Spatial frictions in consumption and retail competition*

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Abstract

In this paper, we empirically quantify spatial consumption frictions and the degree of local retail competition. We exploit a unique data set including 1.5 billion daily transactions in combination with detailed characteristics of more than 3 million households. Our estimates are based on a quasi-experimental approach to estimate the causal effect of store openings. We find that a same-chain store opening in the proximity of households' residences reduces their expenditures at incumbent stores by 30% in the first month. Smaller effects for competitors suggest imperfect substitutability between retail chains. Exploiting more than 350 openings, we identify causal consumption gravity functions, which allow us to quantify spatial consumption areas. We document significant heterogeneities across regions and socio-demographic groups, indicating substantial inequalities in consumption access.

Keywords: economic geography, consumption, consumption access, consumption inequality, spatial competition

JEL-codes: R1, R2, L14.

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1 Introduction

The importance of local amenities for a household's location decision is well understood.

This paper focuses on consumption access – a dimension that has so far been underexplored.[1] However, a positive link between store openings and house prices suggests that households value consumption access positively (Pope and Pope, 2015; Hausman et al., 2022). Thus, it is crucial to understand better its role for the spatial distribution of economic density. What are the distance costs of shopping? Do shopping trips interact with other local characteristics like restaurants or the density of stores? What is the relation between commuting and shopping trips? Do we observe differences in distance gradients between socio-demographic groups or between urban and rural places? The answers to these questions not only inform about households' choices but also have important policy implications. Zoning laws segment land into zones of commercial versus residential areas to internalize spillovers and coordinate infrastructure. For such planning decisions, it is crucial to understand spatial consumption frictions. Consumption access is also important from a welfare perspective and may contribute to spatial disparities. The response of households to the entry of new stores also provides critical information about the degree of local competition. A related question concerns the more recent developments in consumption behavior caused by the rise in e-commerce. We study a period before, during and after the COVID pandemic which induced a substantial increase in e-commerce. This allows us to infer whether and how consumption areas have changed with the shift towards e-commerce.

Analyzing consumption in space is complicated, as residential choice and store locations are highly interdependent. To understand the role of distance for consumption expenditures, we need to disentangle both dimensions. In this paper, we achieve this by exploiting quasi-experimental variation from store openings within a difference-in-differences setting using rich geo-referenced household-store-linked consumption data. We argue that we can interpret the change in access to stores as exogenous from the household's perspective in the short run and identify the causal change in consumption patterns with regard to the number of visits to specific stores and the expenditures by volume and product class. The empirical analysis builds on expenditure data for food, beverages, and household products of more than 3 million Swiss households (85% of the population) and 1.5 billion daily transactions collected through the loyalty program of the largest Swiss retailer (with a market share of approximately one third) for the years 2019-2021. Households live in 315'000 grid cells, measuring 100×100m, and we have coordinate-level precision for stores. Together with hand-collected store openings of both the same retailer and competitors, we can estimate consumption decay functions at a high spatial resolution.

We estimate four different specifications. First, we derive the average treatment effect identified from household consumption responses to store openings within 30 minutes of their home compared to households who receive that treatment at a different point in time in the form of staggered difference-in-differences regressions (see, e.g., de Chaisemartin and D'Haultfœuille 2020; Callaway and Sant'Anna 2021). Second, parametric and non-parametric extensions shed

[1] A related exception is Miyauchi et al. (2022), who use GPS data to track people across space.

light on the distance decay of consumption expenditures. Third, we explore the dynamic adjustment based on event studies over ten months after store openings. This further helps to inspect parallel trends prior to treatment. Fourth, we document heterogeneities in spatial and socio-demographic dimensions.

We find that the average monthly household expenditure at the three favorite stores (in terms of expenditure) declines by 6.0% in response to a store opening of the same chain. The number of visits drops by 3.9%. For the entry of discounters, these numbers are somewhat lower at 3.4% and 2.7%, respectively, indicating imperfect substitutability across chains.[2] Including distance functions allows us to compute the geographical size of consumption areas. Defining the boundaries as the distance from home at which households no longer consume, we obtain thresholds of 5.6 km or 16 minutes of car travel time. We derive these numbers from openings of the same chain to not confound spatial frictions with imperfect substitution effects across different chains. We further learn from event studies that households adjust their spatial consumption pattern quickly after the opening of a new store. For branches of the same chain, expenditures at the three favorite stores decline by 30% within the first month and remain persistent after ten months. For the entry of competitors, the effect is about half as big.

Finally, we study differences in spatial characteristics and heterogeneity across socio-demographic groups. We find sizeable differences between retailers. On the one hand, residents in urban and high-income areas significantly adjust their expenditures after an own-chain opening. On the other hand, the main competitor is particularly attractive in rural and low-income areas, and families favor discounters. We further explore how consumption access interacts with local characteristics – Is it more likely to visit stores based on job availability or other local amenities? The first channel would confirm the role of interlinked commuting and consumption trips, the latter channel indicates complementarities between different types of consumption. We find strong evidence for trip-chaining between cafés, other stores, and the main competitor, while complementarities are less relevant for own-chain openings. Our findings are robust to various robustness checks, where we focus on the period before the Covid-19 pandemic, address the issue of multiple treated units, and explore different specifications.

This article contributes to a recent and still small strand of research that examines the role of consumption in space. Agarwal et al. (2022) find that household expenditures decay more in distance for goods with lower storability, while Eizenberg et al. (2021) use credit card data at the neighborhood level for Jerusalem to document that residents from areas with a higher average income shop in more distant stores with lower product prices. Marshall and Pires (2018) use household-store-level data to show how customers trade off travel costs with prices and variety, and Miyauchi et al. (2022) build a quantitative spatial model to disentangle consumption access from other local amenities. Our paper exploits highly granular expenditure data containing precise geographical information on place of residence and store location. We use shop openings of branches of both the same chain and competitors to identify the size of local consumption areas conditional on local (area-level) and socio-demographic (household-level) characteristics.

[2]For the main competitor, the reductions are 8.0% and 5.8%, respectively.

A second line of research explores spatial consumption at the store level. For example, there is evidence that store entry reduces revenues of incumbent supermarkets (Arcidiacono et al., 2020) and facilitates access to cheaper goods, implying positive welfare effects (Hausman and Leibtag, 2007). Looking at endogenous location decisions, there is evidence that restaurants in Milan cluster close to each other (Leonardi and Moretti, 2022) and Big Box stores in the U.S. tend to locate close to complementary stores (Schuetz, 2015). In contrast to this literature, our analysis is not carried out at the store level. Instead, it focuses on changes in household-level expenditure in response to store openings within a certain distance. This turns out to be relevant, as the impact of store entry on incumbents depends largely on the location relative to the residence of potential consumers rather than on the distance to competitor stores.

Third, and more broadly, we relate to the amenity literature highlighting, among other things, sorting across heterogeneous agents (Diamond, 2016; Ahlfeldt et al., 2022; Almagro and Domínguez-Iino, 2022); access to workplaces (Monte et al., 2018); pollution (Heblich et al., 2021); noise (Ahlfeldt et al., 2019) or the value of leafy streets (Han et al., 2022).

The structure of the paper is as follows. Section 2 introduces the data we combine with our identification strategy detailed in Section 3 to derive results that we present in Section 4. Section 5 addresses the robustness of our findings. Section 6 concludes.

2 Data

We combine unique consumption data with web–scraped and administrative spatial data on a resolution of 100 $\times$ 100 m. This section describes the different data sets and shows a set of corresponding descriptives.

Transaction data. The most important ingredient for our analysis are household-store-linked grocery expenditures collected through the loyalty program of the largest Swiss retailer called Migros. We focus on in-store expenditures for food, beverages, and household articles, where Migros' 621 supermarkets achieved a market share of 32.7% in 2020. Importantly, Migros charges the same prices throughout the country, independently of local purchasing power, wages, and costs. Stores of similar size also generally offer a similar assortment of goods, except for local products. The loyalty program allows participating households to record their expenditures for exclusive discounts. It is Switzerland's most successful loyalty program, capturing 79% of total Migros sales. Its 3 million registered households (85% of the population) make it also the most inclusive. The group additionally owns 250 specialized stores (sports, electronics, etc.) and 838 stores of Denner, the largest discounter. It engages 87'000 employees, making it the sixth-largest employer in the country (GfK, 2021).

We use the universe of 1.5 billion daily transaction records in this program for the period 2019-2021 (second quarter). The data set groups individual product purchases into 41 categories. Household characteristics include the location of the residence on a 100$\times$100m grid, age of the cardholder, and household type.[3] We restrict the recorded transactions as follows. First, we exclude implausible observations with expenditures below 0 CHF or above 2'000 CHF. Second, we eliminate trips to stores further away than a 30 minutes car drive to exclude unregistered movers, far-distance commuters, and family members running their own household. Third, we only consider expenditures at supermarkets and exclude each household's entrant to measure the effect on the incumbents. Fourth, we select in each period a household's three favorite supermarkets to eliminate spontaneous, irregular shopping trips.[4] Fifth, we restrict the sample to those households that are regular users of the program and spend at least 20 CHF per month on average over the entire time horizon, resulting in 2.1 million cardholders. Sixths, we only observe household characteristics at the end of the sample period (2021 Q2). This introduces a measurement error, as 10.2% of the Swiss population moved in 2020 according to the Federal Statistical Office. To control for these movers, we eliminate households whose average travel time to spend 1 CHF has changed significantly within two years around the treatment.[5] Eventually, we aggregate the remaining transactions to monthly expenditures and the number of visits per household, which yields 23 million observations for 772,523 households in the final data set.[6]

A limitation of this data is that we do not observe work locations. But the *Federal Statistical Office* reports that 70% of Swiss employees work outside their municipality and commute on average 14 kilometers within 30 minutes. Some of these households likely include their commuting trips in the planning of their grocery shopping, and Miyauchi et al. (2022) show that 40% of all non-commuting consumption trips to goods and services in Tokyo include the workplace (although the number for shopping trips is likely lower). Thus, we implicitly have to assume that all shopping-trips start and end at home.

Figure A1 describes the transactions in terms of weekdays and household types. Most customers do their grocery shopping on a Friday or Saturday, and the average shopping basket is also larger on these days. Further, families visit a grocery store more often than small households or pensioners, and they also spend more money on average. A2 illustrates the typical basket. Twenty percent of all trips include some convenience food, but they make up only 9% of all expenditures. Also, 19% of all shopping bags include fruit and vegetables, but they account only for 12% of spending. Instead, customers spend most of their money on meat and fish (21%) and household products (14%). Panel A of Table 1 describes the final data set. The mean cardholder in the sample is 58 years old and part of a family household in 30% of the cases. She visits one of her three favorite stores 26 times in a given month, and spends 361 CHF. She lives in a municipality with a 34,000 CHF per capita income. The average (uncongested) car drive to spend 1 CHF takes 5.6 minutes (or 4.6 km road distance). 29% of the customers in

[3]These household types include the categories *small households*, *young families*, *established families*, *golden agers*, and *pensioners*.

[4]Figure A3 shows that there are very few households who spend a significant amount at more than three Migros stores in a given month.

[5]Namely, if the travel time by car increased or decreased by more than a factor of 3 or by more than 5 kilometers of road distance. Also, the favorite stores a year after the treatment have to account for at least 70% of expenditures a year before. This should ensure that shopping behavior stays constant, except for the treatment. Our results are also robust to different adjustments of these windows.

[6]These 23 million correspond to a data set only including households that will receive a treatment at some point. All results will be based on this data set, unless indicated otherwise.

our sample live in urban places, which is close to the overall population share of 30%.

Store entries. All stores that entered the retail market between 2019 and 2021 Q2 are potential treatments. While we know the exact timing and location for Migros entrants, we use web-scraped data for competitors' entries. We construct them using a monthly panel on the location of supermarkets, with a spatial resolution of 100 × 100m. We restrict the data set by manually excluding gas stations and stores too small to likely matter in that neighborhood. To check for possible errors in the scraping process, we use the official data provided by one of the competitors and cross-check with newspaper announcements on *Factiva*, a global database of more than 400 news agencies. We select 351 entries between 2019Q1 and 2021Q2 as treatments. Migros opened 31 new supermarkets, the main competitor Coop 69, the discounters 159, and smaller chains (Spar and Volg) contributed 96 openings that are mainly present in rural areas. Figure 1 shows the geographical distribution of all 351 openings across Switzerland. Seventy-five stores entered the market in Urban areas (which corresponds to 21% of entries for 30% of the population), and all cantons, except for two, received at least one new supermarket.[7] The correlation between the cantonal number of entrants and population is 0.91.

The household's treatment is then defined as her closest entrant within half an hour by car. Following this definition, we come up with the 772'523 households in Table 1 that receive a treatment at some point in our sample (which corresponds to 76.7% of those in the final data set, including never-treated units). Figure A4a shows the composition of the treatment and the control group over time. The number of the switchers in each period appears similar, and openings occur in every period except for June 2020. A4b additionally presents a household's distance to her closest opening, as well as the distances of actual shopping trips. Entering stores locate significantly further away than the average shopping trips in our data.

Travel times and amenities. We use measures for distance to quantify the effect's decay across space. The API of *search.ch*, a Swiss Search Engine, allows us to measure these distances from the household's residences to incumbent and recently opened stores. Namely, we scrape for each pair road distances in kilometers and travel times by car, walking, and bicycle in minutes. Overall, we calculate distances for all 6.5 million household-store combinations in our transaction data and 2.5 million store-entrant pairs.

Panel B of Table 1 provides an overview of the average distance from households to new openings of different retailers, reported separately for three types of locations with regard to density (low, medium, high) and measured both in terms of driving time and road distance. Overall, distances in urban locations are nearly half of those in low-density places. We observe that own chain (Migros) and discounter (Aldi, Lidl) openings are about 7.5 minutes away in Urban areas. Coop, the main competitor of Migros, opens stores on average at larger distances to Migros customers in dense urban areas but substantially closer in low-density places.

Additionally, we use the same API access to extract the exact location of various local amenities like stores, cafés, restaurants, or banks to explore interaction effects between an entry and the

[7]Switzerland consists of 26 federal units called cantons. The ones without any opening are Appenzell Innerrhoden and Obwalden.

Table 1: Descriptive Statistics for Households and Entrants

Panel A. Households: Distance to closest store opening

Variable	Mean	SD	Min	p25	p50	p75	Max	Households	Obs.
Transactions (per month)									
No. of Trips	26	17	1	14	23	34	284	772,523	23M
Expenditures	361	290	0	149	292	501	13203	772,523	23M
Households									
Age of cardholder	58	16	2	46	58	71	121	772,523	-
Family dummy	0.3	0.46	0	0	0	1	1	772,523	-
Mun. income (tCHF)	34	11	14	28	32	37	403	772,523	-
Urban share in data	0.29	0.45	0	0	0	1	1	772,523	-
Urban share in population	0.3	0.46	0	0	0	0	1	3,867,390	-
Distance to favorite stores									
By road (km)	4.6	3.8	0	1.7	3.5	6.6	28	772,523	-
By car (min.)	5.6	5.1	0	5.7	8.7	12.6	30	772,523	-

Panel B. Households: Distance to closest store opening

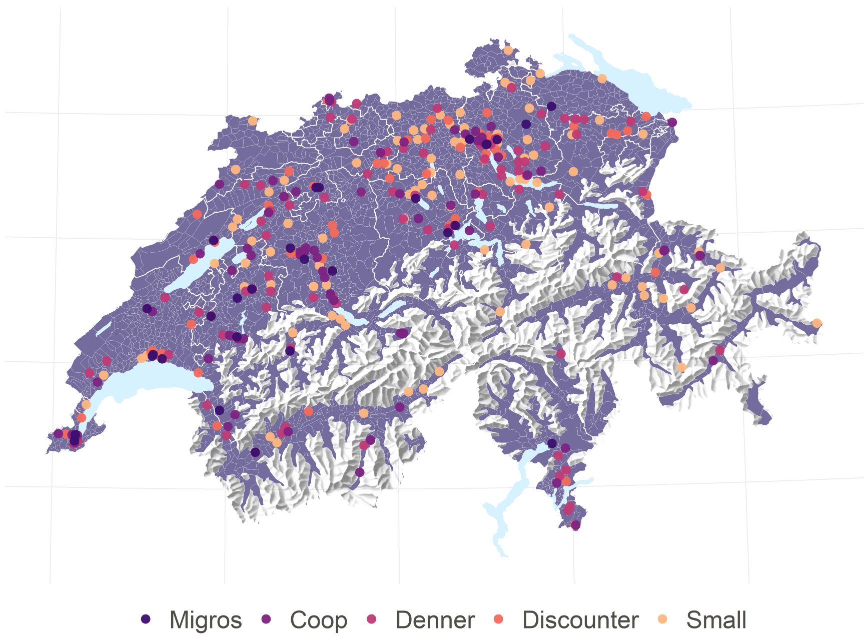
	Road Distances (in km)					Car travel time (in minutes)				
Urban	Migros	Coop	Lidl	Aldi	Denner	Migros	Coop	Lidl	Aldi	Denner
High density	2.4	3.0	2.0	2.0	2.3	7.9	8.9	7.2	7.5	7.8
Medium density	3.8	3.8	2.5	2.8	4.2	9.0	8.6	7.6	7.8	8.8
Low density	8.1	5.2	8.2	9.6	7.1	13.3	9.6	13.8	16.2	11.8

Panel C. Entrants: Location characteristics entrants

	Local economy within 100m				Local economy within 200m			
Amenity	Mean	SD	Min	Max	Mean	SD	Min	Max
Population								
Population	226	445	4	3’091	718	1’390	4	9’085
Employment	143	172	0	1’749	505	571	0	4’059
Firms	26	33	4	257	83	117	4	812
No. of amenities								
All	6.8	80.3	1	57	16.1	26.3	1	204
Stores	0.9	2.2	0	15	1.7	3.7	0	27
Cafés	0.7	1.7	0	13	2.1	5.8	0	49
Restaurants	1.7	2.5	0	17	4.5	7.9	0	49
Schools	0.2	0.0	0	8	0.7	0.0	0	17

Notes: Panel A shows descriptive statistics on the household level. The final data includes 772,523 households, accounting for 23 million monthly transactions. Panel B shows the median distance from a household’s residence to the closest store opening of a specific retailer. Panel C displays descriptives for the density of population, employment, and firms within a given Euclidean radius around the entry’s raster cell. We apply the same approach for a list of amenities.

Figure 1: Spatial distribution of grocery shop openings



Notes: The figure shows the spatial distribution of all 351 store openings in Switzerland between 2019Q1 and 2021Q2. We show openings for Migros, as well as the main competitor Coop, the discounters Denner, Lidl and Aldi and smaller openings in rural areas.

surrounding local economy. According to the lower part of panel C of Table 1, there are, on average, 1.7 stores, 2.1 cafés, 4.5 restaurants, and 0.7 schools within 200 meters of an entrant.

Geospatial administrative data. Finally, we use spatial and socio-demographic data provided by the Swiss Federal Office of Statistics. This includes various maps and highly granular data for employment, population, and firms. The high granularity also allows us to observe these variables even within 100 meters of the entry location of a new store (Panel C of Table 1). New stores locate, on average, in neighborhoods with 718 residents and 83 firms with 505 employees within a 200-meter radius. We further use additional municipality-level data for income and household size.[8]

3 Empirical strategy

In this section, we describe our empirical strategy to estimate the causal effects of distance costs on the consumption decisions of households. There are three major challenges to consider. First, stores and residents do not locate randomly. Thus, we have to deal with omitted variables due to unobserved determinants of a place's attractiveness for retailers to open a store and for customers to locate. Second, we face a simultaneity issue, as customers might attract stores and

[8]In a future version, we will complement this data with administrative register and income data on the 100 × 100-meter grid. This will especially allow us to significantly refine our current income analysis (from the current municipality level to the household level).

vice versa. The ideal experiment to resolve these issues and isolate a causal effect would randomly allocate stores across space as an exogenous supply-shifter. We apply staggered difference-in-differences models to get as close as possible to such a supply shifter. Third, we have to choose an appropriate estimator.

In particular, we base our analysis on a setup that treats the entry of a new shop as an independent event and estimates the response of household consumption patterns. To this end, we exploit the quasi-experimental variation from store openings to infer the effects on households' expenditures and the number of shopping trips. We use both the entry of stores by the same retail chain and entries of competitor stores. Therefore, our empirical analysis builds on three types of models: (i) a static staggered difference-in-differences setting, (ii) a static staggered difference-in-differences setting where the treatment is interacted with a covariate,[9] and (iii) a dynamic staggered difference-in-differences presented in an event-study fashion.

These models isolate the causal effects of interest if the parallel-trend assumption holds. This is unlikely for a control group of never-treated units, as the probability of receiving a treatment depends on location characteristics, and the treatment is, therefore, not randomly assigned. In this case, the treated and untreated households may not be comparable. However, it is credible that the retailers' strategic planning cannot explain short-term differences between opening dates. Instead, the exact opening date is due to administrative and bureaucratic delays, and locations treated within a short period are comparable. Thus, we assume that the treatment is exogenous conditional on being treated within our sample periods. Therefore, we take in all specifications the not-yet-treated units as a control group and exploit short-term variations in the exact timing of an opening.

Additionally, the recent literature (see, e.g., de Chaisemartin and D'Haultfœuille 2020) shows that the constant effect two-way fixed effects (TWFE) estimator is a biased estimator of the average treatment effect (ATT) if the treatment effect is heterogeneous over time and cohorts. Thus, our results may be biased if an opening affects the same household differently depending on whether it happened during a specific point in time or shortly before or after. Examples include the Covid-19 pandemic, openings during holiday seasons, etc. While we can exclude these specific periods from our estimation sample, other less apparent heterogeneities within groups may remain over time. Thus, we expect the effect to vary across cohorts. In addition, households may adjust their consumption habits slowly over time, leading to a dynamic build-up in the effects. This would violate the heterogeneity across time. Hence, we rely on the recent advances in difference-in-differences models allowing for variation across time and cohorts.

To estimate the model in section 3.2, we then need an estimator within this class that allows to interact the binary treatment with a covariate. To the best of our knowledge, the estimator presented in Wooldridge (2022) is the only one so far allowing for this. Hence, we will follow this approach for all static models in sections 3.1 and 3.2. However, Wooldridge (2022) does not directly estimate coefficients for the pre-treatment periods. Thus, we will use for our dy-

[9]This allows us to get parametric as well as non-parametric distance decays in section 4.2 and further heterogeneities in section 4.4.

namic model in 3.3 instead the estimator in Roth and Sant'Anna (2022a). We compare their performance to other recently proposed approaches and the standard TWFE.

3.1 Static DiD: Average effect of entry

Our baseline specification is the extended TWFE model in Wooldridge (2022):

$$\ln(Y_{imt}) = \alpha_i + \gamma_t + \beta_{g,t}(T_{it} \times g_i \times \gamma_t) + \epsilon_{imt}, \tag{1}$$

where Y_{imt} captures monthly expenditure or shopping trips of household i residing at location m in year-month t. We control for time-invariant household-specific unobserved characteristics α_i. These unit fixed effects capture unobserved – but time-constant – idiosyncratic characteristics such as workplace location, school location of children, or other routine trips. The period fixed-effect γ_t absorbs any common time trends and seasonality. The time-constant g_i denotes the year household i is getting its treatment (meaning, it indicates which cohort or group household i belongs to). Finally, the time-varying treatment dummy T_{it} indicates whether household i was treated in period $j \leq t$. These coefficients are consistent under the assumptions of parallel trends and no-anticipation. The extended TWFE model now estimates a treatment effect for every period and cohort combination, $\beta_{g,t}$. We aggregate these results to an overall average treatment effect (ATT) by weighting for the size of the cohorts ($W = \sum_g W_g = 1$):[10]

$$\beta_{ATT} = \sum_{t \times g, t \geq g}^{T,G} W_g \beta_{g,t}.$$

As mentioned in section 2, we define a household's treatment as the opening closest to her location. Also, we consider only openings within a 30 minutes car drive such that the impact is likely to be relevant for the respective neighborhood.[11] This approach has three potential limitations. First, due to our treatment being binary, we ignore multiple openings. We will address the scope of this limitation in the robustness. Second, the staggered setting does not allow units to switch back into the control group, even if the effect vanished with time. However, our results are persistent over the entire sample period, mitigating this problem. Third, we ignore all openings before our initial period.

[10] Note that treatment effects are only estimated for post-treatment period-cohort pairs, meaning $t \geq g$. Finally, standard errors for β_{ATT} are aggregated in the same way by weighting according to cohort sizes.

[11] In the robustness (section 5), we provide results for an alternative treatment definition.

3.2 Static DiD with interactions: Consumption gravity and heterogeneities

We want to make this baseline model more flexible for two applications. On the one hand, we are particularly interested in the distance costs of consumption and local complementarities. Hence, we want to use extensions of Equation (1), where we interact the treatment with a distance measure. On the other hand, we want to analyze a variety of heterogeneities. This also requires us to interact the treatment in Equation (1) with a (potentially demeaned) covariate. The Wooldridge (2022) model can be extended to allow for interactions with a time-constant covariate in the following way:

$$\ln(Y_{imt}) = \alpha_i + \gamma_t + \delta_{g,t}(T_{it} \times g_i \times \gamma_t \times \tilde{X}_i) + \beta_{g,t}(T_{it} \times g_i \times \gamma_t) + \xi_t(\delta_t \times X_i) + \epsilon_{imt}, \qquad (2)$$

where X_i is the time-constant covariate we want to interact the treatment with. The remaining notation is as before. Demeaning a continuous covariate in the first term for each cohort ($\tilde{X}_i = X_i - \bar{X}_g$) centers the treatment effect such that we can interpret the $\beta_{g,t}$ as average treatment effects. Then, we again aggregate the weighted estimated effects for $\beta_{g,t}$ and $\delta_{g,t}$ to get an average effect for the treatment and the interaction for all period-cohort pairs that have a common support for X_i:

$$\beta_{ATT} = \sum_{t \times g, t \geq g}^{T,G} W_g \beta_{g,t}, \qquad \delta_{ATT} = \sum_{t \times g, t \geq g}^{T,G} W_g \delta_{g,t}.$$

Results are consistent under the assumptions of parallel trends and no-anticipation, conditional on X_i. This model allows for our two applications. First, we can calculate distance decay functions. Here, $X_m = f(\psi_{is})$ will be a measure for the distance between the household's place of residence m and the location of the new store s. We will consider in section 3.2 a parametric log-functions such that $f(\psi_{is}) = \ln(Dist_{is})$. Then, the parameter δ_{ATT} reflects the distance elasticity. Additionally, we allow for a more flexible decay, by setting non-parametric distance bins d for store entry. In particular, $d = [2, 5, 10, 15, 20, 30]$ specifies events where store entry occurred within 0-2 minutes, 2-5 minutes, etc., and δ_d reflects then the bin-specific distance decay.

Finally, in section 4.4, we analyze in the same way socio-demographic and spatial differences in the effects. Here, X_i will represent flexible functions for varying characteristics. We analyze household-level variables as well as attributes of the entry's location, such as other consumption amenities or the number of workplaces nearby. The latter informs about the link between commuting and consumption trips and provides information about the complementarities of different consumption amenities, e.g., restaurants and shops.

3.3 Dynamic DiD: An event-study style approach

Additionally, we report dynamic event-study style estimates. There are two additional benefits of this approach. First, these estimates are informative per se, as one might expect a gradual build-up of the effect over time. Second, they allow for placebo tests of the parallel-trend assumption. Hence, we want to estimate a coefficient for every pre- and post-treatment period of interest. We write this model in the following form:

$$\ln(Y_{imt}) = \alpha_i + \gamma_t + \sum_{\substack{k=-10 \\ k\neq -1}}^{10} \beta_k T_{i,t}^k + \epsilon_{imt}, \tag{3}$$

where $T_{i,t}^k$ is a set of dummies indicating that at time period t household i got a treatment $k \in [-10, 10]$ months ago. The remaining notation is as before. The exclusion of $k = -1$ normalizes the coefficients to the period preceding the treatment.

We can aggregate the estimated results in subsection 3.1 in an event-study fashion to estimate the model in Equation (3). However, as Wooldridge (2022) does not compute pre-treatment coefficients, we will instead estimate this model by applying Roth and Sant'Anna (2022a).[12] This estimator explicitly exploits the quasi-random rollout of a treatment at different points in time. This assumption is stronger than the conventional parallel trends assumption but fits the intuition of our identification strategy. Also, it does not allow for anticipation of the treatment. Under these assumptions, Roth and Sant'Anna (2022a) derive the most efficient estimator for the β_k's, allowing for variation of the effects across time and cohorts.

4 Results

We next present our empirical results. We first investigate the impact of a store entry on average expenditures and the number of shopping trips to incumbent stores (Section 4.1). Second, we quantify the geographical size of consumption areas and the distance gradients in consumption by exploiting the distances between households' residences and store entries (Section 4.2). Third, we focus on the dynamics of expenditure shifts caused by the entry of a new store (Section 4.3). This allows us to test the identifying assumption of common trends of treated and control units and provides important information about the adjustment process of households over time. Fourth, we look at heterogeneities in the effects across different socio-demographic groups, and the responses regarding characteristics of the new stores' location (Section 4.4).

We generally distinguish two types of store entries: i) new stores belonging to the same retail chain, and ii) competitor stores belonging to different chains, which can be further decomposed into the main competitor Coop and discounter retailers. Coop provides a more comprehensive

[12] We also apply other estimators from the recent difference-in-differences literature to compare our results to in Section 5.

Table 2: Static average treatment effects after a store entry

	ln (Expenditures) *Level-Mean:* 232 CHF					ln (No. of visits) *Level-Mean:* 20
	(1) (Overall)	(2) (Meat)	(3) (Vegetables)	(4) (Convenience)	(5) (Other Food)	(6) (Overall)
A. Own-Chain Opening						
Entry	-0.060***	-0.03***	-0.034***	-0.017***	-0.034***	-0.039***
	(0.007)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)
Household and Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,769,520	1,547,827	1,690,542	1,644,257	1,690,542	1,769,520
B. Main Competitor Opening						
Entry	-0.080***	-0.037***	-0.041***	-0.040***	-0.030***	-0.058***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.007)	(0.002)
Household and Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,005,090	3,526,611	3,725,514	3,739,698	3,846,158	4,005,090
C. Discounter Opening						
Entry	-0.034***	-0.014	-0.029	-0.020	-0.020	-0.027***
	(0.002)	(0.108)	(0.017)	(0.019)	(0.014)	(0.002)
Household and Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,236,800	4,613,447	4,873,050	4,894,758	5,029,620	5,236,800

Notes: The table shows average treatment effects of a store entry within 30 minutes for overall expenditures and visits in columns (1) and (6). Columns (2)-(5) show average effects for expenditures by product category. Expenditures and visits are aggregated to a month-household level for the three favorite stores in each period. Their mean is displayed for the pre-treatment period. Panel (A) reports results for a Migros opening, Panel (B) for the main competitor (Coop), and Panel C for discounters (Aldi, Lidl). Estimation is done for a window spanning 10 periods before and after the treatment, and we use a staggered difference-in-differences following Wooldridge (2022). We aggregate estimated period-cohort coefficients to an overall ATT. We report standard errors clustered at the household level in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

range of products, similar to Migros supermarket. On the other hand, the discounters differentiate themselves through more competitive prices. Exploring the effect of store openings for branches of the same chain delivers a clean estimate of the distance costs of shopping since both product variety and prices are almost identical across shops. Running separate regressions for store openings of competitors sheds light on the degree of substitutability and hence competition.

4.1 Average effect of store entry

As discussed in section 2, we define *incumbent stores* as the three favorite stores of each household (in terms of expenditure) in each period. We show the results for overall aggregated monthly expenditures and visits, and for different categories of goods. Panel A of Table 2 shows the responses at the incumbent stores following the entry of a Migros store within a radius of 30 minutes of car travel time from the household's place of residence.[13] These stores can be seen as perfect substitutes in terms of product bundles and prices for our customers. Columns (1) and (6) show the corresponding average treatment effects for all products. As expected, new entries cause significant competition for incumbent stores. The average monthly household expenditure drops by 6% in incumbent stores, and the number of visits declines by about 4%, which suggests only a mild reduction in expenditures per visit.

Panels B and C in Table 2 show the same outcomes but focus on entries of competitors belonging to different retail chains. This could shed light on the dimensions of prices and product differentiation in terms of their relevance for consumption behavior. We observe an expenditure reduction of roughly 8% and a decline in the number of visits of 6% for an entry of the main competitor, while effects are smaller for the discounters (3.4% and 2.7%, respectively). Hence, effects are slightly larger for the main competitor and smaller for the discounters compared to Migros. This may be surprising, as we would instead expect much larger effects for Migros due to the perfect substitutability between stores. However, comparing average effects across all stores within half an hour does not take into account the distribution of distances of openings within the 30min radius.[14] Nonetheless, the average effects of entry provide evidence for significant competition in retail expenditure and suggest that spatial frictions play a decisive role. Accordingly, in the following subsection, we focus on the distance costs.

Before that, we may also analyze average responses to openings across different goods' categories. This is interesting, as the role of distance, prices, and variety may vary in relevance across goods. We build the corresponding data sets by aggregating the expenditures for the four largest categories in terms of volume. We use the same sample selection we discussed in section 2 for the overall data set. Columns (2)-(5) of Table 2 split the results by good-categories and focus on the effect on expenditures. We see that the percentage reduction in expenditures is quite symmetric across different categories for the entry of a new store belonging to the same retail chain, varying between 1.7% and 3.4% for Migros, while the coefficients are between 3.0% and 4.1% for the main competitors. No individual category is significant for the discounters.
Thus, there are no significant differences in average reactions between goods. This indicates that, on average, people switch entire shopping trips, instead of going to a store only to buy a specific group of products. However, distance costs may also be decisive for substituting these categories.

4.2 The size of consumption areas and distance gradients

After discussing the results for the average treatment, we now turn to the decay of these effects with distance. To this end, we apply the static model with an interacted covariate laid out

[13] Following the approach in section 3, we estimate the static regressions with and without interactions using Wooldridge (2022). We also compare these results to the standard TWFE model. The differences are minor, but the standard errors of the TWFE are often smaller, as fewer coefficients are estimated.

[14] In fact, we explain this surprising result in the following subsections by the narrow catchment areas of Migros entries. Own chain entries are more distant from existing stores than competitor entries such that the average effects for own-chain entry and competitor entry are not (yet) directly comparable.

Table 3: Static gravity elasticities of a store entry

	ln (Expenditures) *Level-Mean:* 232 CHF			ln (No. of visits) *Level-Mean:* 20		
	(1)	(2)	(3)	(4)	(5)	(6)
A. Own-Chain Opening						
Entry at mean	-0.054***	-0.058***	-0.064***	-0.031***	-0.035***	-0.043***
	(0.006)	(0.005)	(0.004)	(0.005)	(0.003)	(0.003)
Entry × ln (road distance in km)	0.082***			0.066***		
	(0.006)			(0.004)		
Entry × ln (car distance in min)		0.110***			0.089***	
		(0.008)			(0.006)	
Entry × ln (public dist. in min)			0.124***			0.095***
			(0.008)			(0.006)
Household and Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,769,520	1,769,520	1,769,520	1,769,520	1,769,520	1,769,520
B. Main Competitor Opening						
Entry at mean	-0.078***	-0.080***	-0.078***	-0.058***	-0.059***	-0.058***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Entry × ln (road distance in km)	0.009***			0.011***		
	(0.003)			(0.002)		
Entry × ln (car distance in min)		0.027***			0.026***	
		(0.004)			(0.003)	
Entry × ln (public dist. in min)			0.011***			0.017***
			(0.003)			(0.004)
Household and Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,005,090	4,005,090	4,005,090	4,005,090	4,005,090	4,005,090
C. Discounter Opening						
Entry at mean	-0.034***	-0.035***	-0.041***	-0.027***	-0.027***	-0.030***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Entry × ln (road distance in km)	0.034***			0.027***		
	(0.003)			(0.002)		
Entry × ln (car distance in min)		0.053***			0.042***	
		(0.003)			(0.002)	
Entry × ln (public dist. in min)			0.041***			0.034***
			(0.002)			(0.003)
Household and Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,236,800	5,236,800	5,236,800	5,236,800	5,236,800	5,236,800

Notes: The table shows elasticities for the estimated causal effect of a store entry within 30 minutes. Expenditures and visits are aggregated to a month-household level for the three favorite stores in each period. Their mean is displayed for the pre-treatment period. Distance is measured either by travel time by car or by road distance. Note that the covariate is demeaned, such that the entry effect coefficient is the average treatment effect. Panel (A) reports results for a Migros opening, Panel (B) for the main competitor (Coop), and Panel C for discounters (Aldi, Lidl). Estimation is done for a window spanning 10 periods before and after the treatment, and we use a staggered difference-in-differences following Wooldridge (2022). We allow the treatment to vary with the distance covariate and aggregate estimated period-cohort coefficients to an overall ATT. We report standard errors clustered at the household level in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

in Equation (2) as discussed in section 3.2. This means, we discuss parametric distance decay functions and non-parametric distance bins.

Table 3 shows the corresponding results for a parametric log-interaction with distance. We consider again all openings within 30 minutes of car driving time and report separate results for distance decays measured by driving time, road distance, and public transport. Panel (A) shows elasticities for own-chain openings by Migros, while the Panels (B) and (C) do the same for the main competitor and discounters.

Doubling the car driving time between household residences and a Migros entry reduces expenditure by 11 additional percentage points. For the other specifications, we find a reduction of 8.2 percentage points for road distance and 12.4 percentage points for public transport.[15] Hence, the point estimates imply that the effect of an own-chain entry reaches zero after a roughly 16 minutes car drive, 5.6 km of road distance or 12 minutes by public transport.[16] Based on these parametric distance gradient estimates, we obtain a non-circular spatial consumption area that spans a 16 minutes distance radius for the average household in our sample. Taking the functional form and the estimated parameter values, we can compute the surplus obtained by each household located within this area. Spatial frictions directly cause these differences in consumer surplus. The results for the number of visits turn out very similar, although slightly lower, as illustrated in columns (4)–(6).

While the above results show the distance elasticity regarding a comparable store that offers identical products, another question concerns the elasticity with entrants that differ in quality and prices. Regarding the main competitor Coop, Panel B of Table 3 illustrates the effects of a competitor entry belonging to a different retail chain. The average decrease in expenditures is now less pronounced (compared to the previous results that ignore distance decays). The difference concerning the distance elasticity is even more striking. We observe that households are willing to travel a much larger distance to shift expenses from their favorite stores to a new competitor retail chain. The distance elasticities are six to eight times larger in the case of a same-chain entry than in the case of competitor entries. The results for discounters lie in between. Accordingly, the point estimates suggest that competitor entries up to 30 minutes distance to customers' residences still negatively impact the expenditures at the incumbent stores. In comparison, discounters have a catchment area of roughly a 21 minutes car drive. This difference between the maximum radius with positive consumer surplus for own chain and competitor chain shows that quality and price differentiation shift the consumer surplus to a higher travel distance.[17]

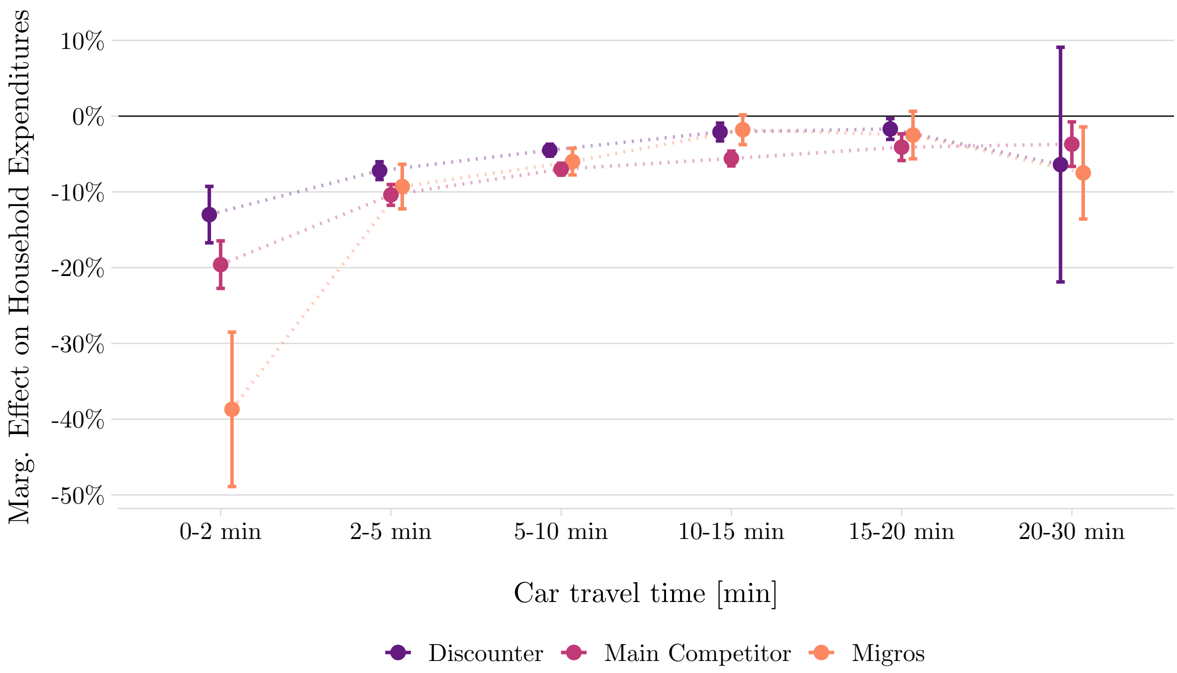
Table A 1 shows the elasticities for the four major product categories. Compared to the average coefficients in section 4.1, we see here significant variation for the role of distance, while the general picture is similar across retailers. Customers consume fresh vegetables and fruit locally, with a fast decay coefficient of 0.09 for Migros (0.02 and 0.04 for competitors and discounters,

[15] Figure A 2 shows the gravity regressions for walking and bicycle trips.

[16] Note that we can calculate the x-intercept as follows: $exp[mean(ln(\text{distance})) + \beta(\text{treat})/\beta(\text{interaction})]$.

[17] In a future version, we might dig deeper about quality and prices to compute the substitution rate between goods prices and distance costs.

Figure 2: Non–parametric distance gravity of store openings



Notes: The figure shows static marginal treatment effects on overall household expenditures for different retailers within distance-bins between [0, 2, 5, 10, 15, 20, 30 min]. Expenditures are aggregated to a month-household level for the three favorite stores in each period. Estimation is done for a window spanning 10 periods before and after the treatment, and we use a staggered difference-in-differences following Wooldridge (2022). We aggregate estimated period-cohort coefficients to an overall ATT for each bin and competitor. We cluster standard errors at the household level.

respectively). In contrast, the decay is almost flat for easily storable household articles. Results are again comparable but smaller for visits.

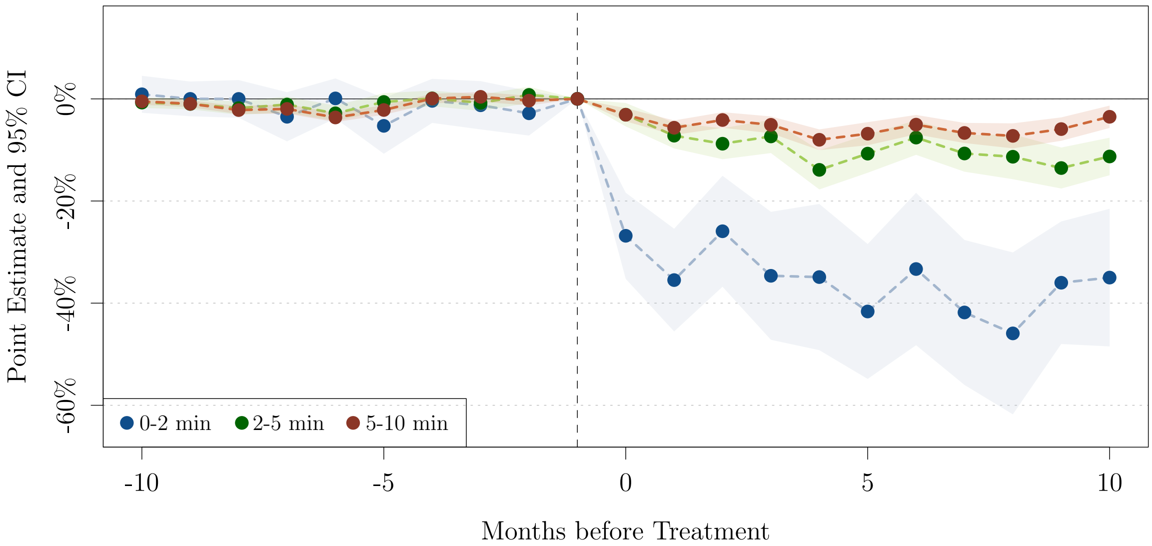
In Figure 2, we display the non-parametric versions of the distance gradients for own-chain entries, as well as for competitors and discounters. Therefore, we estimate again the regression model specified in Equation (2) while replacing the logarithmic distance with dummies for distance-bins with cut-offs [0, 2, 5, 10, 15, 20, 30 min]. These specifications generally support the parametric estimates and suggest a much steeper distance decay for own-chain entries compared to competitors. The 95%-confidence bound starts to include zero at above 15 minutes travel distance. We observe a much smaller effect for the competitors at short distances (10-20 percent expenditure reduction compared to 40 percent for same retail chain entries). The catchment area for discounters reaches its boundary after 20 minutes, while a competitor entry still has a marginally negative effect after 30 minutes. Overall, the non-parametric estimates suggest a somewhat steeper decay function than the log specification. Note that the area between the zero line and the point estimates of the consumption gravity in Figure 2 can be interpreted as the consumer surplus realized for consumption trips at the respective distances.[18]

[18]Or the upper confidence band for a more conservative measure.

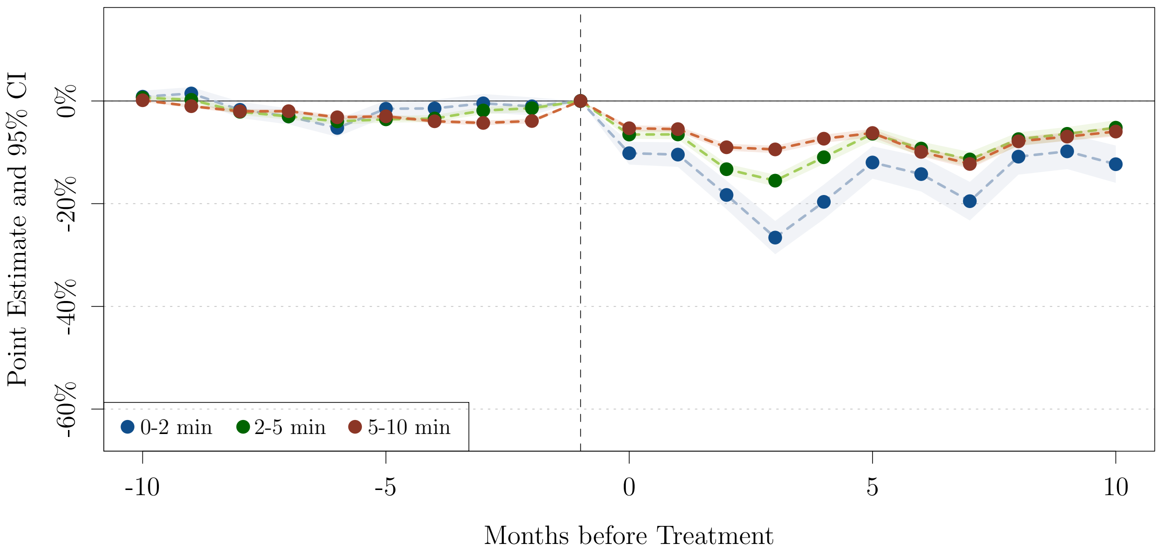
4.3 Dynamic effect

Figure 3: Treatment effect dynamics of store openings

(a) Same Chain Opening (Migros)



(b) Competitor Opening (Main and Discounters)



Notes: The figure shows dynamic average treatment effects on overall household expenditures for different retailers within distance-bins between [0, 2, 5, 10 min]. Expenditures are aggregated to a month-household level for the three favorite stores in each period. Estimation is done for a window spanning 10 periods before and after the treatment. Estimation follows the staggered dynamic difference-in-difference estimator in Roth and Sant'Anna (2022a). Panel (a) reports results for Migros openings. Panel (b) does the same for competitors.

Next, we extend the static approach in the previous sections to dynamic event-study style models. This gives two further insights. First, it shows any build-up or persistence in the effects. Second, it gives a placebo test for the parallel trends assumption.[19]

[19]We get back to this in more detail in section 5.

Hence, we split the sample by retailer, use the same distance bins as in the previous subsection (with cutoffs of 0, 2, 5, and 10 minutes by car) and focus now on the time-dimension. Figure 3 shows the dynamic estimation results for the difference-in-differences model in Equation (3). We group the main competitor and retailers together. This leads to the following conclusions. First, we don't observe any dynamic build-up of the effect. Therefore, we find no evidence for a gradual readjustment of habits, as the observed households adjust their consumption patterns instantaneously. Second, in the month of a Migros entry, the mean household expenditures for a treated unit decrease statistically significantly by almost 30% on a 5%-level compared to the period before the store opening. The coefficients are smaller for larger distances but still significant for all periods. In subsequent periods, the effects then fluctuate around the static ATTs reported in Figure 2. Third, looking at competitor openings, we see a mild build-up over the first months, followed by a gradual reversion to the contemporaneous results. The results are again consistent with the corresponding static ATTs and significant for all bins and periods. Fourth, we see that the retailer type influences a customer's response only for very close openings. If the entry happens more than two minutes away from her residence, there is no apparent difference.

Additionally, the dynamic model allows for placebo tests of the parallel-trend assumption. For close same-chain openings, all pre-treatment coefficients are insignificant. Hence, we conclude that the pre-treatment trends between the treated and the not-yet-treated groups are comparable and that the latter can be used as a valid comparison group. In the case of competitor openings, confidence intervals for the leads are estimated more precisely as the sample is bigger, and some pre-treatment estimates are significant. Thus, we want to analyze the validity of our approach further. To do so, we will in a future version apply in section 5 the sensitivity analysis proposed in Roth and Sant'Anna (2022b) and Rambachan and Roth (2022). This allows us to test, formally, how sensitive our results are to potential violations of parallel trends.

Finally, the choice of the estimator may be important, as other ones in the new difference-in-differences literature may lead to different conclusions (see de Chaisemartin and D'Haultfœuille (2020) for an early overview). Thus, we present in Figure A5 a comparison with different staggered difference-in-differences estimators.[20] We see that for Migros and competitor entries, the coefficients vary only mildly and that our preferred estimator (Roth and Sant'Anna, 2022a) performs well in terms of precision and pre-treatment parallel trends. Figure A5 also validates our choice of the Wooldridge (2022) estimator for our static results, although it does not directly estimate the pre-treatment coefficients.

4.4 Heterogeneities

This subsection builds again on the previous ones and shows a series of heterogeneities for the static average treatment effects in Section 4.2. This indicates where the treatment leads to the

[20]Namely, we compare our preferred estimator Roth and Sant'Anna (2022a) with Wooldridge (2022), Callaway and Sant'Anna (2021), Gardner (2022), and the Standard TWFE model. In all cases, we use the same control group of not-yet-treated units.

Table 4: Heterogeneity for household characteristics

	ln (Household Expenditures) *Level-Mean:* 232 CHF			ln (No. of Trips) *Level-Mean:* 20		
	Own	Main competitor	Discounter	Own	Main competitor	Discounter
Model:	(1)	(2)	(3)	(4)	(5)	(6)
A. Age (Mean: 58)						
Treat at mean	-0.082***	-0.093***	-0.056***	-0.060***	-0.071***	-0.041***
	(0.005)	(0.003)	(0.003)	(0.004)	(0.002)	(0.002)
Treat × ln (Age)	-0.023	0.02	0.017	-0.034***	0.018***	0.018***
	(0.020)	(0.011)	(0.089)	(0.014)	(0.008)	(0.006)
B. Family Dummy (Mean: .30)						
Treat	-0.071***	-0.093***	-0.054***	-0.055***	-0.070***	-0.039***
	(0.006)	(0.003)	(0.003)	(0.004)	(0.002)	(0.002)
Treat × Family Dummy	-0.001	0.009	-0.113***	0.004	0.004	-0.065***
	(0.011)	(0.006)	(0.010)	(0.008)	(0.004)	(0.007)
C. Mun. Income p.c. (Mean: 34)						
Treat at mean	-0.089***	-0.080***	-0.060***	-0.067***	-0.062***	-0.044***
	(0.006)	(0.003)	(0.003)	(0.004)	(0.002)	(0.002)
Treat × ln (income)	-0.243***	0.191***	-0.028	-0.174***	0.150***	-0.020
	(0.034)	(0.021)	(0.020)	(0.024)	(0.015)	(0.014)
D. Urban Dummy (Mean: .29)						
Treat	-0.060***	-0.188***	-0.070***	-0.037***	-0.141***	-0.053***
	(0.011)	(0.005)	(0.004)	(0.008)	(0.003)	(0.003)
Treat × Urban Dummy	-0.165***	0.144***	0.037***	-0.134***	0.104***	0.031***
	(0.022)	(0.008)	(0.007)	(0.016)	(0.005)	(0.005)
Household and Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,055,100	2,393,850	3,454,440	1,055,100	2,393,850	3,454,440

Notes: The table shows household-level heterogeneities for the estimated causal effect of a store entry within 10 minutes car travel time for three types of retailers. Expenditures and visits are aggregated to a month-household level for the three favorite stores in each period. Their mean is displayed for the pre-treatment period. Note that the continuous covariates are demeaned, such that the entry coefficient is the average treatment effect. Estimation is done for a window of 10 periods before and after the treatment, and we use a staggered difference-in-differences following Wooldridge (2022). We allow the treatment to vary with the covariate of interest and aggregate coefficients to an overall ATT by demeaning each covariate for each cohort. We report standard errors clustered at the household level in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

most pronounced re-optimization of shopping patterns. We analyze results for different socio-demographic and geographic characteristics and complementarities with the local economy.

Heterogeneity across socio-demographic groups

First, we discuss heterogeneous treatment effects for different customer characteristics. We use the static difference-in-differences model with an interaction term (Equation 2). We consider continuous covariates for age and municipality income and dummies for households living in a family or urban areas. We report results separately for Migros entries, discounters, and all competitors. Table 4 shows the estimation results. The panels present for each covariate the treatment effect at the mean (for continuous variables) or for the base category (for binary variables) and estimates for the interaction.

Results show that there are considerable differences between the retailers. First, a 10% older person reduces the visits to her favorite stores by 0.34 percentage points after a new Migros opening. Compared to that, competitor and discounter entries attract more younger people. However, there is no significant effect of age on expenditures at Migros. Second, families react very strongly to a discounter entry, reducing their spending by almost 17%. Third, as a measure of the socio-economic status of a household's neighborhood, municipality income shows diverging results. People react very strongly to Migros entries in high-income municipalities, while a Coop opening in a low-income municipality even increases Migros expenditures. Surprisingly, we do not find any significant effects for discounters. Fourth, households react also differently to entrants in urban and rural areas. On the one hand, comparing the distance elasticities in rural and urban areas for Migros, we find elasticities of 0.06 and 0.225. Hence, a doubling of distances reduces expenditures by almost four times in urban compared to rural areas (22.5% versus 6%). This implies that urban residents react more elastically to a store entry nearby. On the other hand, for competitors and discounters, urban households reduce their expenditures less in response to a treatment (-4.4% vs. 18.8% for the main competitor and -7.0% vs. 3.3% for discounters).

We dig again deeper by providing separate results for different product groups. Figure A 3 displays the corresponding interaction terms. Overall, the results are consistent with the previous findings in sign. Magnitudes are often similar across products, with the highest coefficients for meat and vegetables. Again, the most striking finding is the strong reaction of families to discounters, which holds across all groups.

Interaction with other local amenities and commuting

Finally, this subsection analyzes differences in the attractiveness between comparable stores. One might expect that if there are complementarities between stores and their surrounding local economy, stores in high-amenity neighborhoods should be more attractive. Therefore, we expect households to be more likely to visit entrants in high-amenity areas. This complements the evidence on *trip-chaining*, as analyzed for example in Relihan (2022) or Miyauchi et al. (2022). We rely upon the same strategy as the previous subsection to test this hypothesis. We estimate the static difference-in-differences model in Equation (2) with interactions for the amenities in Table 1, Panel C. These include stores, cafés, restaurants, etc. We restrict the sample to a window of car travel time between 5 and 10 minutes because too short distances likely do not matter for planned trip-chaining.

Table 5 shows the estimation results. Columns (1)-(3) interact the treatment with a dummy

Table 5: Heterogeneity for spatial amenities

	ln (Household Expenditures)					
	Own	Main competitor	Discounter	Own	Main competitor	Discounter
Model:	(1)	(2)	(3)	(4)	(5)	(6)
	(*Measure: Dummy if Any*)			(*Measure: ln (Continuous Count)*)		
A. Other Stores (Mean: 2.2)						
Treat at mean	0.005	-0.034***	-0.039***	-0.103***	-0.122***	-0.050***
	(0.012)	(0.008)	(0.009)	(0.020)	(0.007)	(0.003)
Treat × Stores in 200 m	-0.014	-0.108***	0.003	0.039	-0.003	-0.013***
	(0.011)	(0.09)	(0.014)	(0.023)	(0.006)	(0.003)
B. Restaurants (Mean: 4.6)						
Treat at mean	-0.035	-0.007***	-0.056	-0.024	-0.124***	-0.047***
	(0.300)	(0.015)	(0.056)	(0.014)	(0.045)	(0.003)
Treat × Restaurants in 200 m	0.002	0.048***	0.007	-0.045***	-0.022	-0.009***
	(0.296)	(0.016)	(0.056)	(0.016)	(0.035)	(0.002)
C. Cafes (Mean: 2.3)						
Treat at mean	-0.067***	0.024	-0.026***	-0.068***	-0.087***	-0.048***
	(0.022)	(0.037)	(0.006)	(0.011)	(0.004)	(0.004)
Treat × Cafes in 200 m	-0.013	-0.133***	-0.047***	-0.020***	-0.006***	-0.004***
	(0.022)	(0.037)	(0.006)	(0.009)	(0.002)	(0.001)
D. Post Offices (Mean: 1.0)						
Treat at mean	-0.016***	-0.103***	-0.045***	-0.066***	-0.088***	-0.028***
	(0.006)	(0.006)	(0.006)	(0.014)	(0.004)	(0.004)
Treat × Post Offices in 200 m	-0.020***	0.039***	0.024***	-0.071***	-0.002	0.005
	(0.009)	(0.008)	(0.009)	(0.022)	(0.002)	(0.003)
E. Banks (Mean: 0.9)						
Treat at mean	-0.087***	-0.178***	-0.020***	-0.100***	-0.201***	-0.041***
	(0.025)	(0.038)	(0.005)	(0.012)	(0.031)	(0.004)
Treat × Banks in 200 m	-0.056	0.056	-0.023***	-0.031***	0.028***	-0.007***
	(0.039)	(0.039)	(0.007)	(0.008)	(0.011)	(0.003)
Observations	1,055,100	2,393,850	3,454,440	1,055,100	2,393,850	3,454,440
Household and Month FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table shows entry–level heterogeneities for the estimated causal effect of a store entry within 10 minutes car travel time for three types of retailers. Columns (1) – (3) interact the treatment with a dummy for the presence of this amenity in 200m. Columns (4) – (6) interact the treatment with the log of the amenity. Expenditures are aggregated to a month–household level for the three favorite stores in each period. Estimation is done for a window of 10 periods before and after the treatment, and we use a staggered difference-in-differences following Wooldridge (2022). We allow the treatment to vary with the covariate of interest and aggregate coefficients to an overall ATT by demeaning each continuous covariate for each cohort. We report standard errors clustered at the household level in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

whether the specific amenity exists within 200m around the opening. First, we find almost no evidence for any complementarities for Migros openings. But if the main competitor opens a supermarket next to a café or another store, we find strong negative coefficients (-13.3 and -10.8 percentage points, respectively). Hence, this is significant evidence for trip-chaining in this case. Finally, there is only a mild complementarity between discounters and coffee shops.

5 Robustness and Sensitivity

In this section, we address three concerns about the validity of our results and discuss potential violations of the parallel trend assumption that would invalidate our conclusions.

First, recall that we focus on a binary treatment and ignore multiple ones. Thus, we are concerned that additional openings bias our coefficients. Further, the problem may vary with distance. Within two minutes, 97% of all treated households get only one treatment. However, for the bins up to 5 and 10 minutes, the share of once–treated units decreases to 88% and 61%, respectively. Therefore, if this biases our results, the bias should especially be pronounced for the wider bins. Second, note that our strategy allows for heterogeneity between cohorts and periods. However, we are still concerned that the Covid-19 pandemic led to a change in grocery shopping behavior that our approach can not capture. Third, note that we define in section 2 the treatment as the entry closest to a household's residence. However, this does not consider the place's surroundings or the observed shopping behavior. We address these issues as follows.

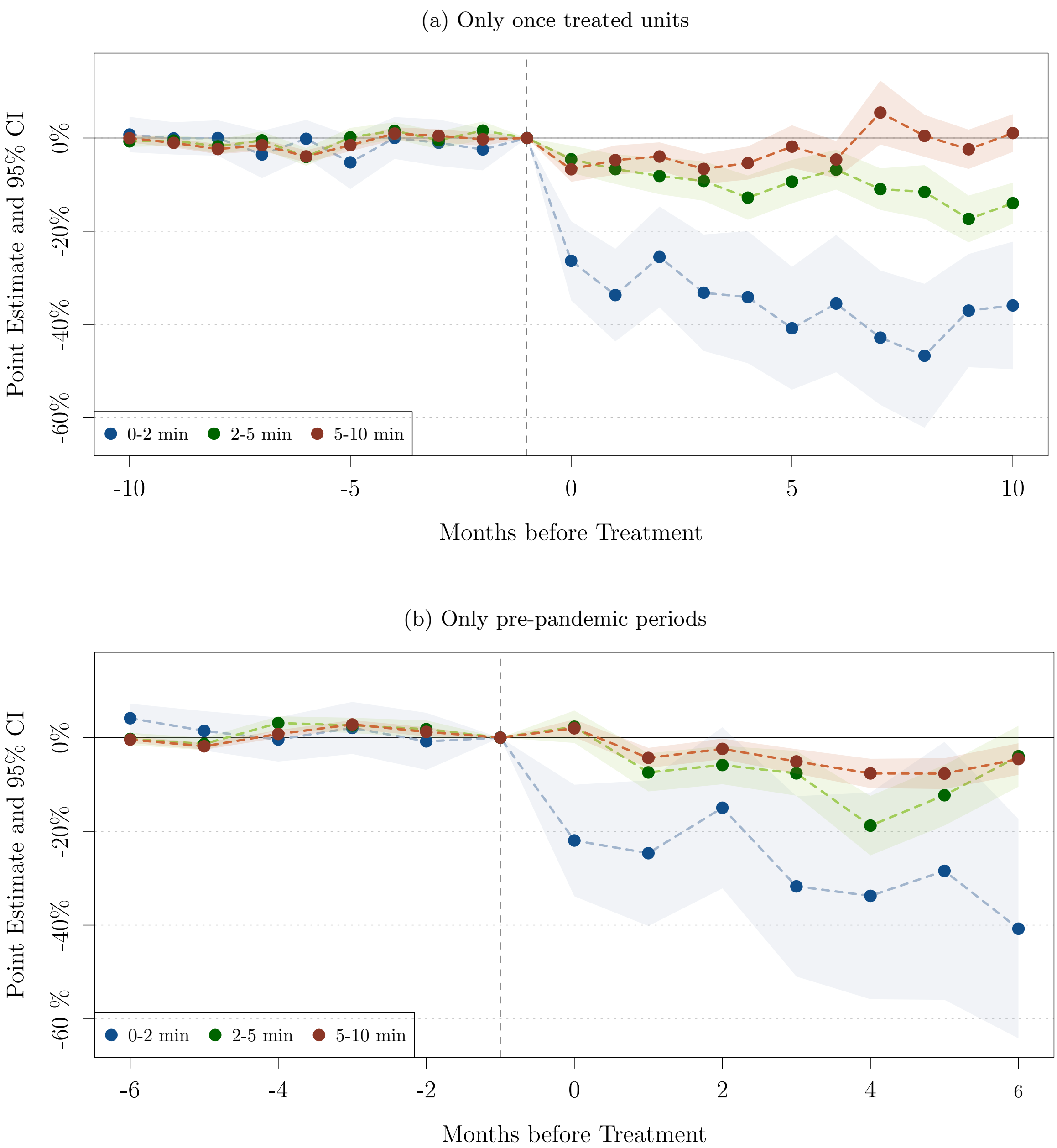
To tackle the first issue, we present a robustness check for own-chain openings within the event-study setting in section 4.3, as this gives a direct proxy for the parallel trend assumption. We focus on a sub-sample including only once–treated units. Figure 4a presents the estimation results. For openings within five minutes, changes are indeed negligible. For the largest radius, point estimates are close to our main results in section 3.3, but become insignificant after half a year. Pre-treatment coefficients are insignificant, indicating no violation of the parallel trends assumption. Overall, we see this as ensuring our findings.

We address the second issue by restricting our analysis to a sub-sample that only includes observations before the start of the pandemic in Switzerland (namely, for the periods January 2019 to February 2020). Figure 4b shows analogous results within the event-study setting. Again, we find similar results across all bins that further ensure the credibility of our findings. However, note that confidence bands are significantly wider, especially for the narrowest radius, due to the smaller sample size. Hence, our ignorance of multiple treatments and the Covid-19 pandemic should not invalidate our main findings.

Third, we use an alternative treatment definition. Compared to our main results, we define an entry as a treatment if it reduces the household's average travel time to spend 1 CHF.[21] The advantage of this approach is that it takes into account the local surrounding and actual consumption behavior of a household. However, the disadvantage is that we cannot say anything about the role of distance itself. We estimate this with the static model in Equation (2) and

[21] In detail, we weight, for the year before the treatment, the car travel time to the three favorite stores with the corresponding expenditures.

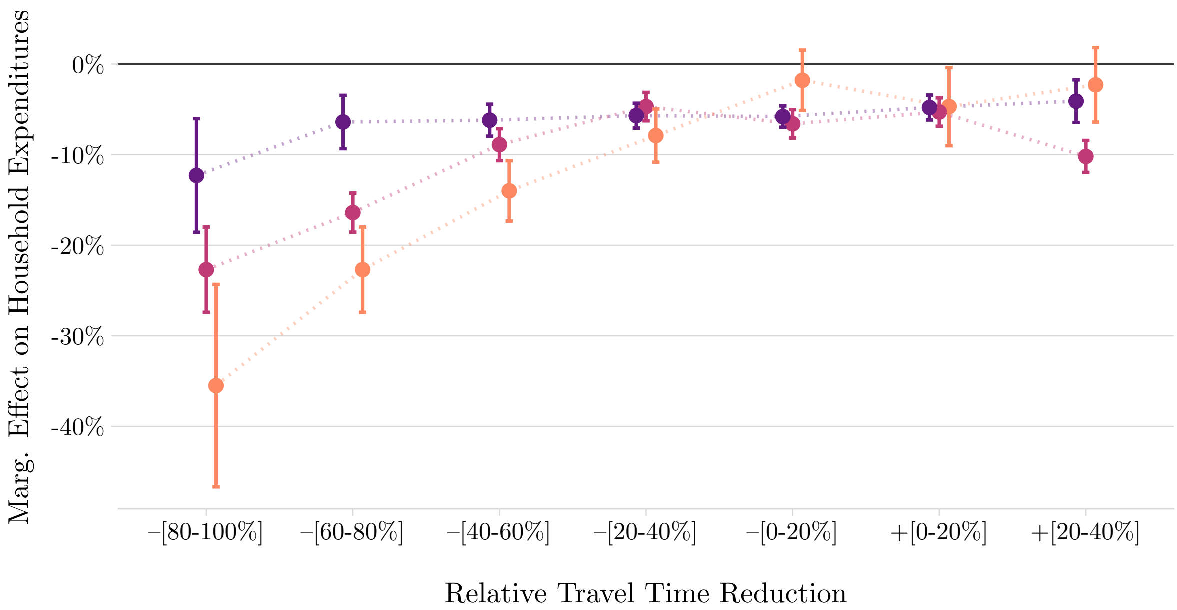
Figure 4: Alternative treatment effect dynamics of Migros store openings



Notes: The figure shows dynamic average treatment effects on overall household expenditures for Migros within distance-bins between [0, 2, 5, 10 min]. Expenditures are aggregated to a month-household level for the three favorite stores in each period. Estimation is done for a window spanning 10 periods before and after the treatment. Estimation follows the staggered dynamic difference-in-differences estimator in Roth and Sant'Anna (2022a). Panel (a) reports results for a sub-sample of once-treated units. Panel (b) only uses pre-pandemic periods.

use again distance bins as in Figure 2. This time, we use cut-offs between a –100% and +40% change in relative travel time. Figure 5 shows the associated marginal effect for expenditures. The results are similar to the ones based on our preferred treatment definition in Figure 2. Two observations are noteworthy. First, the decay is slower if we take into account the actual shopping trips. Second, the effects turn insignificant for own-chain openings as soon as the potential gain

Figure 5: Alternative distance gravity of store openings



Notes: The figure shows static marginal treatment effects on overall household expenditures for different retailers, and distance bins. Treatment is defined as the driving time to the treatment relative to a household's average distance to spend one CHF. We show bins between a 100% reducation and a 40% increase. Expenditures are aggregated to a month-household level for the three favorite stores in each period. Estimation is done for a window spanning 10 periods before and after the treatment, and we use a staggered difference-in-differences following Wooldridge (2022). We aggregate estimated period-cohort coefficients to an overall ATT for each bin and competitor. We cluster standard errors at the household level.

in travel-time disappears. This highlights the costs of distance under perfect substitutability of the stores. However, we still find significant decay parameters for competitors that are relatively far away. This highlights the households' valuation of increased variety.

6 Conclusions

This paper exploits a unique data set of households' transaction records from the largest retailer in Switzerland. The data set includes 1.5 billion transactions of more than 2 million households in Switzerland and is highly representative. Our empirical identification relies on quasi-experimental store openings. The key identifying assumption is the randomness of openings in the short run. Our results are three-fold. First, average monthly expenditures drop immediately by 6.0% if a same-chain store opens within a large radius of 30 minutes driving time. Within two minutes, the decline amounts to 30%. Effects are persistent over time. Second, the effect turns insignificant after 16 minutes of car travel time, indicating the supermarkets' catchment area or local consumption area. Third, we quantify a series of heterogeneities across spatial and socio-demographic characteristics. We find a vital role of municipality income that varies by retailer. The main competitor is particularly attractive in rural and low-income areas, and families favor discounters. Further, we find evidence for trip-chaining combined with visits to the main competitor, with no indication for own-chain and discounter entries.

We want to extend the paper in the following directions. First, we will dig deeper into the observed heterogeneities by exploiting register-data income. Second, we will analyze the capitalization of our findings into rent prices. We hypothesize that the areas where we identify narrow consumption areas should face the highest rise in rents. Third, the derived consumption gravity estimations can compute location-specific surplus. We will exploit the effect of entry on aggregate revenues of the retailer to provide further information about the degree of competition. Using information about prices allows us to compute marginal rates of substitution between distance costs and product costs and characteristics informing, e.g., about variety preferences.

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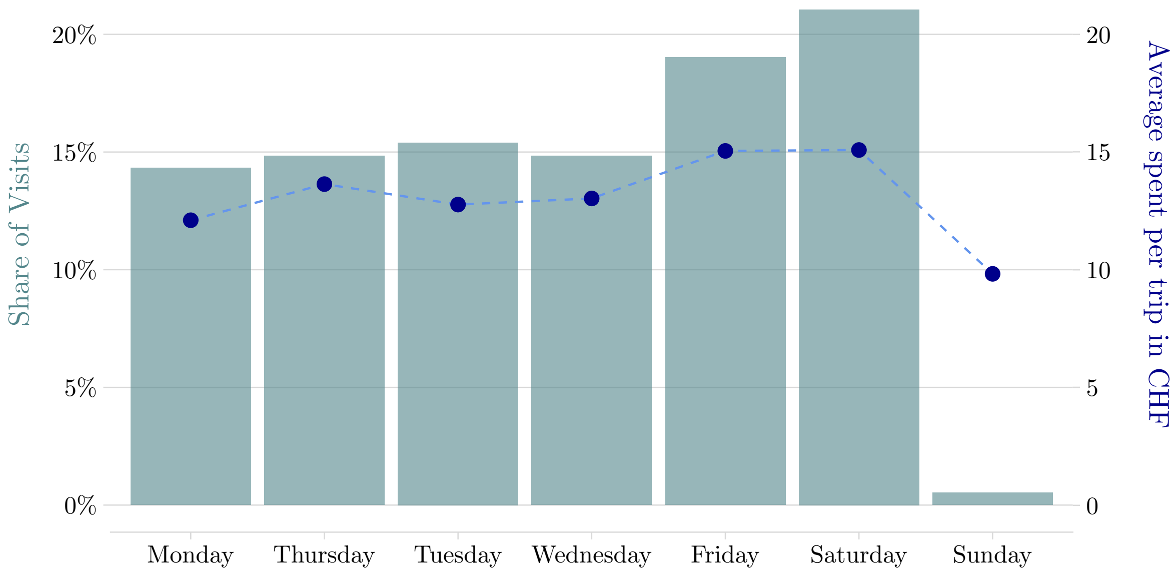
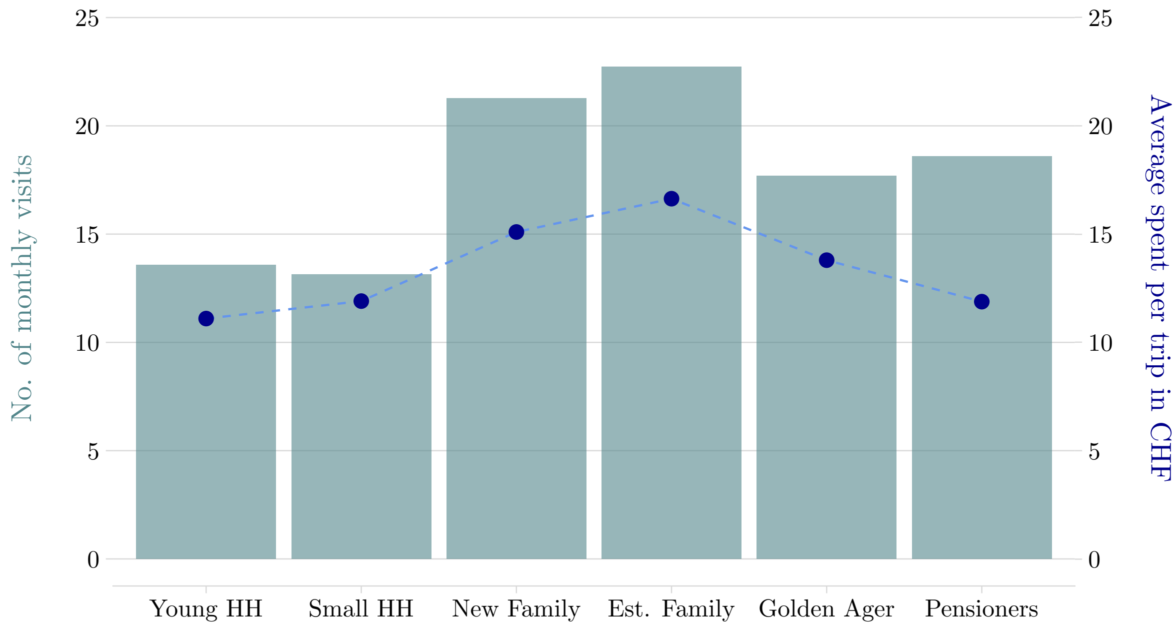
A Appendix

Figure A1: Descriptives of the transactions

(a) Transactions by day of the week

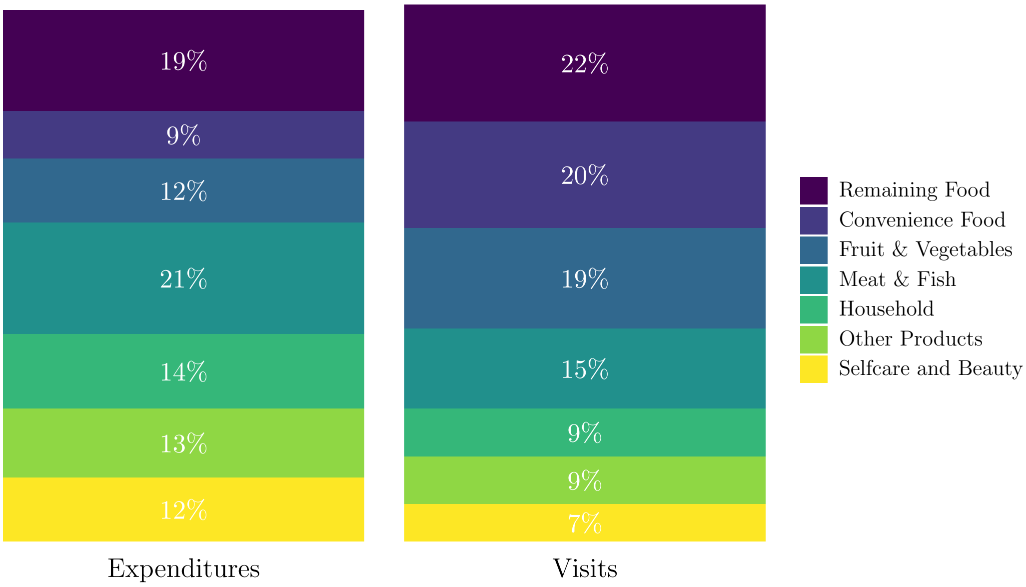


(b) Transactions by household type



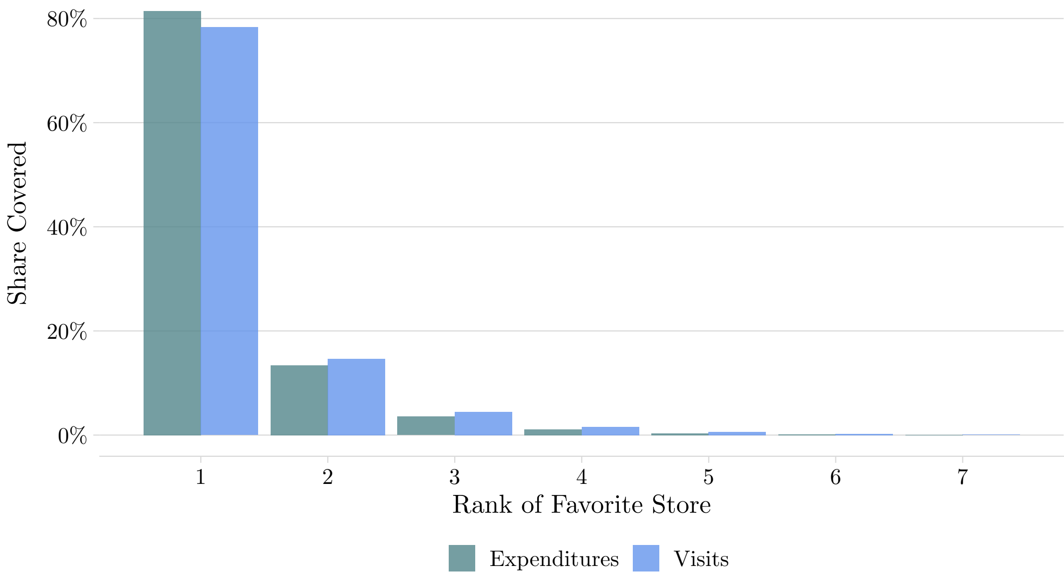
Notes: Subfigure (a) shows the relative number of shopping trips and the average amount spent per trip in CHF for each weekday. Subfigure (b) shows the absolute number of trips and the average amount spent in CHF for each household type. The figure aggregates all 1.5 billion transactions between 2019 and 2021 Q2 that have non-negative amounts and are at supermarkets within 30 minutes by car from the household's residence.

Figure A2: Composition of Shopping Trips



Notes: The figure shows the product groups' shares of sold goods at Migros. The left bar shows the shares for expenditures, the right one for visits. The figure aggregates all 1.5 billion transactions between 2019 and 2021 Q2 that have non-negative amounts and are at supermarkets within 30 minutes by car from the household's residence.

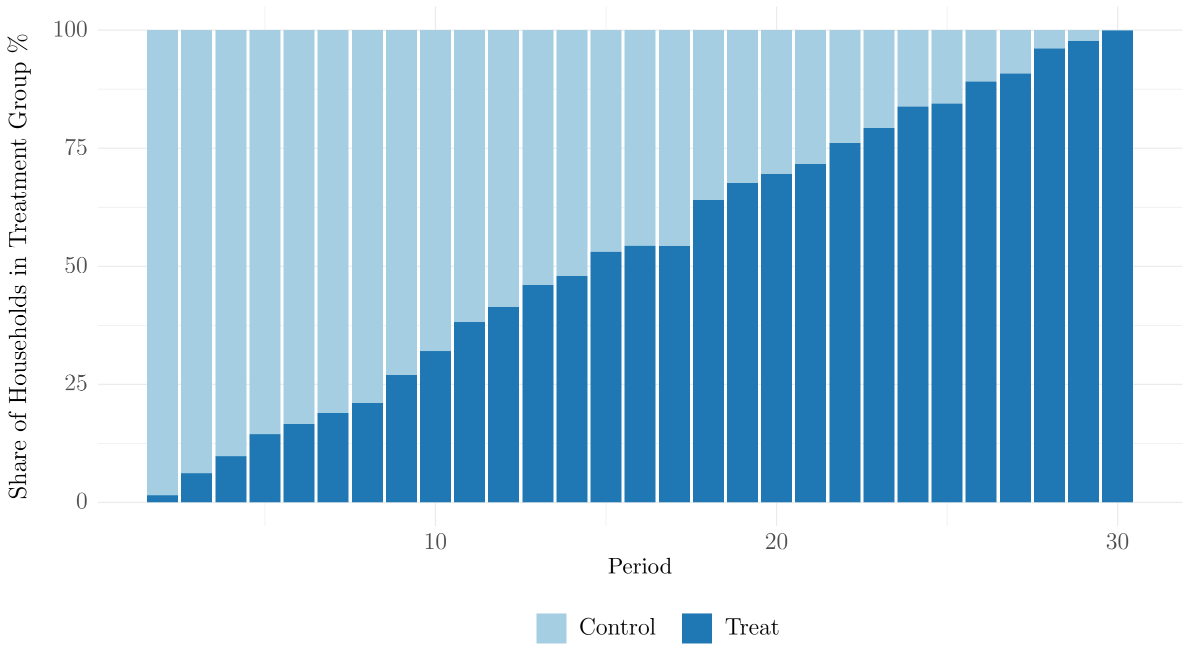
Figure A3: Ranking of Favorite Stores



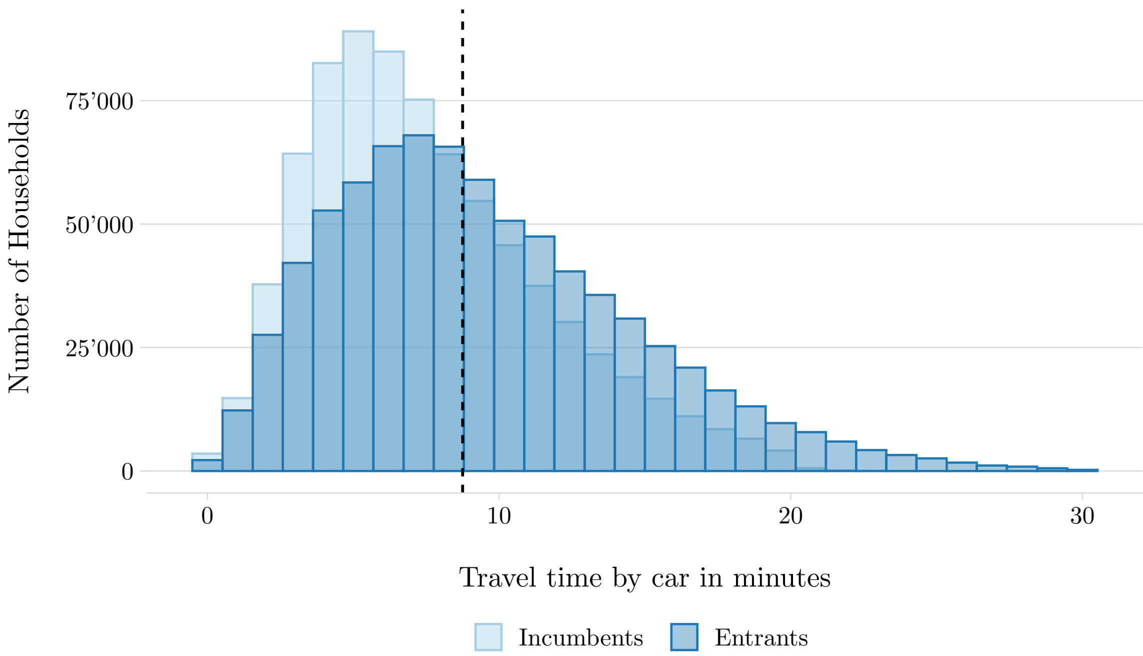
Notes: The figure shows the share of households' visits and expenditures at their ranked favorites. The figure aggregates all 1.5 billion transactions between 2019 and 2021 Q2 that have non-negative amounts and are at supermarkets within 30 minutes by car from the household's residence.

Figure A4: Descriptives of the treatments

(a) Composition of treatment and control groups



(b) Distance to closest treatment



Notes: Subfigure (a) shows how the composition of treatment and control group changes over time as more and more households switch into the treatment group. Subfigure (b) presents the distribution of the car travel time to the closest opening against the average distance a household travels to spend 1 CHF. The vertical line shows the mean distance for the entrants.

Table A 1: Static gravity elasticities of a store entry by product category

	ln (Household Expenditures) *Level-Mean:* 232 CHF			ln (No. of Trips) *Level-Mean:* 20		
	Own	Main competitor	Discounter	Own	Main competitor	Discounter
Model:	(1)	(2)	(3)	(4)	(5)	(6)
A. Meat and Fish						
Treat at mean	-0.031***	-0.019***	-0.015***	-0.023***	-0.017***	-0.014***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Treat × ln (car distance in min)	0.077***	0.029***	0.019***	0.062***	0.022***	0.014***
	(0.007)	(0.002)	(0.002)	(0.005)	(0.001)	(0.002)
Observations	1,467,258	3,526,611	4,613,447	1,467,258	3,526,611	4,613,447
B. Vegetables and Fruit						
Treat at mean	-0.025	-0.041***	-0.029***	-0.026	-0.036***	-0.022***
	(0.151)	(0.002)	(0.010)	(0.122)	(0.001)	(0.007)
Treat × ln (car distance in min)	0.091***	0.021***	0.048	0.066***	0.018***	0.032
	(0.007)	(0.003)	(0.176)	(0.005)	(0.002)	(0.122)
Observations	1,769,520	4,005,090	5,236,800	1,769,520	4,005,090	5,236,800
C. Convenience Food						
Treat at mean	-0.020	-0.040***	-0.020	-0.019	-0.039***	-0.021***
	(0.137)	(0.002)	(0.011)	(0.102)	(0.001)	(0.008)
Treat × ln (car distance in min)	0.082***	0.019***	0.031***	0.062***	0.020***	0.027***
	(0.006)	(0.003)	(0.003)	(0.005)	(0.002)	(0.002)
Observations	1,644,257	3,739,698	4,894,758	1,644,257	3,739,698	4,894,758
D. Household Products						
Treat at mean	-0.005	-0.024***	-0.010***	-0.004***	-0.019***	-0.008***
	(0.004)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Treat × ln (car distance in min)	0.049***	0.013***	0.006***	0.049***	0.011***	0.006 ***
	(0.007)	(0.002)	(0.002)	(0.004)	(0.001)	(0.001)
Observations	1,467,258	3,345,874	4,357,447	1,467,258	3,345,874	4,357,447
Household and Month FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table shows elasticities for the estimated causal effect of a store entry within 30 minutes by product types. Expenditures and visits are aggregated to a month-household level for the three favorite stores in each period. Their mean is displayed for the pre-treatment period. Distance is measured either by travel time by car. Note that the covariate is demeaned, such that the entry effect coefficient is the average treatment effect. Estimation is done for a window spanning 10 periods before and after the treatment, and we use a staggered difference-in-differences following Wooldridge (2022). We allow the treatment to vary with the distance covariate and aggregate estimated period-cohort coefficients to an overall ATT. We report standard errors clustered at the household level in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

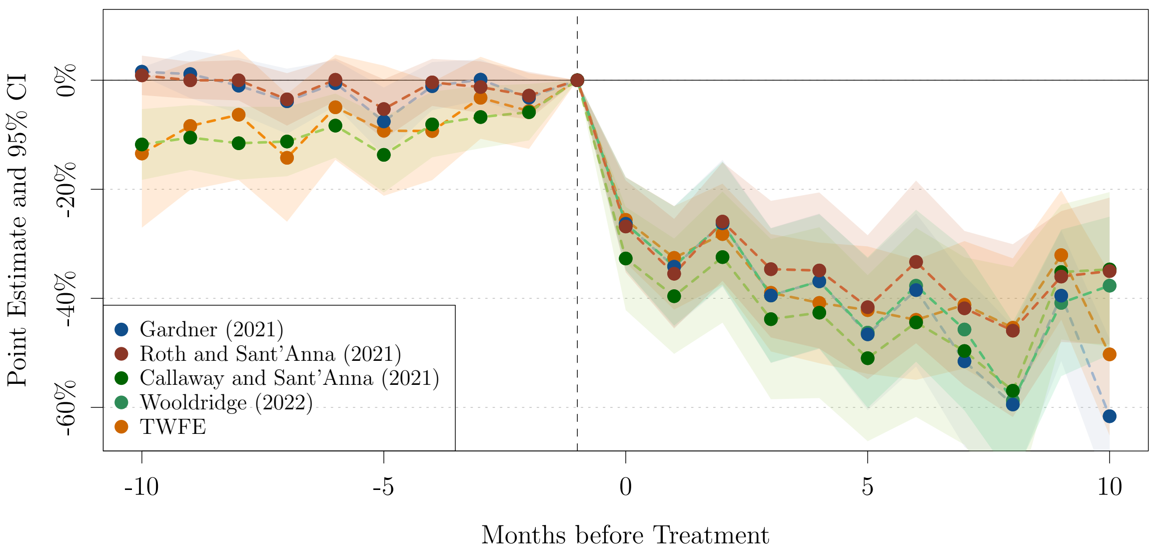
Table A 2: Static gravity elasticities of a store entry: Pedestrians and Bicycles

	ln (Expenditures) *Level-Mean:* 232 CHF		ln (No. of visits) *Level-Mean:* 20	
	(1)	(2)	(3)	(4)
A. Own-Chain Opening				
Entry at mean	-0.054***	-0.061***	-0.030***	-0.041***
	(0.008)	(0.004)	(0.005)	(0.003)
Entry × ln (bicycle dist. in min)	0.086***		0.069***	
	(0.006)		(0.004)	
Entry × ln (walking dist. in min)		0.080***		0.063***
		(0.006)		(0.004)
Household and Month FE	Yes	Yes	Yes	Yes
Observations	1,769,520	1,769,520	1,769,520	1,769,520
B. Main Competitor Opening				
Entry at mean	-0.078***	-0.078***	-0.058***	-0.057***
	(0.002)	(0.002)	(0.002)	(0.002)
Entry × ln (bicycle dist. in min)	0.013***		0.014***	
	(0.003)		(0.002)	
Entry × ln (walking dist. in min)		0.010***		0.011***
		(0.003)		(0.002)
Household and Month FE	Yes	Yes	Yes	Yes
Observations	4,005,090	4,005,090	4,005,090	4,005,090
C. Discounter Opening				
Entry at mean	-0.046***	-0.035***	-0.032***	-0.027***
	(0.002)	(0.002)	(0.002)	(0.002)
Entry × ln (bicycle dist. in min)	0.029***		0.024***	
	(0.002)		(0.002)	
Entry × ln (walking dist. in min)		0.027***		0.023***
		(0.002)		(0.002)
Household and Month FE	Yes	Yes	Yes	Yes
Observations	5,236,800	5,236,800	5,236,800	5,236,800

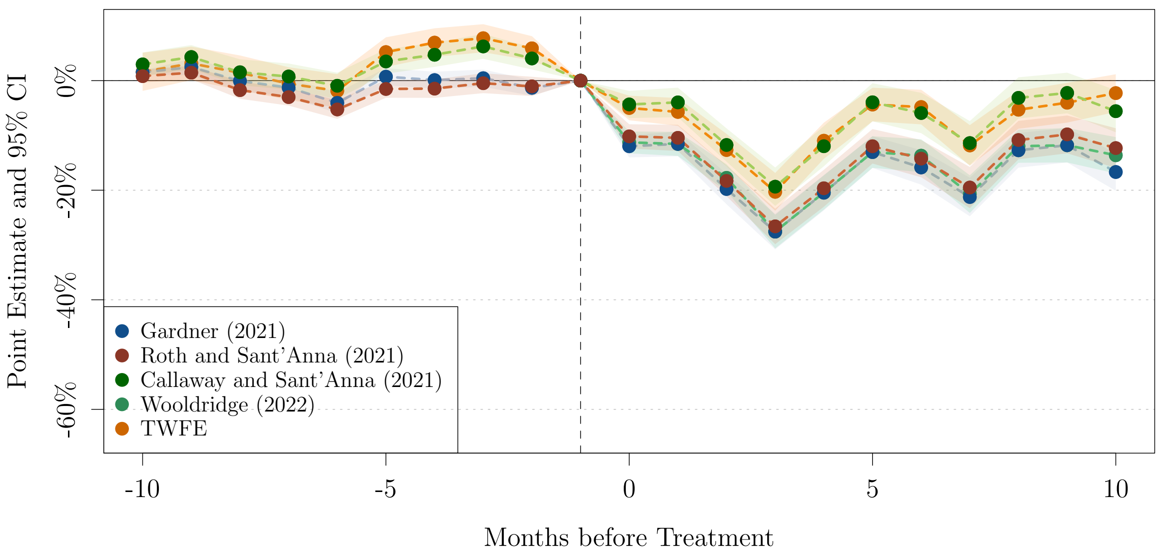
Notes: The table shows elasticities for the estimated causal effect of a store entry within 30 minutes. Expenditures and visits are aggregated to a month-household level for the three favorite stores in each period. Their mean is displayed for the pre-treatment period. Distance is measured either by travel time by walking or bicycle. Note that the covariate is demeaned, such that the entry effect coefficient is the average treatment effect. Panel (A) reports results for a Migros opening, Panel (B) for the main competitor (Coop), and Panel C for discounters (Aldi, Lidl). Estimation is done for a window spanning 10 periods before and after the treatment, and we use a staggered difference-in-differences following Wooldridge (2022). We allow the treatment to vary with the distance covariate and aggregate estimated period-cohort coefficients to an overall ATT. We report standard errors clustered at the household level in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Figure A5: Treatment effect dynamics of store openings

(a) Same Chain Opening (Migros)



(b) Competitor Opening (Main and Discounters)



Notes: The figure shows dynamic average treatment effects on overall household expenditures for different retailers within a distance-bin of two minutes. Expenditures are aggregated to a month-household level for the three favorite stores in each period. Estimation is done for a window spanning 10 periods before and after the treatment. Estimation compares the difference-in-differences estimators in Gardner (2022); Roth and Sant'Anna (2022a); Callaway and Sant'Anna (2021) and Wooldridge (2022) to the standard TWFE estimator. Panel (a) reports results for Migros openings. Panel (b) does the same for competitors.

Table A 3: Heterogeneity for household characteristics by product group

	ln (Household Expenditures) *Level-Mean:* 232 CHF				
	(Meat)	(Vegetables)	(Convenience)	(Other Food)	(Household)
Model:	(1)	(2)	(3)	(4)	(5)
A. Migros					
Treat × Urban	-0.092***	-0.127***	-0.108	-0.098***	-0.066***
	(0.016)	(0.043)	(0.331)	(0.029)	(0.016)
Treat × Family	0.017**	0.013	-0.009	0.000	0.033***
	(0.005)	(0.009)	(0.009)	(0.009)	(0.006)
Treat × ln (Age)	-0.056***	-0.085***	-0.016	-0.018	-0.007
	(0.009)	(0.009)	(0.015)	(0.014)	(0.015)
Treat × ln (Mun. Income p.c.)	-0.118***	0.016	-0.098***	-0.098***	-0.152***
	(0.030)	(0.012)	(0.031)	(0.029)	(0.034)
Observations	978,572	980,679	981,804	1,008,907	874,578
B. Competitor					
Treat × Urban	0.021***	0.081***	0.049	0.076***	0.025***
	(0.003)	(0.007)	(0.079)	(0.006)	(0.004)
Treat × Family	-0.015***	-0.016***	-0.009	-0.020	-0.012***
	(0.005)	(0.005)	(0.005)	(0.028)	(0.006)
Treat × ln (Age)	0.020***	0.026***	-0.016	0.011	0.016
	(0.009)	(0.009)	(0.015)	(0.008)	(0.009)
Treat × ln (Mun. Income p.c.)	0.096***	0.114***	0.093***	0.121***	0.052***
	(0.018)	(0.018)	(0.018)	(0.016)	(0.020)
Observations	2,104,136	2,224,679	2,236,269	2,299,588	1,995,241
C. Discounter					
Treat × Urban	0.043	0.021	0.007	0.014***	-0.008
	(0.181)	(0.019)	(0.214)	(0.006)	(0.006)
Treat × Family	-0.062***	-0.073***	-0.058***	-0.082***	-0.063***
	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)
Treat × ln (Age)	0.025***	-0.001	-0.051	0.000	-0.002
	(0.002)	(0.146)	(0.832)	(0.015)	(0.005)
Treat × ln (Mun. Income p.c.)	0.011*	0.025***	-0.028	0.003	0.013*
	(0.006)	(0.006)	(0.018)	(0.032)	(0.013)
Observations	3,025,961	3,210,795	3,226,958	3,316,685	2,862,061
Household and Month FE	Yes	Yes	Yes	Yes	Yes

Notes: The table shows household-level heterogeneities for the estimated causal effect of a store entry within 10 minutes car travel time for three types of retailers. The results are reported by product category. Expenditures are aggregated to a month-household level for the three favorite stores in each period. Estimation is done for a window of 10 periods before and after the treatment, and we use a staggered difference-in-differences following Wooldridge (2022). We allow the treatment to vary with the covariate of interest and aggregate coefficients to an overall ATT by demeaning each continuous covariate for each cohort. We omit the ATT in the table to improve readability. We report standard errors clustered at the household level in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.