated to the online channel. The campaigns launched in these two months were expensive also in absolute terms, about $7M each, more than twice the cost of the campaigns launched in mid-2016. Most of the entries that we observed in our sample occurred during 2017, especially in December 2017 (24 entries overall and 21 first entries) and in the first three months of 2018 (23 entries overall and 21 first entries). While this pattern may imply that Shufersal anticipated these massive entries, we are careful about providing a causal interpretation since our sample period was a period of massive expansion of the online channel, which can be accounted for by an expansion of rivals into new markets and by increasing advertising.

As a further investigation, we explore whether the incumbent also changed service time on low-demand days in markets that did not experience entry but were served by the same fulfillment center of markets that experienced entry. We classify each of the 172 markets in our sample to one of Shufersal's 32 fulfillment centers based on distance traveled and define entry at the fulfillment center level (restricting attention to the first entry we observe for each fulfillment center). Then we estimate specifications similar to Equation (2) by including in the sample only markets that did not experience entry (the control markets in our main analysis which we refer here as untreated adjacent markets) where the treatment is at the fulfillment center.[33] The results are reported in Table F2, where we distinguish whether entry was to a monopolistic market (Columns (1)–(3)) or to a non-monopolistic market (Columns (4)–(6)), and between entries by any online grocer (Panel A) and by an aggressive online grocer (Panel B). Overall, the estimates show small and insignificant effects on the incumbent's service time in an untreated adjacent market before a rival entered a market served by the same fulfillment center, and a marginally significant decrease in service time after an aggressive rival entered a monopolistic market served by the same fulfillment center. These results may suggest that the incumbent knew in advance where the entry was likely to happen, nevertheless, this analysis can also be viewed as a placebo test, implying that our results in the main analysis are not confounded by spillover effects to control markets.[34]

We also conducted interviews with individuals holding a range of positions in the retail industry.[35] We started all our interviews with a short description of our paper and were encouraged that all individuals found our basic hypotheses plausible. In particular, they all agreed that grocers use industry intelligence to learn about their rivals' intentions. Also, all grocers work with the same suppliers, and workers

[32]The percentages were calculated by dividing the expenses of Shufersal's online campaigns that were launched in each month by the expenses of all of Shufersal's campaigns that were launched in that month. For example, the 80% in November 2017 means that 80% of the costs of all campaigns that were launched in November 2017 were allocated to the online channel. The campaigns themselves continued for more than one month.

[33]The entry indicator takes the value of one if an entry occurred in an adjacent local market that was served by the same fulfillment center as the untreated adjacent market.

[34]Possible explanations for the decrease in service time following entry by an aggressive grocer into a market served by the same fulfillment center can be either due to a significant decrease in demand for online service in the market that experienced entry, which freed up resources that were being used by the incumbent's fulfillment center to improve service times in untreated adjacent markets, or due to a strategic response of the incumbent.

[35]We interviewed a senior manager of the online channel for one of the chains, a senior manager of a retail supplier, a government agency economist, a management professor, an operations professor, and a law professor. Full names and job descriptions are available upon request.

move from one supermarket chain to another, making it easier to learn about rivals' actions. While such encouragement should not be overstated, it is reassuring that none of these experts had an obvious alternative explanation for the empirical pattern we find in the data.

4.4.2 Alternative identification strategy

Our event study and the DiD identification strategies require an assumption that the incumbent knows the likelihood and the timing of entry. To test whether our results are sensitive to this assumption, we exploit Victory's expansion patterns and offer an alternative identification strategy that relies on cross-sectional variation in the threat of entry, and that does not require an assumption that the incumbent knows exactly which local market the rival intends to enter.

In January 2017, Victory, one of Shufersal's aggressive rivals (see Section 3.2.1), launched an online website, and subsequently expanded its online services massively, first to the center of Israel and in December 2017 into several local markets in the south (see Figures C8 and F1).[36] We take advantage of this shock to examine the change in Shufersal's service times in the southern markets before and after December 2017, using markets in the north of the country as the control group.[37] Specifically, we keep in the sample only 39 markets in the south and in the north of the country and estimate the following specification:

$$Log(service\_time)_{it} = \alpha_t + \delta South_i + \sum_{k=-j} \beta_k \mathbb{1}[t - t_{Dec2017} = k] * South_i + \lambda Z'_{it} + u_i, \quad (3)$$

where $\mathbb{1}[t - t_{Dec2017} = k]$ is an indicator for the months k relative to December 2017 in month t and $South_i$ is an indicator for whether market i is in the South (i.e. the treatment group). Similar to Equation (1), β_k captures the change in the incumbent's service in a given month k before or after December 2017 relative to its average value in the excluded period, which is more than j months before December 2017. The vector Z'_{it} includes sociodemographic characteristics of market i in month t and the time-variant variables that were included also in the main analysis. Specifically, it includes population growth, population size, average income per capita, number of vehicles per capita, and fixed effects for the socioeconomic and periphery indices, as well as the number of rival stores within a 10 km radius of the local market, and dummies for exits and subsequent entries in the same market. Standard errors are clustered at the locality level; however, using robust standard errors yields similar confidence intervals.

Figure F4 in Appendix F plots the point estimates and the 95 percent confidence intervals for the β_k coefficients in Equation (3) for $k = -12$ to $k = 12$ (the specification is estimated with a full set of relative indicator variables for $k \geq -12$). The estimation results for low- and high-demand days of the week are shown separately. Note that the sample includes 39 markets that did not experience any entry before December 2017, 18 markets in the south (in 12 of them Shufersal was a monopoly before December 2017),

[36] In 2017, three Victory stores in the south began to offer online service, and toward the end of the year Victory entered 8 markets in the south, of which 5 were monopolies before the entry.

[37] We choose to use the markets in the north of the country as the control group since neither the northern region nor the southern region experienced entries before December 2017.

and 21 markets in the north (in all of which Shufersal was a monopoly before December 2017). Subfigure (a) reports the estimated effects only in pre-entry monopolistic markets, and subfigure (b) reports the estimated effects in all markets.

The results in Figure F4 show similar patterns to those in our main event study analysis, though of a larger magnitude. In concentrated markets, facing a threat of entry by an aggressive rival, the incumbent responds by reducing service time on low-demand days. According to the estimates, in the three months before December 2017, when Victory massively entered markets in the south, Shufersal reduced service time by 40% to 60% in these markets on low-demand days. On the other hand, on high-demand days, the changes in the incumbent's service time are statistically insignificant. These results provide additional support for the robustness of our main event study findings and for our interpretation of the incumbent's anticipation of the rival's entry.

5 Conclusion

There is growing evidence 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. One way that large firms may reduce 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 twice weekly longitudinal data on service time and prices in 172 local markets, we show that online grocers set longer service times in concentrated markets and on high-demand days.

Our main empirical analysis takes advantage of the rapid expansion of online retailers into new local markets and considers the effect of these entries on the incumbent grocer's service time. Notably, in our setting, online retailers set identical prices in different local markets and neither use prices to exploit market power in concentrated markets nor compete in competitive markets. We find that on low-demand days the incumbent improves service time shortly before a rival enters a monopolistic market. We Also find that on high-demand days and in competitive markets, service time does not change before entry and there exists only weak evidence that it improves after entry. While changes in service time after a new rival enters can be explained either by a strategic-competitive response of the incumbent or by changes in demand that the incumbent faces, changes in service time before a new rival enters are likely to reflect only strategic-competitive considerations. Overall, our results suggest that firms use service time to exercise their local market power and that operational considerations affect the extent to which they respond. Our results also suggest that in competitive markets and on high-demand days, consumers may not benefit from increased competition, as both prices and service time do not significantly change as competition intensifies.

Our findings from the regression analysis capture the short-term effect of a rival's entry on the incumbent's service time. In the short run, firms face high adjustment costs, especially on high-demand days when resources are already constrained. For example, short-term improvement in service time can be achieved by increasing working hours, but it is more costly if it requires recruiting new workers. Accordingly, in the regression analysis, we do not find that incumbents improve service time on high-demand days in the months surrounding the entry. In the long run, firms can adjust, add relevant inputs, and change their production technology. This distinction might explain why the descriptive statistics show that service time decreases with the level of competition, not only on low-demand days but also on high-demand days. Thus, in the long run, firms can improve service by adding more resources. We leave this issue for further research.

Our results also speak to the debate about uniform pricing. There is growing evidence that national retail 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 of our findings is that service time replaces price in the standard models of competition. 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. 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.

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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 competition and demand levels. Third, the model captures the trade-off that operations officers and regional managers confront when making decisions about inputs used for online grocery services.

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 (for example on high-demand days), 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 (for example in concentrated markets), retailers set short service times ($\frac{\partial S}{\partial \gamma} < 0$). These predictions are consistent with the descriptive evidence presented in Figures 1 and 2 in Section 2.3. Next, we derive predictions that concern the incumbent's response to entry.

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

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 incumbent offers shorter service times as γ increases ($\frac{\partial S}{\partial \gamma} < 0$). 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 incumbent improves service times more than otherwise.

Pre-entry competition level. In more competitive markets, the marginal effect of a competitor on the incumbent's service time 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 supports it (e.g., Bresnahan and Reiss 1991).

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 being used 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 the incumbent is likely to respond more aggressively by improving service time. We consider entrants that are more likely to poach customers from the incumbent 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 by aggressive retailers 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 simultaneously observe the available service time offered by each grocer. Figures B1 and B2 below show examples of screenshots 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 MySupermarket during the data collection period. The individual customer/order data from MySupermarket cover about 700,000 orders by nearly 85,000 customers. About 70 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. 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 MySupermakert users are helpful to learn about firms' behavior because online grocers are concerned that these users are more likely to switch once a new rival enters the local market.

We use the data from MySupermarket to: 1) examine how the number of online grocery orders changes over days of the week (Figure B3); 2) 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) examine consumers' substitution patterns across grocers, and accordingly characterize which grocers are more aggressive (Panel (b) of Figure B4). We also use the data from MySupermarket to understand to what extent the elasticity of demand with respect to service time differs between Wednesdays and Saturdays (i.e. between high- and low-demand days).

Figure B3 presents the cumulative percentage of orders out of total observed orders for online grocery on Tuesday and Wednesday (i.e., 48 hours before the crawler on Wednesday night), and on Friday and Saturday (i.e., 48 hours before the crawler was active on Saturday night). The figure shows that the cumulative percentage of orders is about three times larger on Wednesdays than on Saturdays. We therefore classify Wednesdays as high-demand days and Saturdays as low-demand days.

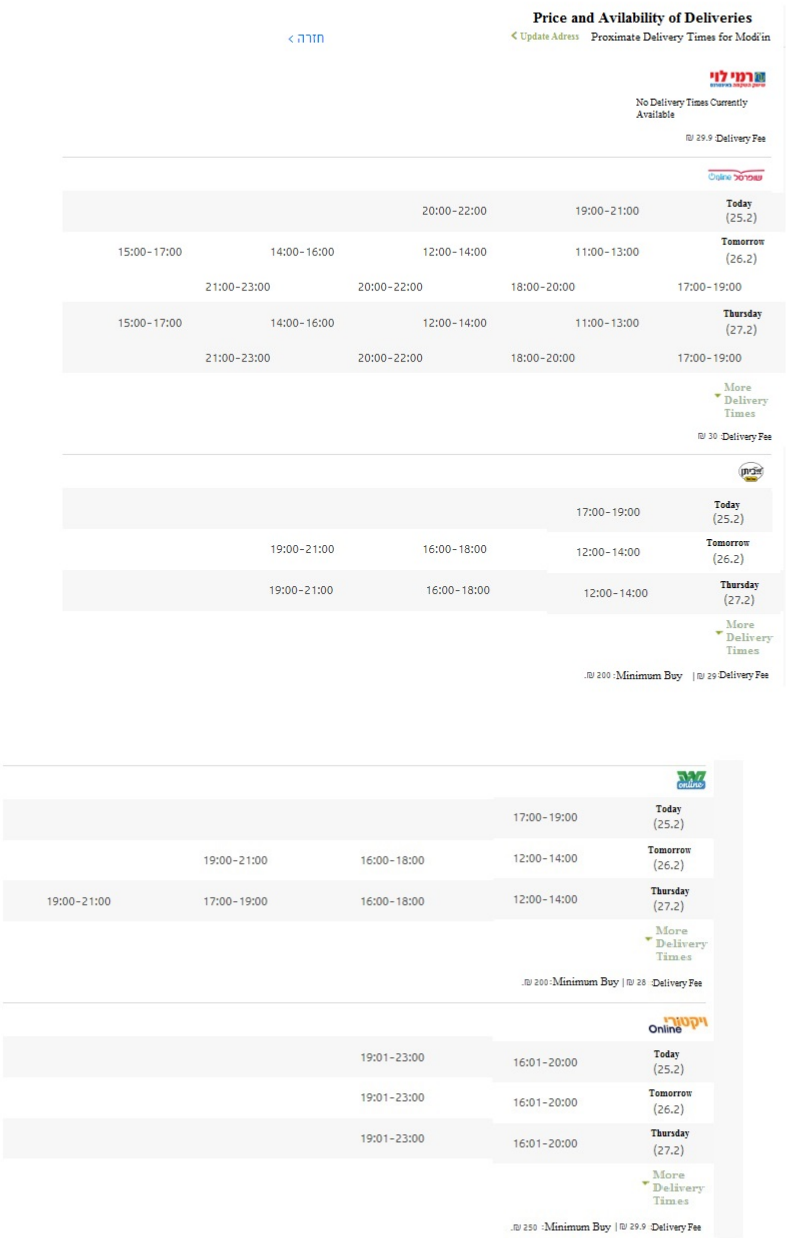
Figure B4 shows the switching patterns of loyal customers. A loyal customer is defined as an individual who used MySupermarket more than 10 times during the sample period and bought from the same online grocer at least 60 percent of times. There are 9,182 loyal customers in the sample, and 2,861 of them are loyal Shufersal customers. Panel (a) shows the percentage of orders placed by loyal customers and examines on which days these customers do not purchase from their regular grocer. More than 17 percent of the switches by loyal customers occur on Thursdays, compared to about 12.5 percent of the switches to a rival grocer on Saturdays and Sundays. These differences are statistically significant. According to the figure, on days characterized by long service time (e.g., Thursdays) loyal customers are more likely to switch to a rival grocer, arguably because 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 loyal Shufersal customers and shows the percentage of orders from rival grocers. According to the figure, about 64% of the switches by loyal Shuferasl customers are to Rami Levy and Victory, which we consider aggressive entrants.

Finally, in Appendix A, we present a version of the newsvendor problem. Our version of the model implicitly assumes that customers do not have (very) different service time elasticities on different days of the week. While we cannot test this formally, we note that almost all 15,252 individuals who used MySupermarket more than 10 times during the sample period shopped at least once on Wednesday or at least once on Saturday, and 70% of them shopped at least once on both days. Panel (a) of Figure B5 shows the average basket price by day of the week, based on all the orders that we observe. Panel (b) shows the average basket price by day of the week, based on orders placed by individuals who used MySupermarket more than 10 times during the sample period and shopped at least once on Wednesday or on Saturday. The figure shows that the price of the orders is not very different on different days of the week. The fact that most customers shopped at least once on both Wednesday and Saturday and that shopping patterns do not seem different on these days of the week suggests that the assumption of similar elasticity of demand with respect to service time is plausible.

Figure B1: Online shopping platform – basket price

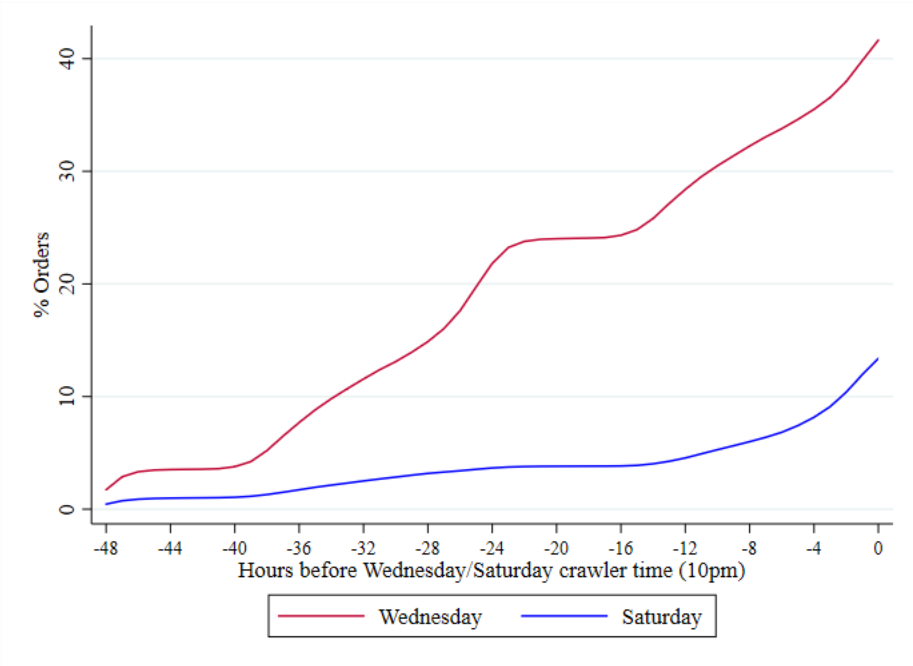
Notes: The figure shows a screenshot from MySupermarket.co.il webpage, where consumers observe the basket price offered by each of the online grocers that offer service to their address and can choose the retailer they want to order from. For instance, Rami Levy offers the cheapest price for this basket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

Figure B2: Online shopping platform – service time



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

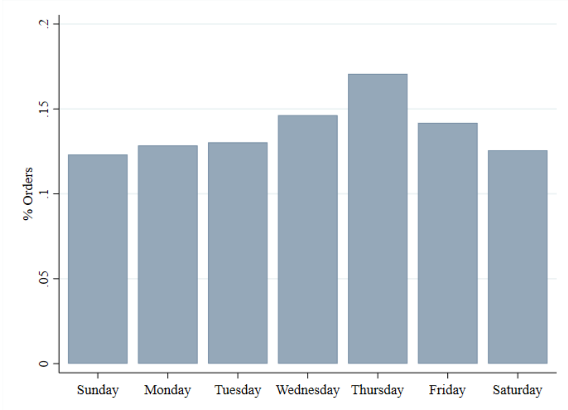
Figure B3: Cumulative number of orders before the crawler time on Wednesday and Saturday



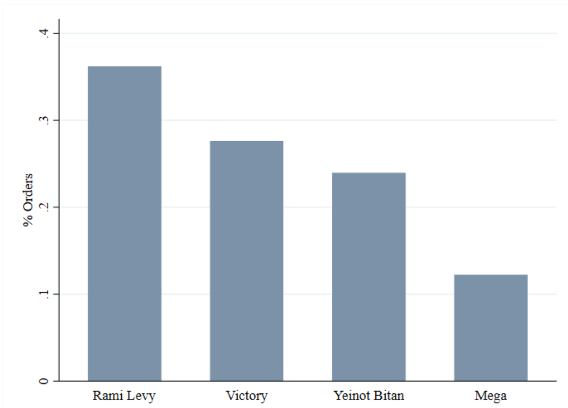
Notes: The figure shows the percentage (normalized by the total number of orders overall) of orders through MySupermarket in the 48 hours that precede the crawler time at midnight on Saturdays and Wednesdays. The figure demonstrates that demand is considerably higher (about three times more) on pre-weekend days (Tuesdays and Wednesdays) than on weekends (Fridays and Saturdays).

Figure B4: Customers' switching patterns at MySupermarket

(a) Switching patterns, by days of the week



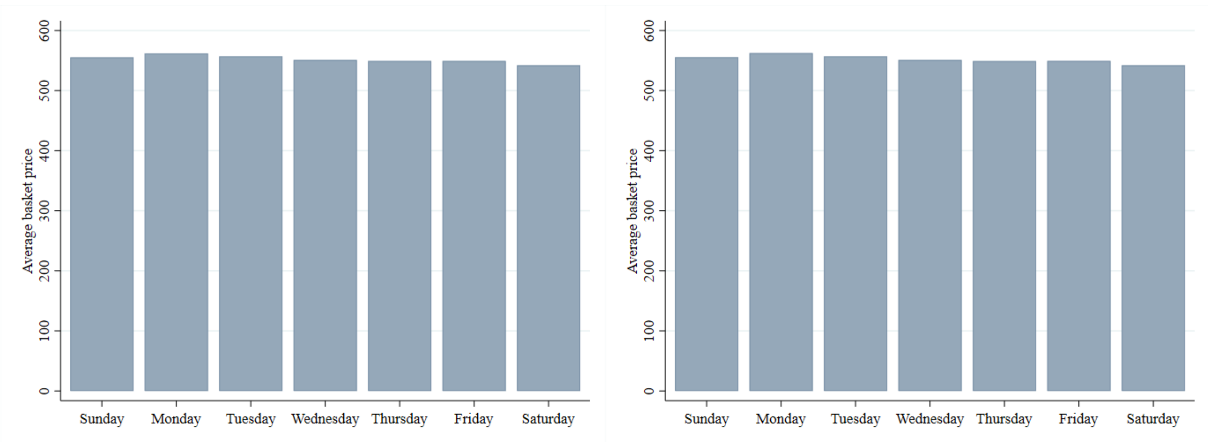
(b) Switching patterns, by online grocer



Notes: The figure shows 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, with at least 60 percent of orders submitted to the same online grocer. There are 9,182 loyal customers in the sample, and 2,861 are loyal Shufersal customers. Panel (a) shows the percentage of orders by all 9,182 loyal customers that were not submitted to their regular grocer, by day of the week. As can be seen in the Panel, on days characterized by long service time (e.g., Thursdays) loyal customers are more likely to switch to a rival grocer: more than 17 percent of switches occur on Thursdays, compared to about 12.5 percent of switches to a rival grocer on Saturdays and on Sundays. These differences are statistically significant. Arguably, the rise in the number of switches on these days happens because customers are unsatisfied with the service time offered by their regular grocer. Panel (b) focuses on loyal Shufersal customers and shows the percentage of orders placed by these customers with rival grocers. As can be seen in the panel, most of the switches by loyal Shufersal customers are to Rami Levy and Victory, which we consider aggressive entrants.

Figure B5: Average basket price, by day of the week

(a) All customers (b) Frequent customers who shop on Wed. and Sat.



Notes: The figure shows the average basket price of orders placed through MySupermarket, by the day of the week. Panel (a) shows the average basket price of all orders placed by all customers. Panel (b) shows the average basket price of orders placed by customers who used MySupermarket more than 10 times during the sample period and ordered at least once on Wednesday or on Saturday.

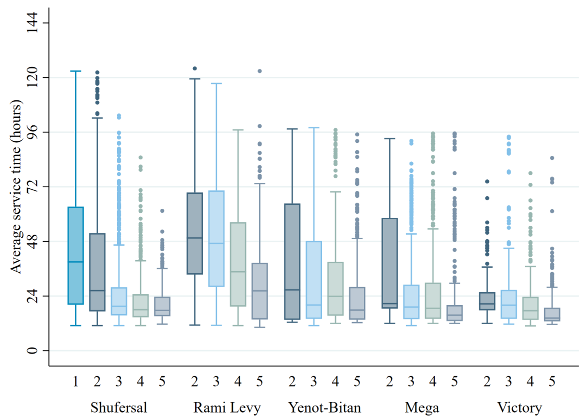
Appendix C Additional Descriptive Statistics

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

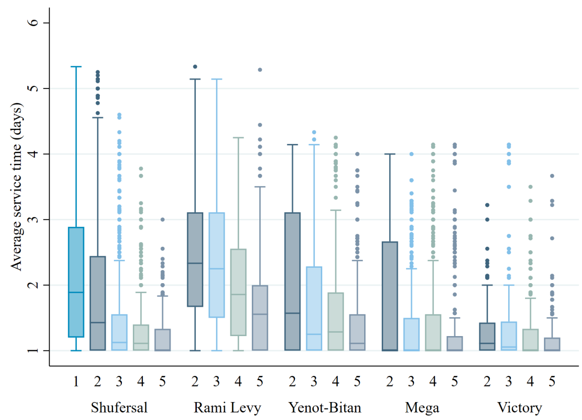
Notes: Black dots show the location of the 172 local markets covered in our sample. Red dots show the location of Shufersal's 32 fulfillment centers.

Figure C2: Service time distribution, by retailer and competition level

(a) Service time in hours



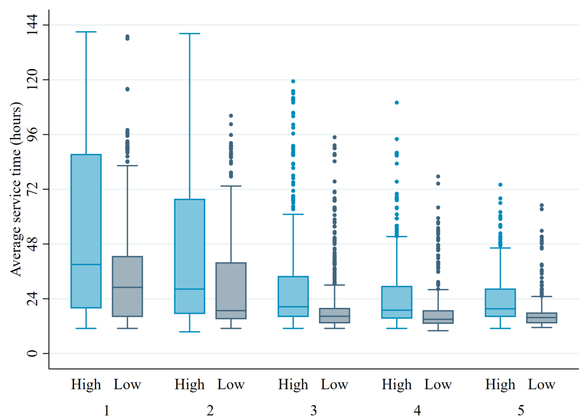
(b) Service time in days



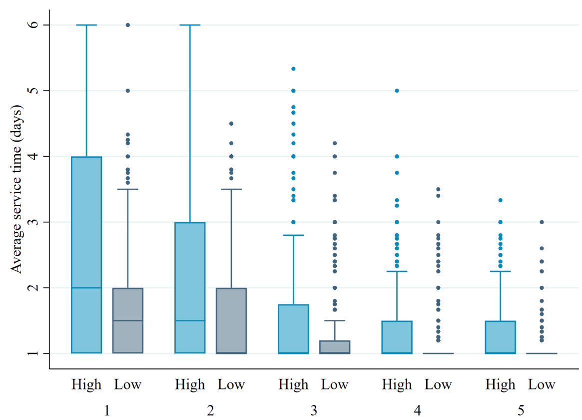
Notes: The figure shows box-and-whisker plots for the distribution of service time for each grocer, by the number of active online grocers in each local market. Panels (a) and (b) show the distribution of service time in hours and days, respectively. The panels reveal that in more competitive markets, service time is shorter and orders are usually delivered within a day. On the other hand, in less competitive markets service time is longer and exhibits greater variation.

Figure C3: The incumbent's service time distribution, by competition and demand levels

(a) Service time in hours



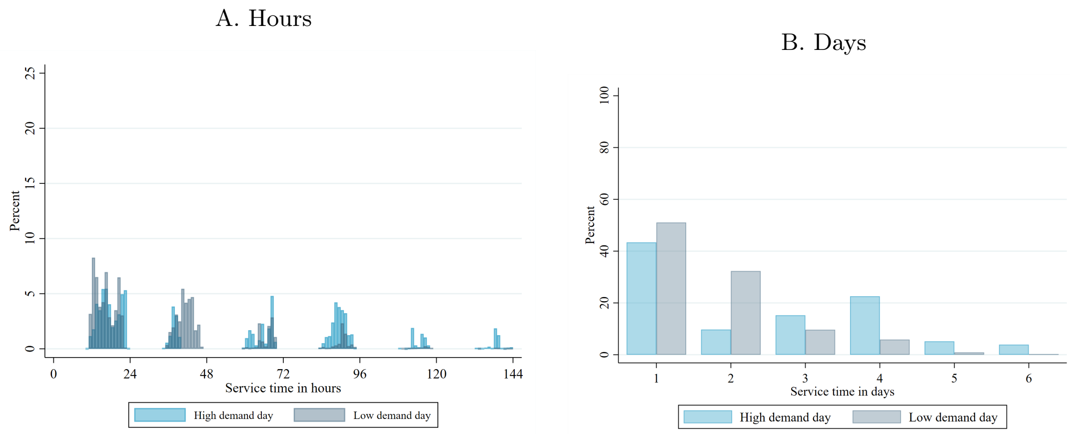
(b) Service time in days



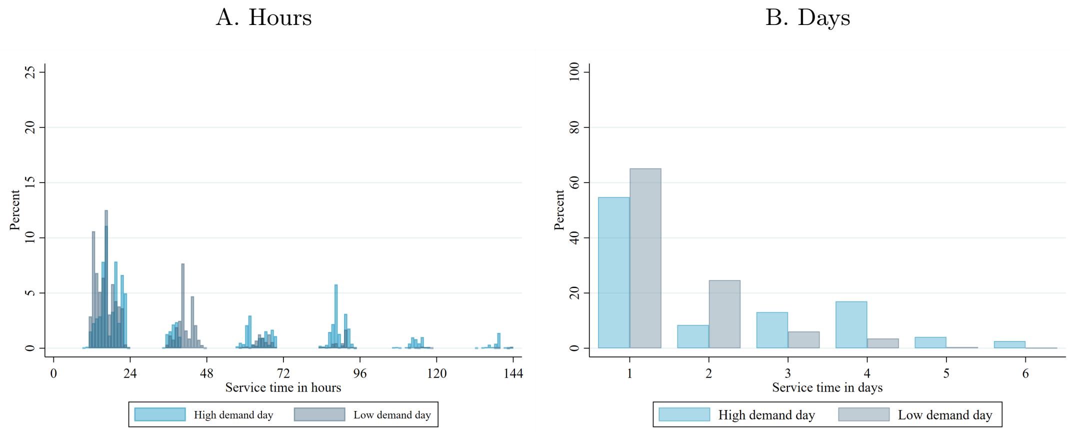
Notes: The figure shows box-and-whisker plots for the distribution of Shufersal's service time, by the number of active online grocers in each local market. Panels (a) and (b) show the distribution of Shufersal's service time in days, separately for high- and low-demand days. The panels reveal that on low-demand days, Shufersal's service time is shorter and orders are usually delivered within a day. On the other hand, on high-demand days Shufersal's service time is longer and exhibits more variation.

Figure C4: The incumbent's service time hours distribution by competition and demand levels

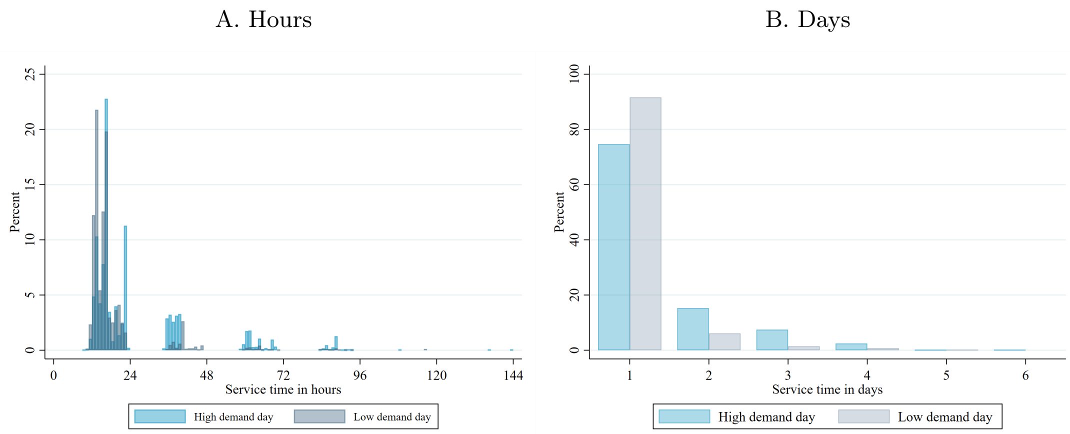
(a) Monopolistic markets



(b) Duopolistic markets



(c) Competitive markets

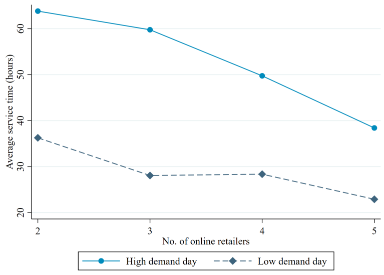


Notes: The figure plots the distribution of Shufersal's service time in hours and days on high- and low-demand days. The figure shows the distribution in the monopolistic markets (Subfigure (a)), duopolistic markets (Subfigure (b)) and competitive markets with 3 or more active online retailers (Subfigure (c)). On high-demand days, service is not available for 40 to 48 hours due to the short working day on Fridays(To account for this, we subtract 24 hours from deliveries scheduled after Saturday/Shabbbat). The subfigures show that same-day delivery is frequent on both high- and low-demand days and in both concentrated and competitive markets; however, it is more common on low-demand days and in competitive markets.

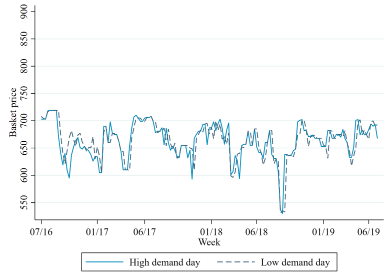
Figure C5: Service time and prices as a function of competition & demand (entrants)

(a) Rami Levy

A. Service time

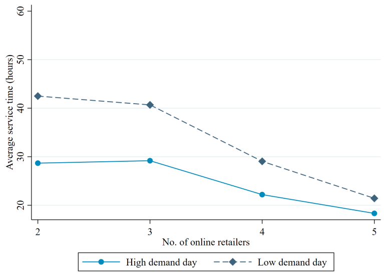


B. Basket price

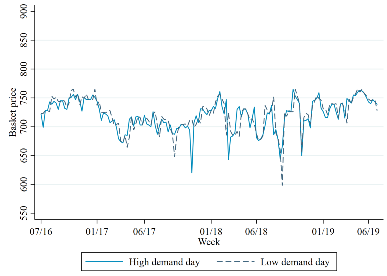


(b) Victory

A. Service time

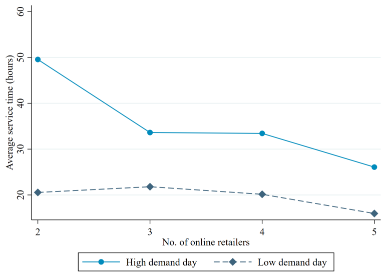


B. Basket price

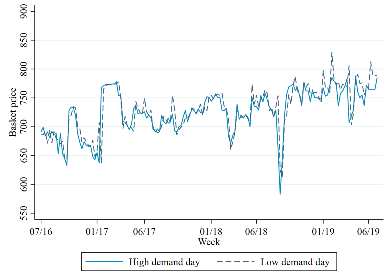


(c) Yenot-Bitan

A. Service time

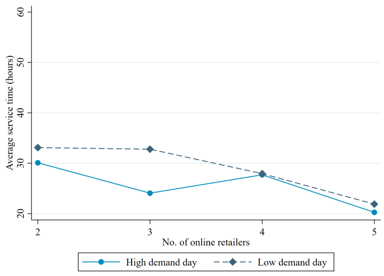


B. Basket price

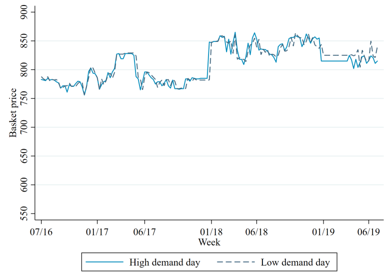


(d) Mega

A. Service time



B. Basket price

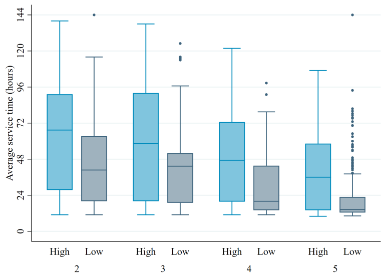


Notes: Panels A show the average service time offered by each grocer (except Shufersal) as a function of the number of active online grocers in the local market, separately for low- and high-demand days. Panels B show the daily price of a basket of 52 products sold by each of the online grocers, separately for Sundays and Thursdays (low- and high-demand days, respectively). The subfigures show that service time decline 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.

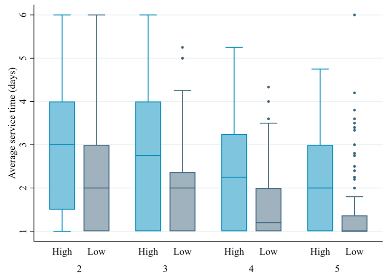
Figure C6: Service time and prices as a function of competition and demand (entrants)

(a) Rami Levy

A. Service time in hours

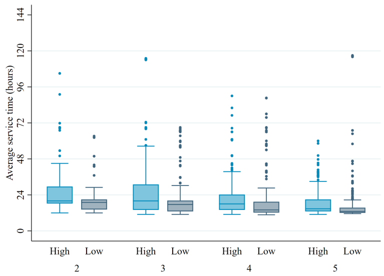


B. Service time in days

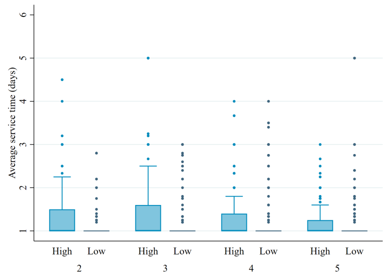


(b) Victory

A. Service time in hours

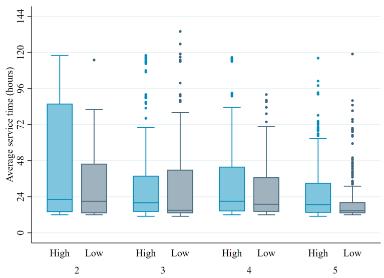


B. Service time in days

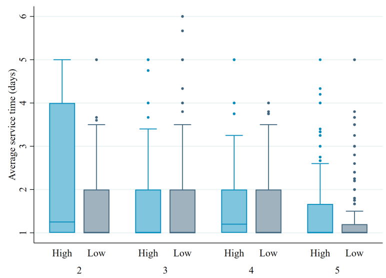


(c) Yenot-Bitan

A. Service time in hours

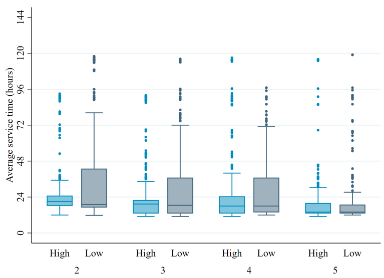


B. Service time in days

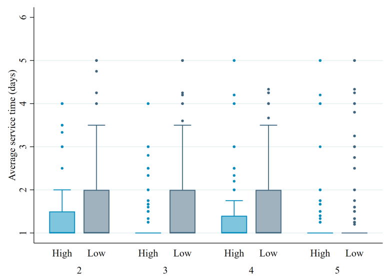


(d) Mega

A. Service time in hours

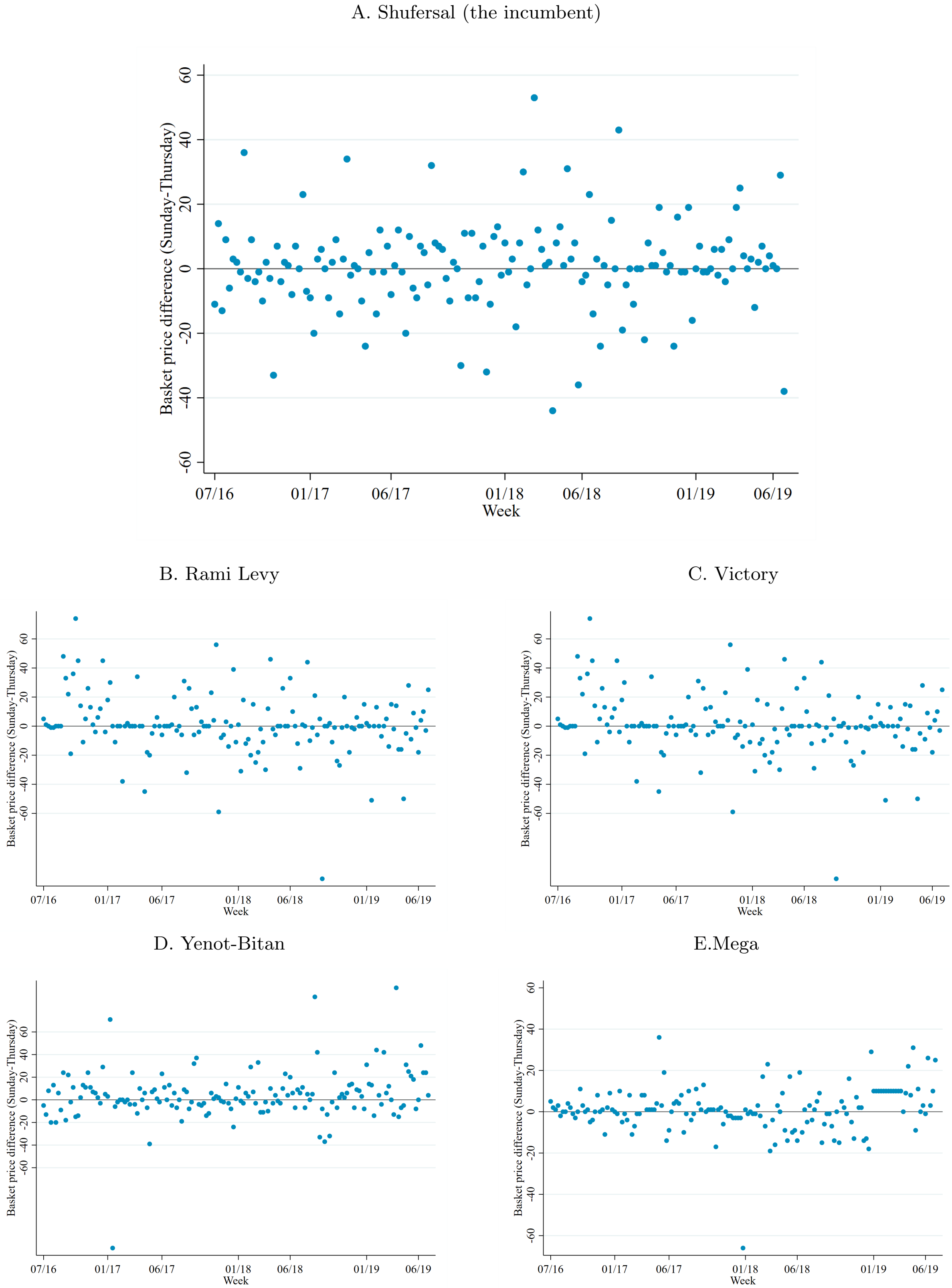


B. Service time in days



Notes: The figure shows box-and-whisker plots for the distribution of each of grocers' (except Shufersal) service time, by the number of active online grocers in each local market. Panels A and B the distribution of each of the grocers' (except Shufersal) service time, separately for high- and low-demand days, in hours and days, respectively. The panels reveal that most grocers offer shorter service times on low-demand days and in competitive markets.

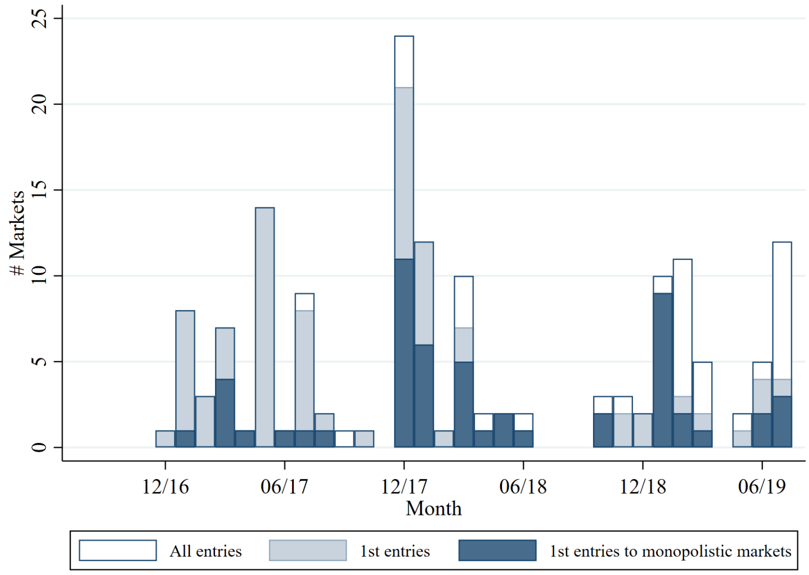
Figure C7: Basket price differences between low- and high-demand days



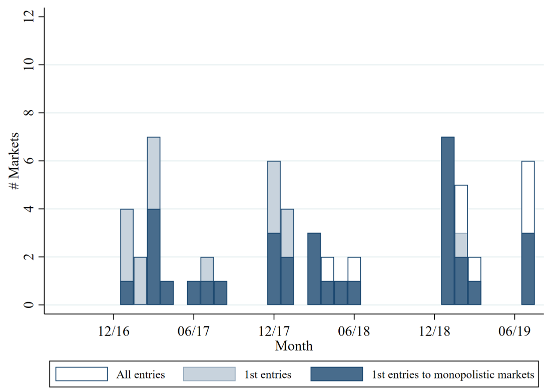
Notes: The figure shows the difference in the daily price of a basket of 52 products sold on each grocer's online channel between Sunday and Thursday of each week from August 2016 to July 2019.

Figure C8: The distribution of the timing of entries

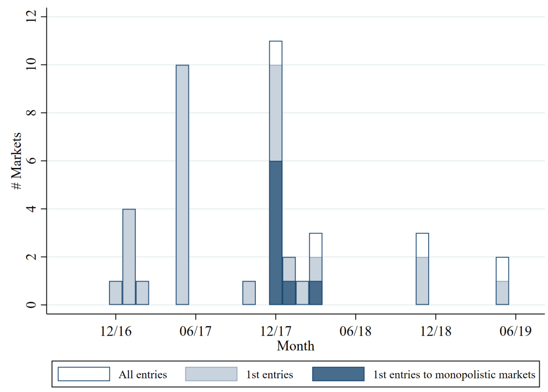
A. Entries by all grocers



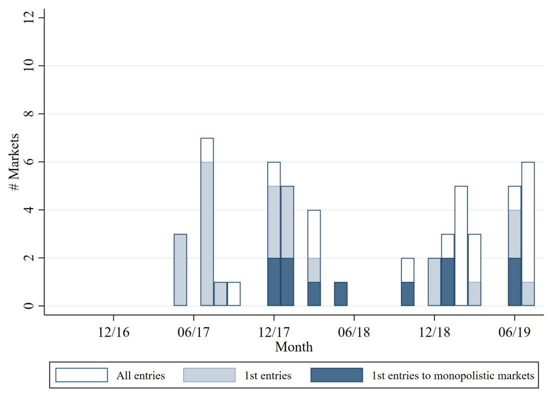
B. Entries by Rami Levy



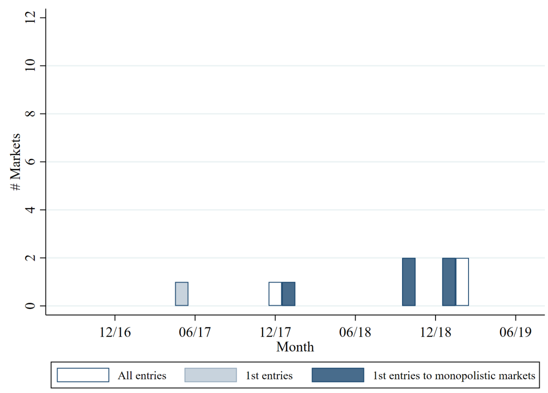
C. Entries by Victory



D. Entries by Yenot Bitan

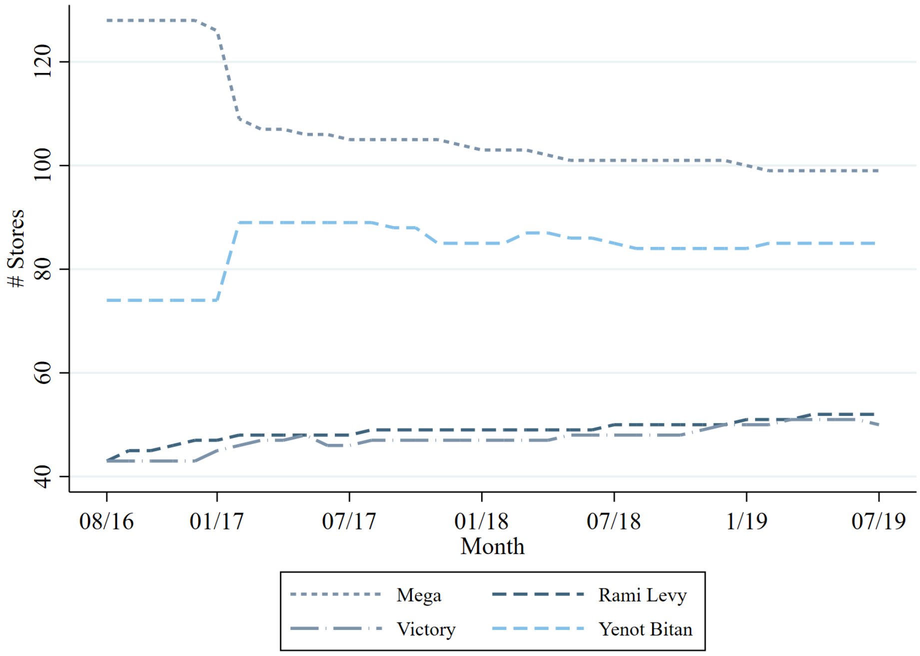


E. Entries by Mega



Notes: The figure shows the number of markets that experienced entry in each month during the sample period, the number of markets that experienced a first entry (light-blue bars), and the number of monopolistic markets that experienced a first entry (dark-blue bars). Panel A shows entries by all grocers. Panels B, C, D, and E shows entries by Rami Levy, Victory, Yenot Bitan, and Mega, respectively. The panels reveal that the timing of entry by Rami Levy and Yenot Bitan is spread over three years of the sample period and the timing of entry by Victory is more concentrated around specific times. Moreover, the panels show that most entries into monopolistic markets were by Rami Levy and Victory.

Figure C9: The number of physical stores operated by entrants



Notes: The figure plots the number of physical stores operated by each of the online grocers over the sample period. The figure shows that Rami Levy and Victory increased the number of stores they operate by 9 and 7, respectively, and Yenot Bitan increased the number of its stores at the expense of Mega.

Appendix D Alternative Estimators for TWFE DiD

As mentioned in Section 3.1, the event study coefficients may 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, 2021, De Chaisemartin and d'Haultfoeuille, 2020, Goodman-Bacon, 2021, Borusyak, Jaravel, and Spiess, 2022 and Callaway and Sant'Anna, 2021). 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 (2021) and Borusyak, Jaravel, and Spiess (2022).

Sun and Abraham (2021) estimate the dynamic effect for each treatment cohort, and then calculate the weighted average of these cohort-specific estimates, with weights equal to each cohort's respective sample share. They use either never-treated cohorts as the control group or, in their absence, the "last cohort treated".[38] 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 are normalized by the total event time periods we are estimating. Figure D1 shows the estimation results using Sun and Abraham (2021) approach. The dark-blue circles indicate 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 pre-entry treated markets. The light-blue diamonds indicate the estimated coefficients from an estimation that uses "last cohort treated" (markets that experienced entry in the last month of the sample) as the control group.[39] The results are qualitatively similar to those in the main text. Callaway and Sant'Anna (2021) require an unconditional parallel trends assumption and no anticipation during the pre-treatment period. While we discuss the validity of the parallel trends assumption in Section 4, the anticipation effect in the two months before entry might bias the results. Accordingly, we also use Borusyak, Jaravel, and Spiess (2022) estimator to verify that our results are unbiased.

Borusyak, Jaravel, and Spiess (2022) provide an imputation estimator that 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, Jaravel, and Spiess (2022) require that the parallel trends assumption based on a linear function of unit and time fixed effects hold, and allow for a shift in the treatment period when there is a known pre-treatment anticipation. Hence, we are able to allow for two months of anticipation with the Borusyak, Jaravel, and Spiess (2022) estimation method.

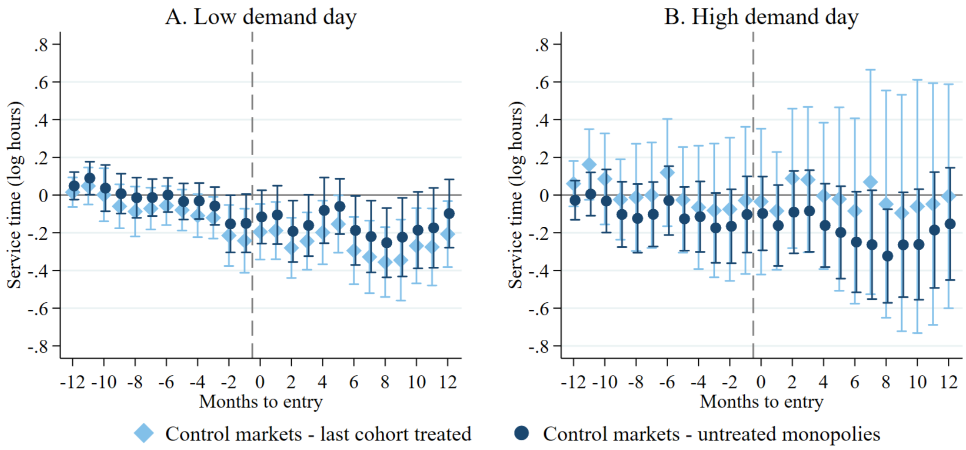
[38] Sun and Abraham (2021) can be considered as a specific case of Callaway and Sant'Anna (2021) estimator. In a setting where there is no never-treated cohort, Sun and Abraham (2021) use the last cohort to be treated as the control group, whereas Callaway and Sant'Anna (2021) use the set of not-yet-treated cohorts.

[39] We do not use all the set of untreated markets as the control group since according to Callaway and Sant'Anna (2021) always treated units should be dropped.

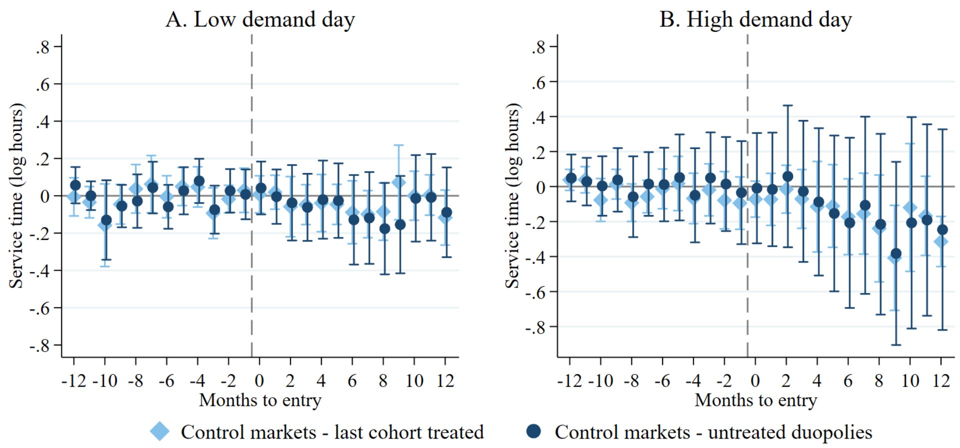
Figure D2 shows the estimation results from using Borusyak, Jaravel, and Spiess (2022) approach, assuming a two-month shift in treatment effect, i.e., $t-2$, and using untreated markets that have at least the same competition level as treated markets (dark-blue circles) or only untreated markets that have the same competition level as treated market pre-entry (light signs). The results are similar to those in Figure 6, in particular, the pre-entry effect, which suggests that our two-way fixed effects estimates for the change in service time before entry are free of both contaminated effects from other periods and heterogeneity treatment effects. The estimates in Figure D2 also show a significant decrease in the incumbent's service time after entry both on high-demand days and in more competitive markets. This is consistent with the results in Tables 2 and 4 and in Figure E1 in Appendix E.

Figure D1: Sun and Abraham (2021) estimator for the effect of entry on incumbent's service time

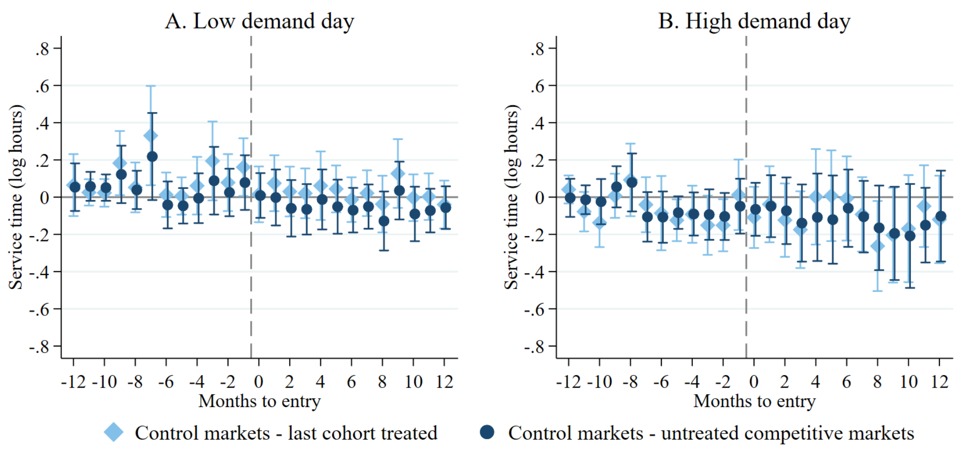
(a) Pre-entry monopoly markets



(b) Pre-entry duopolistic markets



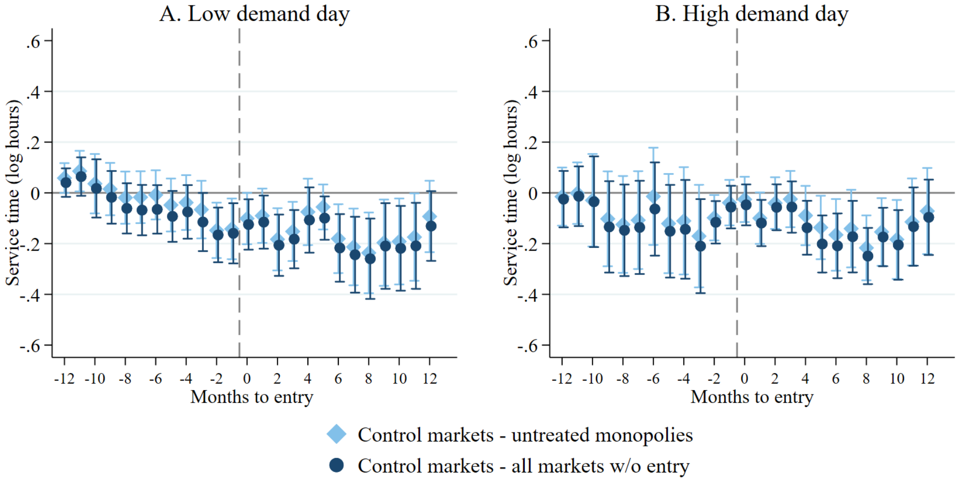
(c) Pre-entry competitive markets



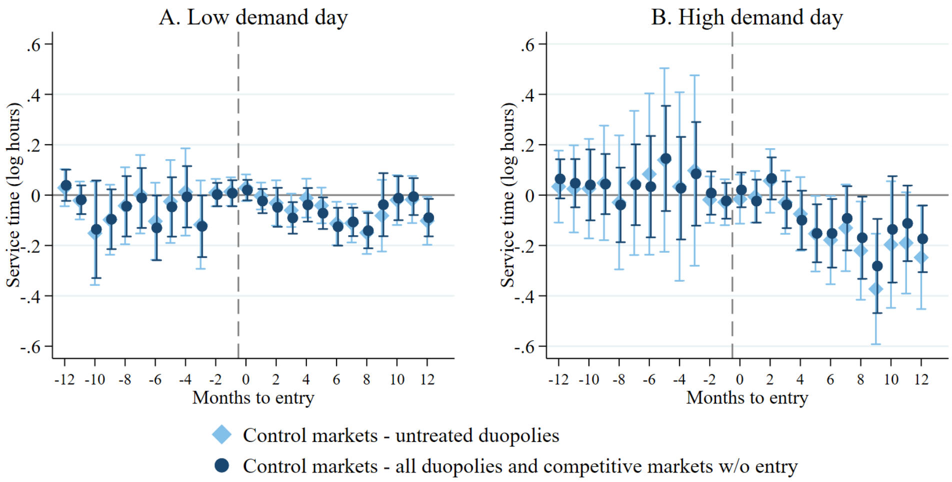
Notes: The figure plots the coefficients of β_j for j ranging from -12 to 12 and their 95 percent confidence intervals. The coefficients are obtained from estimating Equation (1) for different subsamples, using Sun and Abraham (2021) estimation method. Standard errors are clustered at the market level. The dependent variable is the incumbent's log service time in the local market. The estimated results are shown separately for low-demand days and for high-demand days. The figure reports the estimated effects of entry into monopolistic markets (sub-figure (a)), duopolistic markets (sub-figure (b)), and all other markets (sub-figure (c)). The light-blue diamonds indicate the estimated coefficients from a sample that uses as the control group the "last cohort treated," that is, the set of markets that experienced entry in the last month of the sample. The dark-blue circles indicate the coefficients from a sample that uses as the control group the set of markets that did not experience entry and have the same competition level as the treated markets (i.e., the set of never-treated markets since according to Sun and Abraham (2021) always treated units should be dropped). All specifications include market and month fixed effects. The results are qualitatively similar to those of the two-way fixed effects in the main text.

Figure D2: Borusyak, Jaravel, and Spiess (2022) estimator for the effect of entry on incumbent's service time

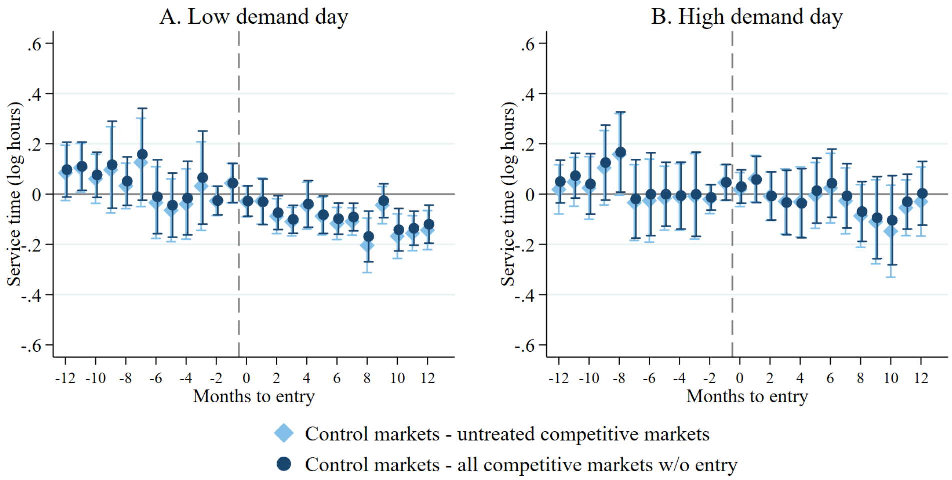
(a) Pre-entry monopoly markets



(b) Pre-entry duopolistic markets



(c) All markets

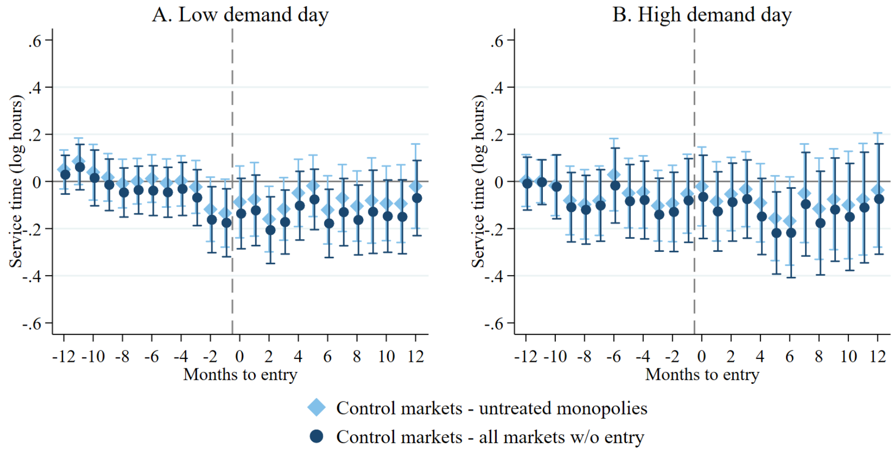


Notes: The figure plots the coefficients of β_j for j ranging from -12 to 12 and their 90 percent confidence intervals. The coefficients are obtained from estimating Equation Equation (1) for different subsamples, using Borusyak et al. (2022) estimation method and assuming two months of shift in treatment period $(t-2)$. Standard errors are clustered at the market level. The dependent variable is the incumbent's log service time in the local market. The estimated results are shown separately for low-demand days and for high-demand days. The figure reports the estimated effects of entry into monopolistic markets (sub-figure (a)), duopolistic markets (sub-figure (b)), and all other markets (sub-figure (c)). The light-blue diamonds indicate the estimated coefficients from a sample that uses as the control group the set of markets that did not experience entry and have the same competition level as treated markets. The dark-blue circles indicate the coefficients from a sample that uses as the control group the set of markets that did not experience entry and have at least the same competition level as the treated markets. All specifications include market and month fixed effects. The results are qualitatively similar to those of the two-way fixed effects in the main text.

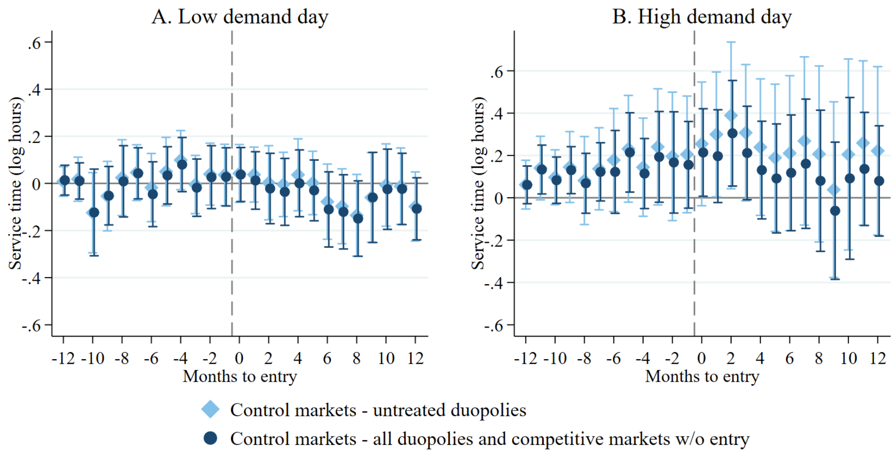
Appendix E Robustness Checks

Figure E1: The effect of entry on service time, by competition and demand levels (with controls)

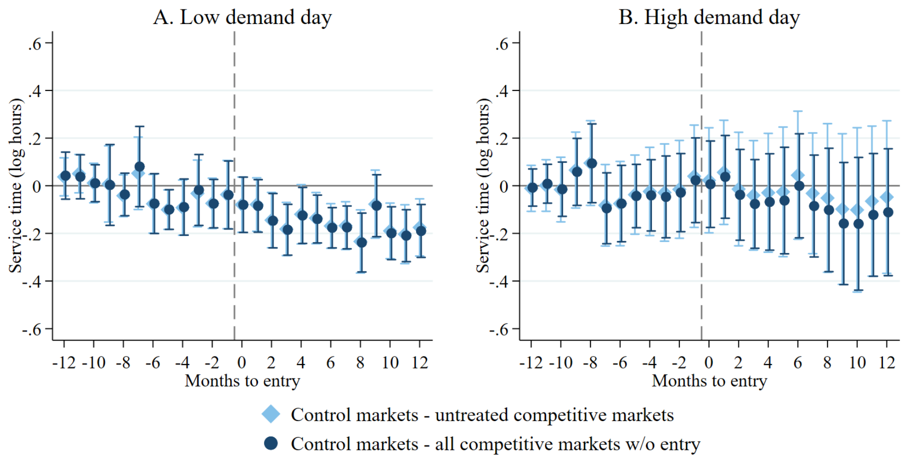
(a) Pre-entry monopolistic markets



(b) Pre-entry duopolistic markets



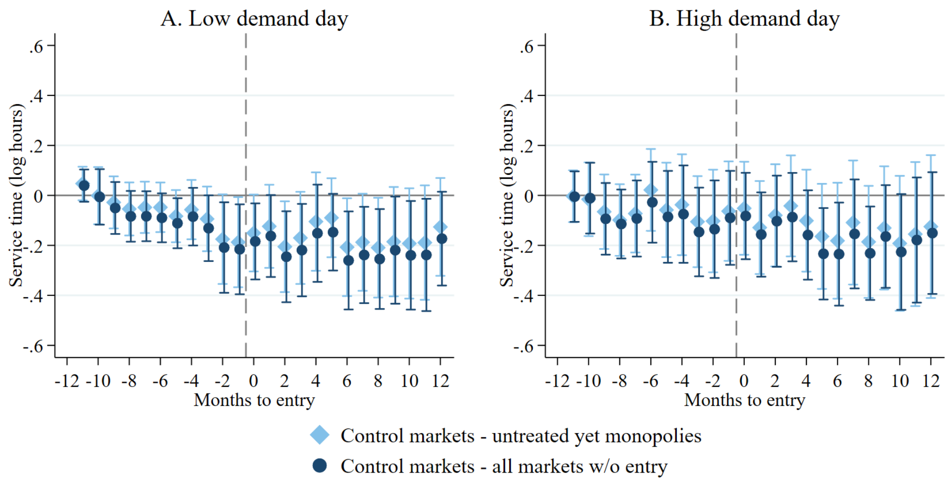
(c) Pre-entry competitive markets



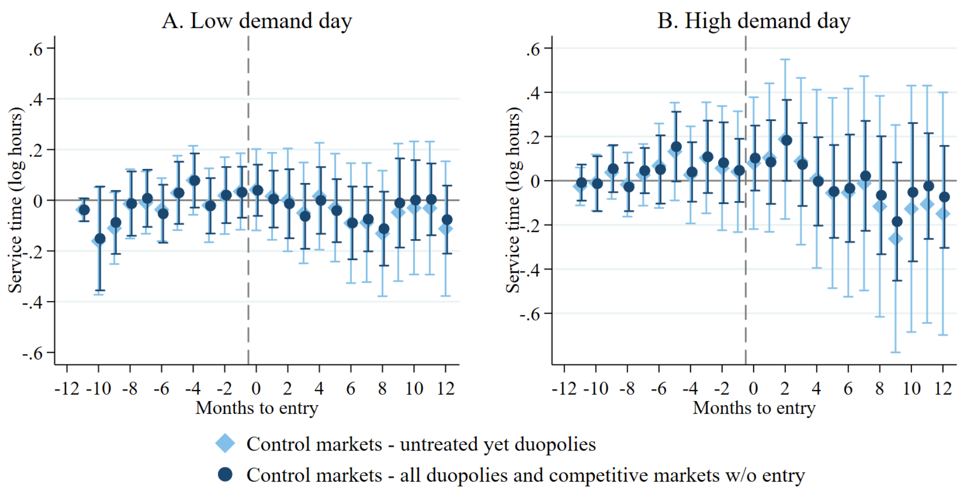
Notes: The figure replicates Figure 6 with specifications that include month fixed effects interacted with quantiles for market growth instead of month fixed effects, and a vector of time-variant variables (i.e., the number of physical stores operated by rivals in the local market within a 10km radius, dummies for exits and subsequent entries, and a specific Shufersal fulfillment center linear time trend). The results are qualitatively similar to those in Figure 6.

Figure E2: The effect of entry on service time, by competition and demand levels (trimming)

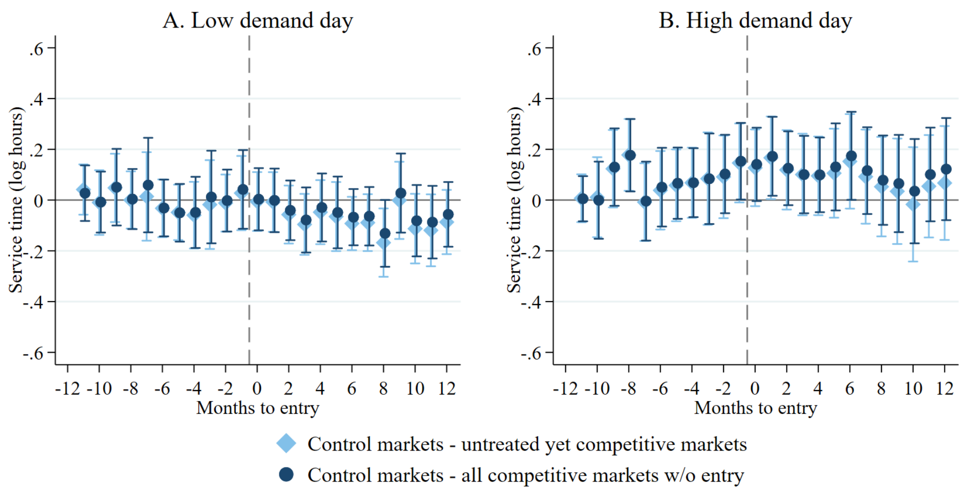
(a) Pre-entry monopolistic markets



(b) Pre-entry duopolistic markets



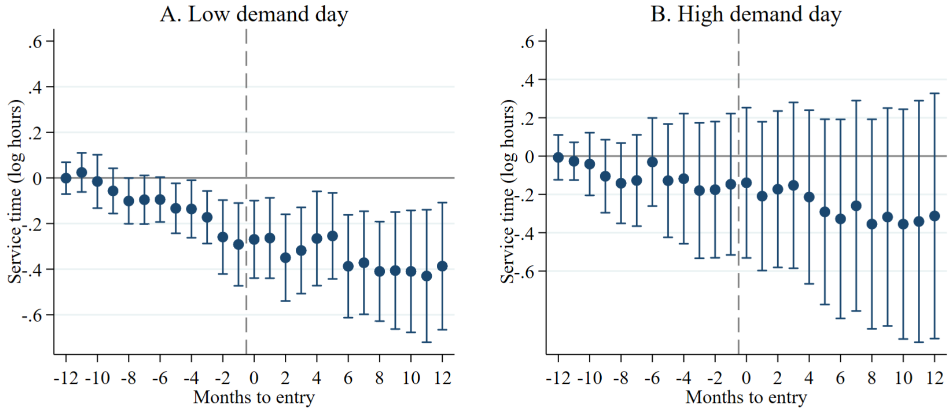
(c) Pre-entry competitive markets



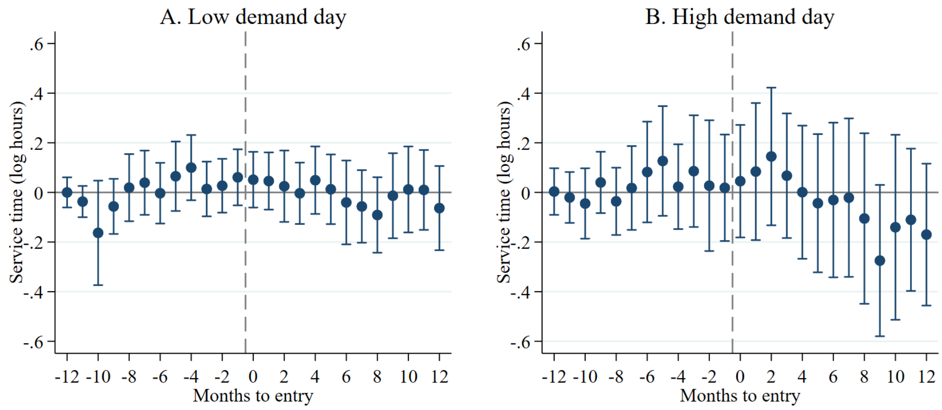
Notes: The figure replicates Figure 6 while restricting the sample to observations within 12 months before and after entry and the excluded period is 12 months before entry. The results are qualitatively similar to those in Figure 6.

Figure E3: The effect of entry on the incumbent's service time using treated markets only

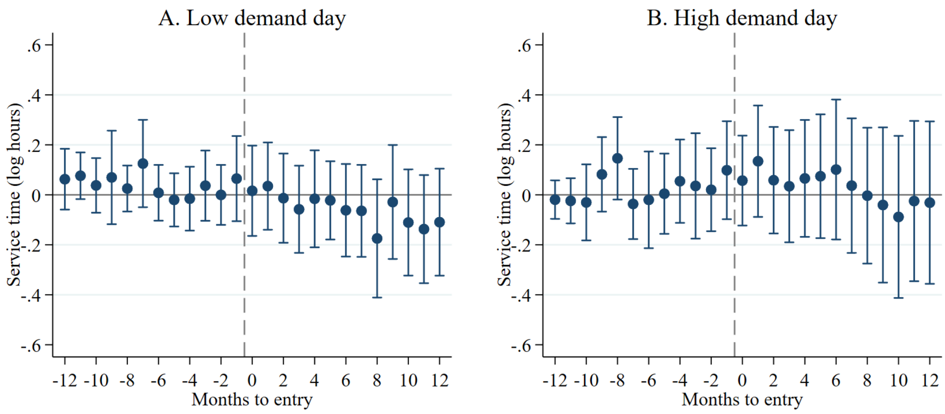
(a) Pre-entry monopolistic markets



(b) Pre-entry duopolistic markets



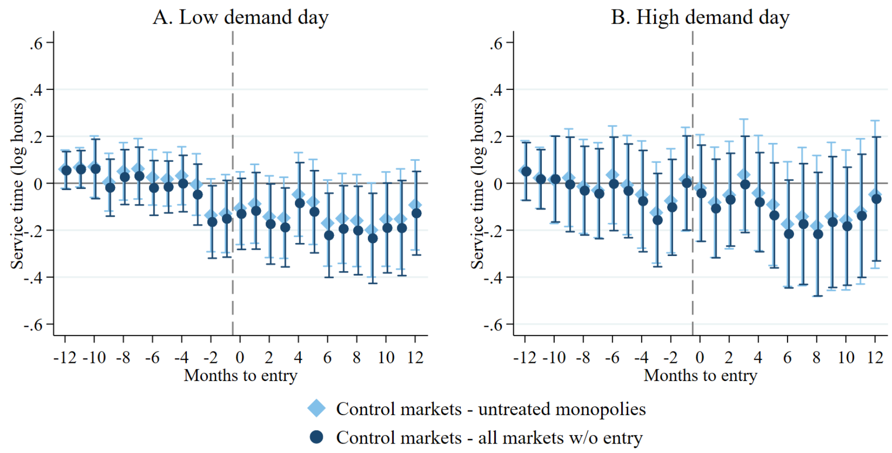
(c) Pre-entry competitive markets



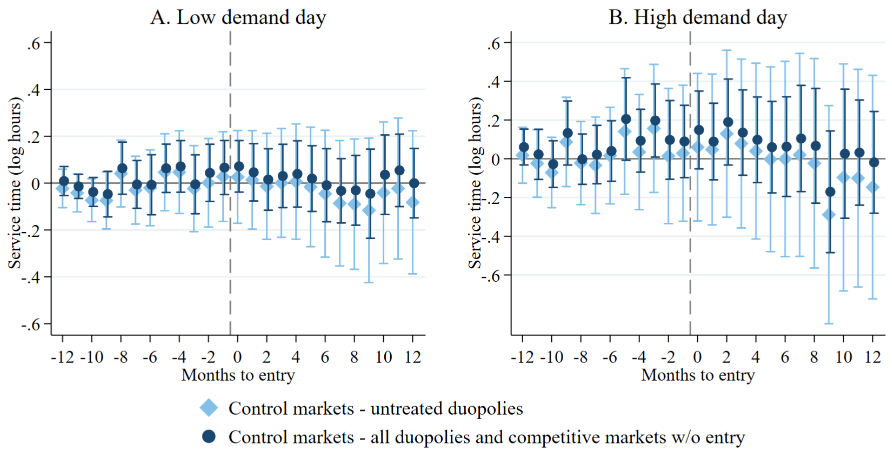
Notes: The figure replicates Figure 6 but uses a sample that includes only treated markets (markets that experienced an entry during the sample period). The results are qualitatively similar to those in Figure 6.

Figure E4: The effect of entry on service time, by competition and demand levels (excluding weeks with holidays)

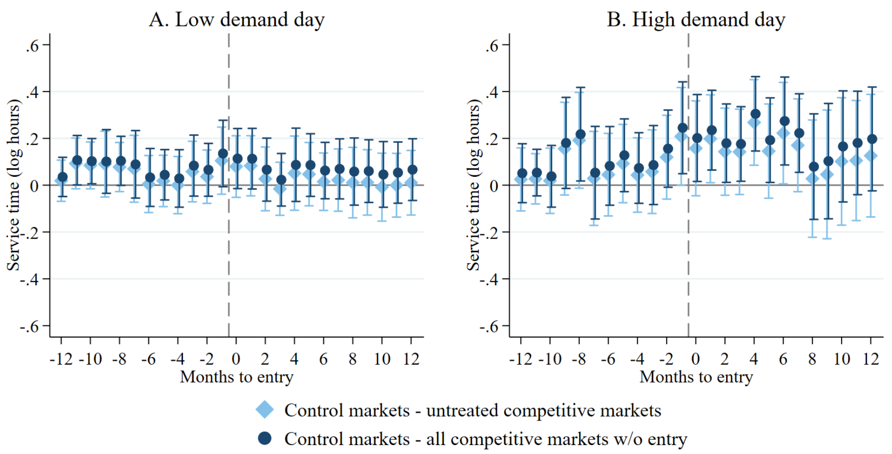
(a) Pre-entry monopolistic markets



(b) Pre-entry duopolistic markets

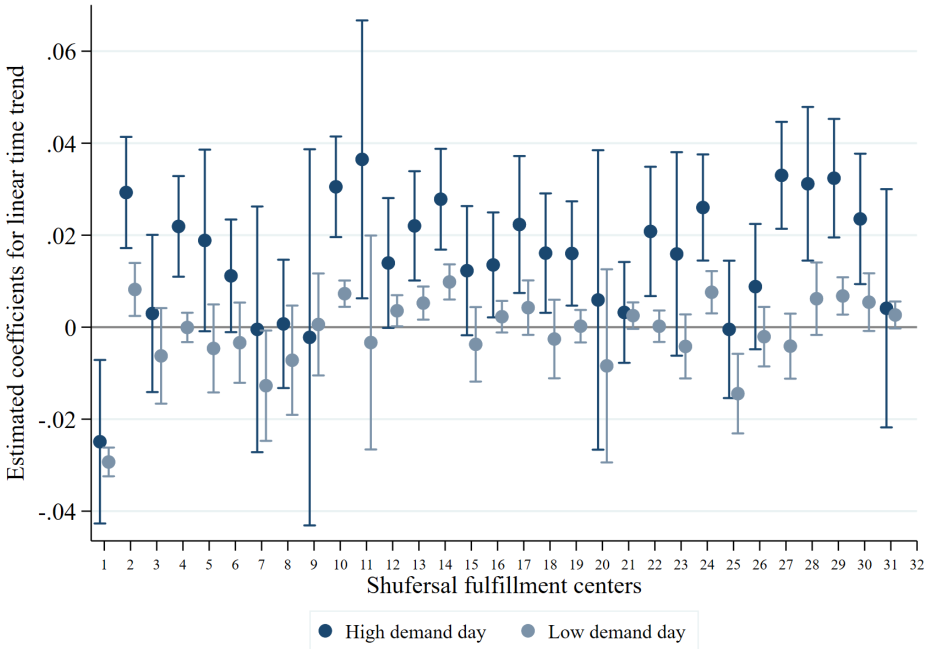


(c) Pre-entry competitive markets



Notes: The figure replicates Figure 6 but uses a sample that excludes weeks with holidays. The results are qualitatively similar to those in Figure 6.

Figure E5: Test for different linear time trends in Shufersal's fulfillment centers



Notes: The figure plots the coefficients from regressing the log of service time on time trend for each fulfillment center controlling for market and time fixed effects, separately for low- and high-demand days. The figure shows that some centers experienced an improvement in service time, mainly on high-demand days, during the sample period.

Table E1: The effect of entry on Shufersal's service time accounting for the presence of rivals' physical stores

	Low-demand day				High-demand day			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Pre-entry monopolistic markets								
Pre-entry	-0.159**	-0.157**	-0.160**	-0.159**	-0.039	-0.043	-0.037	-0.038
	(0.064)	(0.064)	(0.064)	(0.064)	(0.057)	(0.055)	(0.057)	(0.056)
Post-entry	-0.108**	-0.110**	-0.105**	-0.108**	-0.054	-0.050	-0.060	-0.057
	(0.052)	(0.051)	(0.051)	(0.052)	(0.047)	(0.046)	(0.047)	(0.046)
Markets	106				106			
Markets with entry	54				54			
N	3,804				3,809			
Panel B: Pre-entry duopolistic markets								
Pre-entry	0.041	0.044	0.040	0.036	0.043	0.043	0.043	0.034
	(0.039)	(0.039)	(0.039)	(0.038)	(0.059)	(0.058)	(0.059)	(0.059)
Post-entry	-0.018	-0.015	-0.017	-0.024	0.031	0.031	0.031	0.021
	(0.036)	(0.037)	(0.036)	(0.034)	(0.060)	(0.059)	(0.060)	(0.058)
Markets	53				53			
Markets with entry	32				32			
N	1,901				1,901			
Panel C: Pre-entry competitive markets								
Pre-entry	-0.006	-0.006	-0.005	-0.006	0.035	0.035	0.033	0.034
	(0.037)	(0.037)	(0.037)	(0.037)	(0.041)	(0.042)	(0.042)	(0.041)
Post-entry	-0.085**	-0.084**	-0.085**	-0.085**	-0.010	-0.007	-0.012	-0.012
	(0.037)	(0.038)	(0.037)	(0.037)	(0.046)	(0.048)	(0.046)	(0.046)
Markets	48				48			
Markets with entry	34				34			
N	1,723				1,718			
Controls:								
Market FE	✓	✓	✓	✓	✓	✓	✓	✓
Time FE # market growth	✓	✓	✓	✓	✓	✓	✓	✓
Exits and additional entries	✓	✓	✓	✓	✓	✓	✓	✓
Fulfillment center time trend	✓	✓	✓	✓	✓	✓	✓	✓
# rivals' physical stores (5 km)	✓				✓			
# rivals' physical stores (15 km)		✓				✓		
Distance to rivals' 1st store			✓				✓	
Distance to rivals' 2nd store				✓				✓

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

Notes: The table replicates Table 2 except that in each column, the control variable for the number of stores operated by rivals within a 10 km radius is replaced with an alternative control variable to account for the presence and for the opening of rivals' physical stores. The dependent variable in Columns (1)–(4) is Shufersal's log service time in the local market on Saturday night. The dependent variable in Columns (5)–(8) is Shufersal's log service time in the local market on Wednesday night. The control variable for the rivals' stores is the number of stores within a 5 km radius (Columns (1) and (5)), a 15km radius (Columns (2) and (6)) the control variable for rivals' physical stores is the number of stores within a 5 km radius (Columns (1) and (5)), the distance traveled between the market (the crawler address) and the rivals' first store (Columns (3) and (7)), and the distance traveled between the market (the crawler address) and the rivals' second store (Columns (4) and (8)). The results are qualitatively similar to those in Table 2, suggesting that the effect of entry on the incumbent's service time is not sensitive to the presence of an adjacent physical store.

Table E2: The effect of entry on Shufersal's service time, using alternate control markets

	Low-demand day			High-demand day		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Pre-entry monopolistic markets						
Pre-entry	-0.147**	-0.182***	-0.174**	-0.024	-0.023	0.016
	(0.065)	(0.066)	(0.069)	(0.054)	(0.063)	(0.060)
Post-entry	-0.096*	-0.153**	-0.145**	-0.017	-0.044	0.022
	(0.056)	(0.059)	(0.068)	(0.047)	(0.056)	(0.064)
Markets	85	75	54	85	75	54
Markets with entry	54	54	54	54	54	54
N	3,051	2,691	1,938	3,057	2,694	1,942
Panel B: Pre-entry duopolistic markets						
Pre-entry	0.043	0.037	0.043	0.037	0.026	0.0005
	(0.038)	(0.039)	(0.039)	(0.057)	(0.059)	(0.055)
Post-entry	0.009	-0.012	0.040	0.069	0.033	0.041
	(0.036)	(0.037)	(0.038)	(0.062)	(0.061)	(0.066)
Markets	39	46	32	39	46	32
Markets with entry	32	32	32	32	32	32
N	1,398	1,651	1,148	1,400	1,650	1,149
Panel C: Pre-entry competitive markets						
Pre-entry	-0.008	0.009	0.036	0.035	0.067	0.067
	(0.038)	(0.037)	(0.042)	(0.041)	(0.042)	(0.043)
Post-entry	-0.088**	-0.068*	-0.021	-0.010	0.040	0.046
	(0.037)	(0.038)	(0.047)	(0.047)	(0.042)	(0.045)
Markets	48	43	34	48	43	34
Markets with entry	34	34	34	34	34	34
N	1,723	1,544	1,220	1,718	1,538	1,217
Controls:						
Market FE	✓	✓	✓	✓	✓	✓
Time FE # market growth	✓	✓	✓	✓	✓	✓
Exits and additional entries	✓	✓	✓	✓	✓	✓
Fulfillment center linear time trend	✓	✓	✓	✓	✓	✓
# rivals' physical stores (10 km)	✓	✓	✓	✓	✓	✓

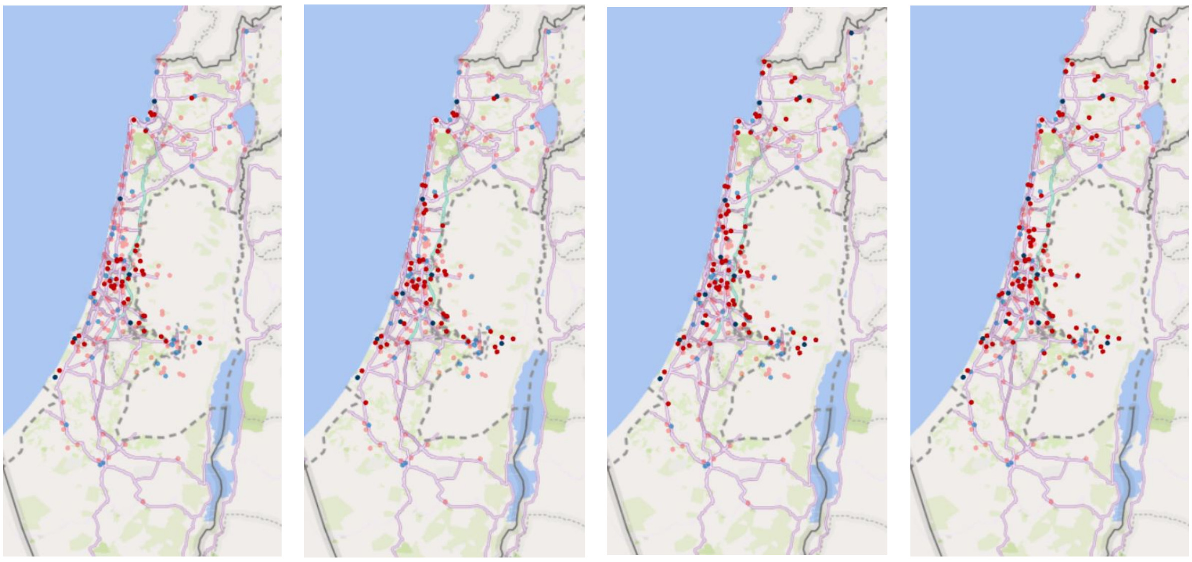
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Notes: The table replicates Table 2 using alternate control markets. The control group in Columns (1) and (3) includes markets that did not experience entry and have the same competition level as pre-entry treated markets. The control group in Columns (2) and (5) includes markets that did not experience entry and have a higher competition level than pre-entry treated markets. The sample in Columns (3) and (6) includes only treated markets (markets that experienced an entry during the sample period). The results are qualitatively similar to those in Table 2.

Appendix F Evidence for the mechanism behind entry decisions and the incumbent's anticipation

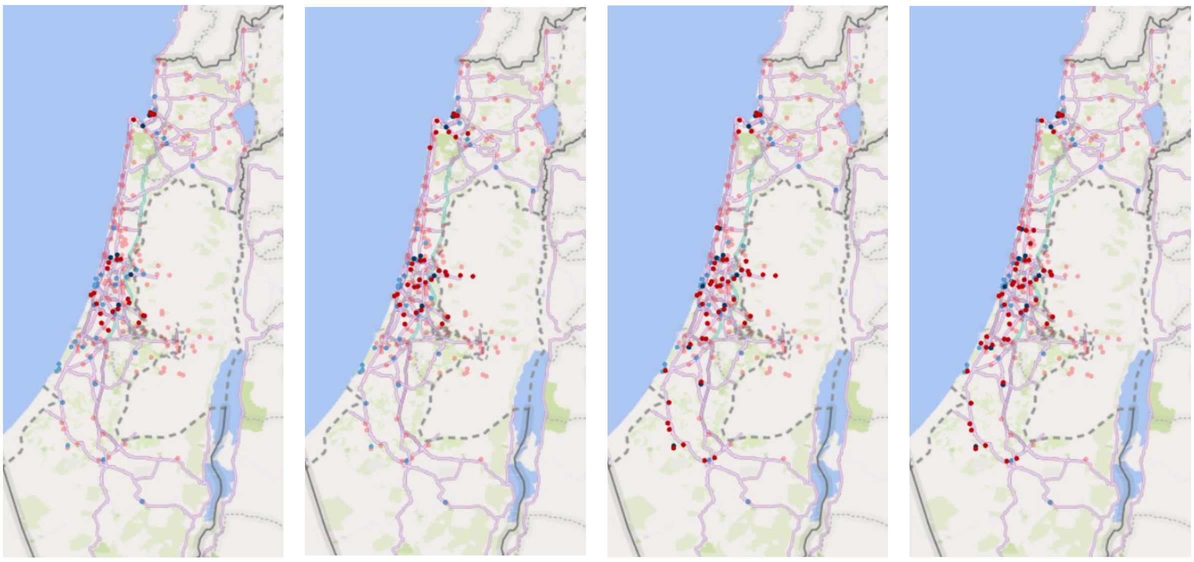
Figure F1: Rivals' online service coverage (red) and physical store locations (blue)

I. Rami Levy



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

II. Victory

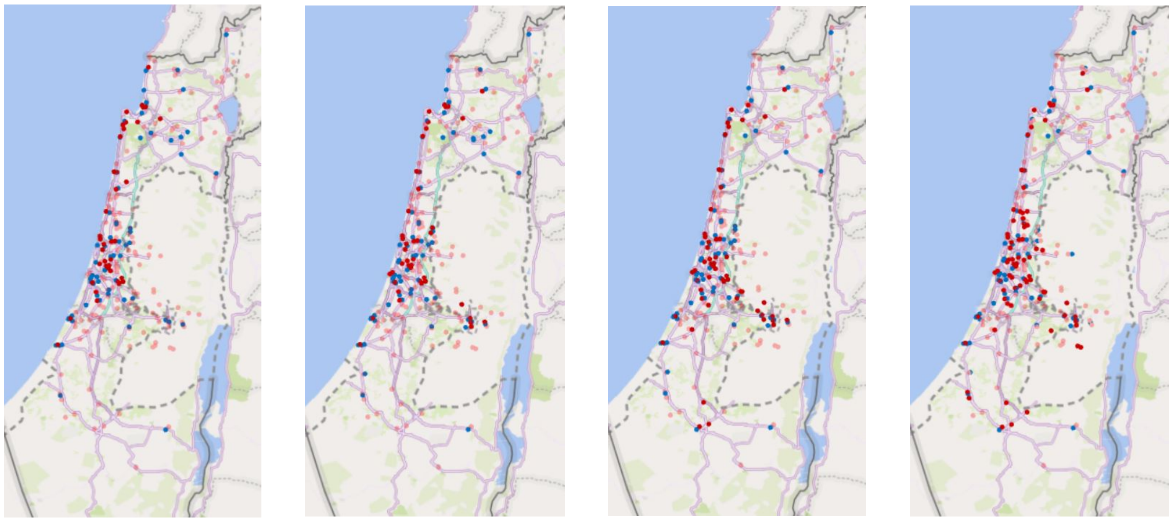


Aug. 2016 | Jul. 2017 | Jul. 2018 | Jul. 2019

Notes: The figure shows rivals' online service coverage (red dots) and rivals' physical store locations (blue dots) for each year in our sample (2016, 2017, 2018, 2019). The light-red dots indicate the 172 markets in our sample and the dark-blue dots indicate physical stores that offer online services (information available only to Rami Levy and Victory). Panel I focuses on Rami Levy and Panel II on Victory. In 2016, both chains offered online service mostly in the Tel Aviv metropolis. Over time, Rami Levy expanded its online service primarily into the north and the east of Israel. Victory expanded mostly into the south.

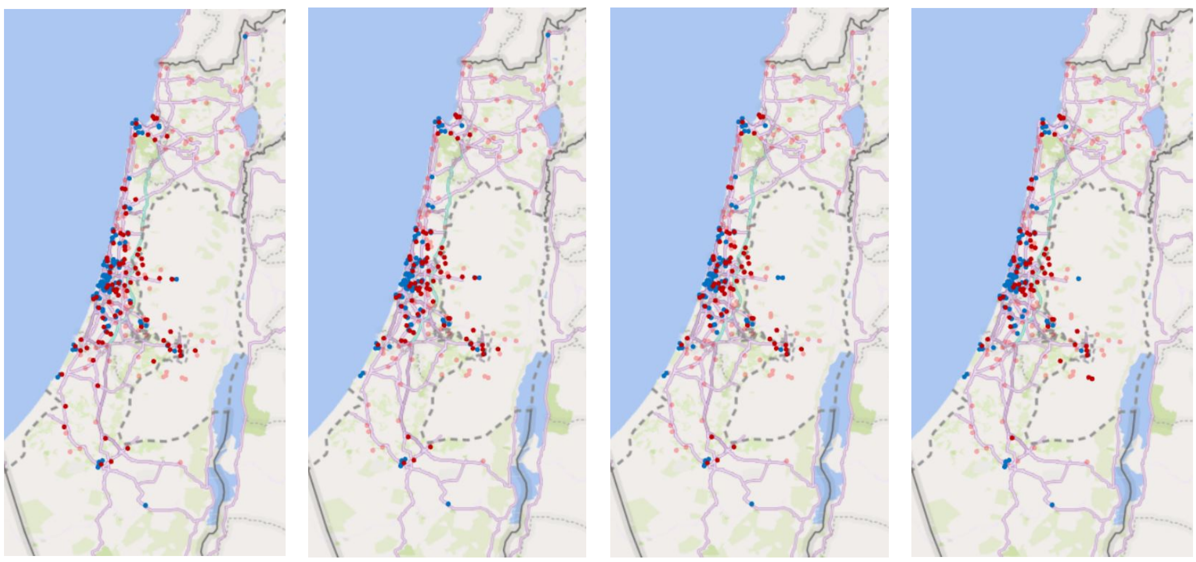
Figure F1 (Cont.): Rivals' online service coverage (red) and physical store locations (blue)

III. Yenot Bitan



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

IV. Mega

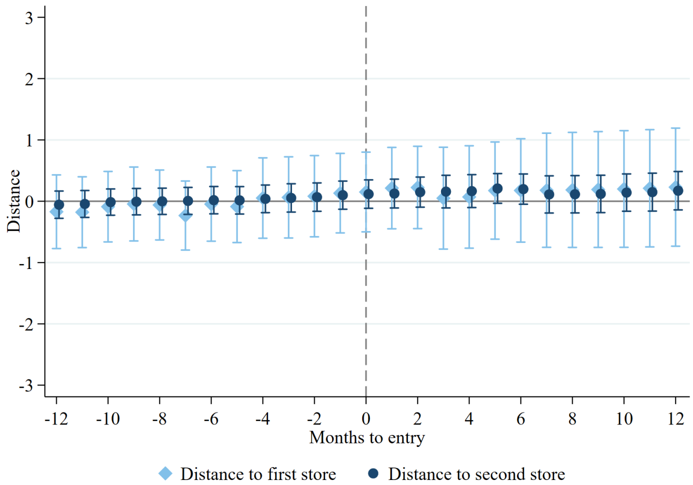


Aug. 2016 | Jul. 2017 | Jul. 2018 | Jul. 2019

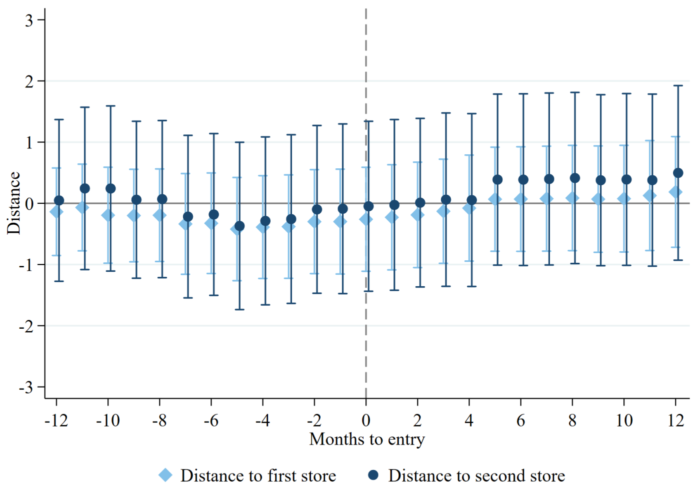
Notes: Panel III focuses on Yenot Bitan and Panel IV on Mega. In 2016, Yenot Bitan offered online services mostly in the Tel Aviv metropolis and along the northern coastal plain. Over time, it expanded primarily into the east. Mega, the second largest chain in 2016, faced considerable difficulties and limited its online service in some areas, such as the southwest. Both Mega and Yeont Bitan offer online services in regions where they operate physical stores. The information on whether a physical store offers an online service is not available for Yenot Bitan and Mega.

Figure F2: The association between a rival entry into a local market and the distance to its physical stores

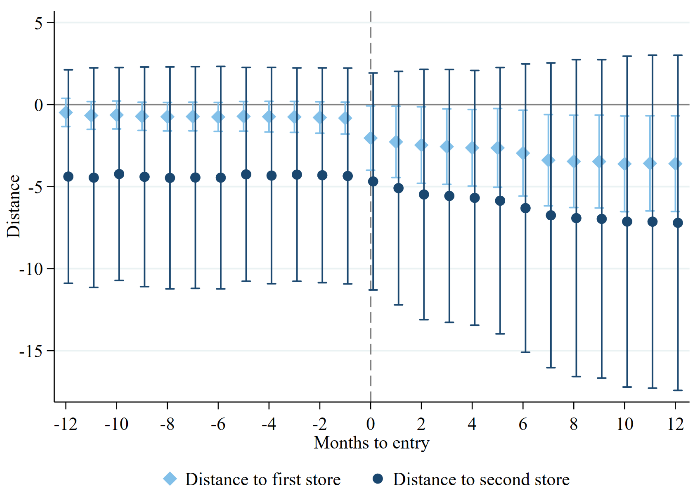
(a) Rami Levy



(b) Victory

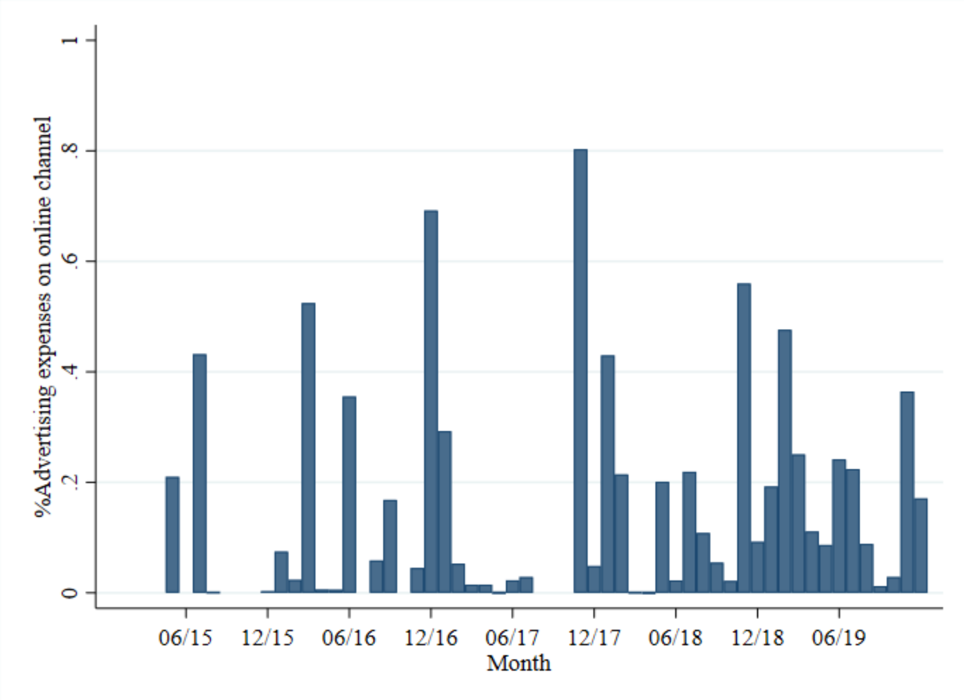


(c) Yenot Bitan



Notes: The figures plot the coefficients of β_k for j running from -12 to 12 and their 95-percent confidence intervals. The coefficients are obtained from estimating a specification similar to Equation (1), with a full set of relative indicator variables for $k \geq -12$, using different subsamples. The excluded period is more than 12 months before entry. Standard errors are clustered at the market level. The dependent variable is the distance traveled (in km) between the local market and the rival's first (light-blue diamond) or second (dark-blue circle) store. The dependent variable is the incumbent's log service time in the local market, and the results are presented separately for low- and high-demand days. The figure reports the estimated changes in the distance to Rami Levy's (Panel (a)), Victory's (Panel (b)), and Yenot Bitan's (Panel (c)) first or second store relative to the month that they started to offer online services to the market. All specifications include market and month fixed effects. The results suggest that there was no significant change in the distance traveled between the local market and the rival's first or second nearest stores in the months leading up to entry.

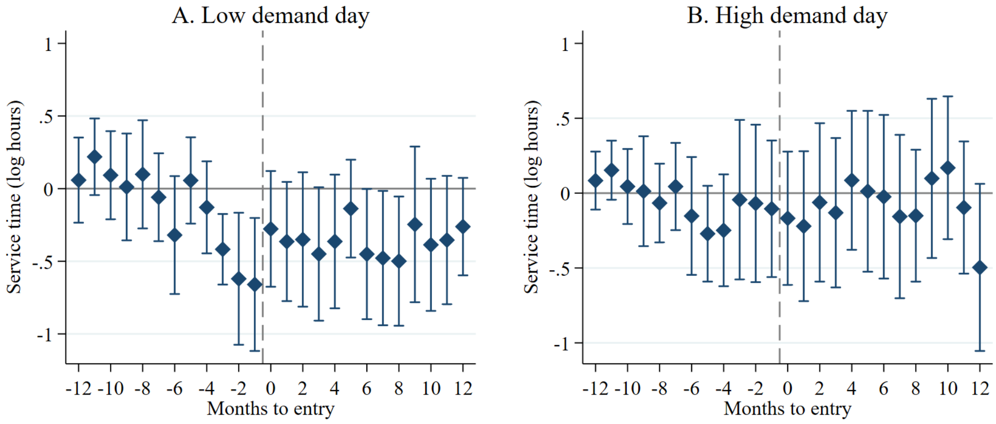
Figure F3: Percentage of Shufersal advertising expenses allocated to the online channel, by month



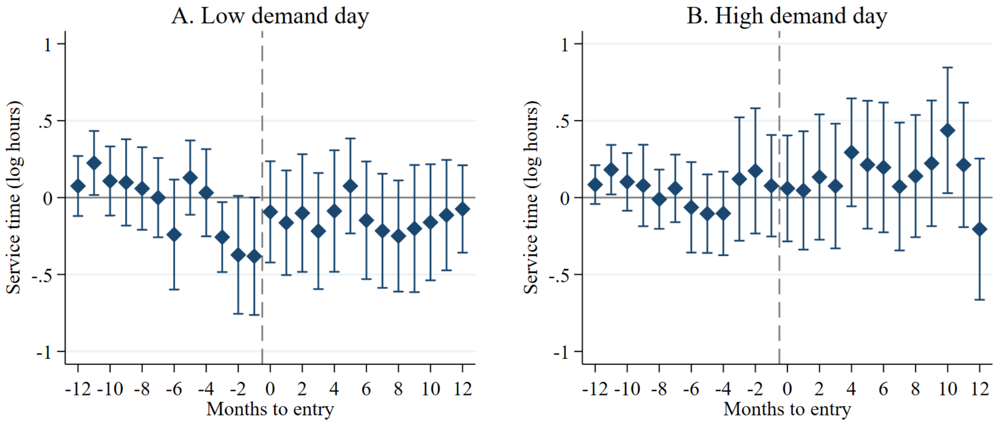
Notes: The figure plots the percent of Shufersal advertising expenses allocated to the online channel by month of launch from January 2015 to December 2019. The figure reveals that in December 2016 and November 2017, most of Shufersal's advertising expenses were allocated to the online channel (70% and 80%, respectively). As can be seen in Figure C8, both of these months preceded massive entries.

Figure F4: The effect of entry threat on incumbent's service time

(a) Pre-entry monopoly markets



(b) All markets



Notes: The figure plots the coefficients of β_k for j ranging from -12 to 12 and their 95 percent confidence intervals. The coefficients are obtained from estimating Equation (3), with a full set of relative indicator variables for $k \geq -12$, using a sample that includes only markets from the south and the north of the country (39 markets). The excluded period is more than 12 months before entry. Standard errors are clustered at the market level. The dependent variable is the incumbent's log service time in the local market, and the results are presented separately for low- and high-demand days. The figure reports the estimated effects of entry threat in pre-entry monopolistic markets (Subfigure (a)) and in all markets (Subfigure (b)). All specifications include month fixed effects and controls for the number of stores operated by rivals within a 10 km radius, dummies for exits and subsequent entries in the same market, and the following sociodemographic characteristics of the market: population growth, population size, average income per capita, vehicles per capita, and fixed effects for the socioeconomic and periphery indexes. The results suggest that the incumbent reduces service time when facing entry threat on low-demand days and that the reduction begins shortly before entry. While the magnitude of the effect is larger, the patterns are similar to those of the event-study estimation reported in Figure 6.

Table F1: Market demographic characteristics, by entry and competition level

	Pre-entry monopolistic markets		Pre-entry duopolistic markets		Pre-entry competitive 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)	10.93	-5.438***	107.5	-105.7**	65.13	1.102
	(19.49)	[1.860]	(263.5)	[49.92]	(71.55)	[12.26]
Population growth	0.015	-0.002	0.018	-0.006	0.019	-0.007*
	(0.025)	[0.003]	(0.024)	[0.005]	(0.028)	[0.004]
Average income per capita	10,242	-24.62	10,799	780.8	10,819	1,923***
	(2,080)	[232.7]	(2,576)	[504.9]	(2,476)	[374.7]
Vehicles per capita	0.330	0.023	0.341	0.004	0.361	0.078***
	(0.070)	[0.022]	(0.089)	[0.018]	(0.086)	[0.014]
Socioeconomic index	6.273	-0.176	6.406	0.594	6.770	1.353***
[1 low to 10 high]	(1.737)	[0.194]	(1.970)	[0.390]	(1.601)	[0.230]
Periphery index	4.574	-0.058	5.813	0.330	6.706	0.794***
[1 very to 10 none]	(1.632)	[0.174]	(1.673)	[0.329]	(1.491)	[0.224]
Markets	54	31	32	7	34	14
N	216	124	128	28	136	56

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

Notes: The table reports means of characteristics (standard deviations in parentheses) in markets that experienced entry (odd columns) alongside mean differences (t-test standard errors in brackets) compared with markets that did not experience entry (even columns). The sample includes markets where only Shufersal was active before the first rival entered or during the entire sample period (Columns (1) and (2), respectively), markets where Shufersal and another retailer were active before another rival entered or the entire sample period (Columns (3) and (4), respectively), and markets where Shufersal and another two or three retailers were active before another rival entered or the entire sample period (Columns (5) and (6), respectively). All market characteristics were measured on a yearly basis from 2016 to 2019. The table shows that more competitive markets are larger in terms of population size, have a higher socioeconomic status, and are closer to the center of Israel. However, in less competitive markets there is no discernible difference in these sociodemographic characteristics, except for population size, between markets that experienced entry during the sample period and markets that did not experience entry.

Table F2: 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)	(5)	(6)
Panel A: Entry by all online grocers						
Pre-entry	-0.020	-0.019	-0.011	-0.026	-0.029	-0.027
	(0.050)	(0.050)	(0.050)	(0.038)	(0.038)	(0.042)
Post-entry	0.020	0.020	0.016	-0.060	-0.063	-0.062
	(0.060)	(0.063)	(0.065)	(0.040)	(0.041)	(0.040)
Markets		52			52	
N		1,866			1,866	
Panel B: Entry by aggressive online grocers						
Pre-entry	-0.054	-0.052	-0.052	-0.053	-0.054	-0.057
	(0.048)	(0.049)	(0.049)	(0.045)	(0.045)	(0.048)
Post-entry	0.028	0.027	0.019	-0.102*	-0.103*	-0.103*
	(0.057)	(0.059)	(0.060)	(0.053)	(0.054)	(0.052)
Markets		52			52	
N		1,866			1,866	
Controls:						
Market FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓		✓	✓	
Time FE # market growth (quantiles)			✓			✓
No. of rivals' physical stores (10 km radius)		✓	✓		✓	✓
Exits and additional entries		✓	✓		✓	✓

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

Notes: The table reports estimation results for a regression similar to Equation (2) on a sample that includes only markets that experienced neither entry nor exit during the sample period. 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 a market served by the same fulfillment center as market i. *post_entry* is an indicator for the month of entry into a market served by the same fulfillment center as market i and for the following months. Entry indicators refer to all entries into nearby markets served by the same fulfillment center (Columns (1)–(3)), and to entries only into nearby monopolistic markets served by the same fulfillment center (Columns (4)–(6)). Entry indicators refer to entries of all grocers (Panel A), and only entries by aggressive grocers (Panel B). All specifications include market and month fixed effects, and in Columns (2) and (5) they also include controls for the number of stores operated by rivals within a 10 km radius, and dummies for exits and subsequent entries in markets served by the same Shufersal fulfillment center. The specifications in Columns (3) and (6) include month fixed effects interacted with quantiles for market growth instead of month fixed effects only. The results suggest that the incumbent does not change service time in an untreated adjacent market in the months before a rival enters a local market that served by the same fulfillment center. However, when an aggressive grocer enters a monopolistic market, the incumbent improves service time post-entry in the adjacent market.