Spatial Frictions in Retail Consumption *

Frédéric Kluser †
University of Bern

Tobias Seidel ‡
University of Duisburg-Essen

Maximilian v. Ehrlich §
University of Bern

First version: January 2022
This version: January 3, 2025
Link to the newest version

Abstract

This paper analyzes spatial consumption frictions by estimating the causal effect of store openings on individual shopping behavior. To this end, we combine unique household-store-linked transaction data with administrative data on income and other socio-demographics. Our findings reveal that spatial frictions significantly influence shopping behavior, with the distance elasticity of expenditures and number of visits being approximately 0.15. Our estimates suggests that consumption areas extend to about 10-20 minutes of travel time, depending on household type. Traditional gravity estimates are shown to be considerably biased due to the endogenous nature of store locations. By combining distance elasticities with a simple model of shopping behavior, we derive store-specific attraction parameters and compute a measure of local grocery market access. Market access varies significantly across different locations, and consistent with spatial equilibrium theory, this variation is reflected in local rents. Consumption frictions are more pronounced for older and smaller households and vary with income, primarily in non-urban areas. Overall, spatial variations in market access are more significant than spatial dispersion in income. Combined with the positive correlation between income and market access, this suggests an important role for real income disparities.

Keywords: economic geography, consumption access, consumption inequality
JEL-codes: R1, R2, L14.

---

*This paper previously circulated under the title "*Spatial frictions in consumption and retail competition*". We thank Gabriel Ahlfeldt, Costas Arkolakis, Pierre-Philippe Combes, Marcel Henkel, Jessie Handbury, Christian Hilber, Gabriel Loumeau, Raphaël Parchet, Martina Pons, Lindsay Relihan, Frédéric Robert-Nicoud, and various seminar participants for their helpful comments and suggestions. We thank Migros and the Swiss Federal Statistical Office for providing the data, and we acknowledge funding from the Swiss National Science Foundation's NFP 77 "Digital Transformation" (Project 407740 187443) and the Berne University Research Foundation. The usual disclaimer applies.

† frederic.kluser@unibe.ch

‡ tobias.seidel@uni-due.de

§ maximilian.vonehrlich@unibe.ch

1 Introduction

Modern spatial equilibrium models highlight the importance of access to consumption amenities as a factor enhancing the attractiveness of residential locations (see, for example, Brueckner and Zenou, 1999, Couture and Handbury, 2020, and Handbury, 2021) and the concept of a spatial equilibrium suggests that households in locations with fewer amenities require higher real wages as compensation (see, for example, Rosen, 1979, Roback, 1982, Caliendo et al., 2019, and Ahlfeldt et al., 2022). To understand the spatial dynamics of non-tradable consumption and the value of consumption access across different areas, reliable estimates of spatial frictions are essential. These estimates are crucial not only for understanding household choices but also for informing policy decisions. For instance, zoning laws differentiate land into commercial and residential zones to manage spillovers and coordinate infrastructure effectively. Understanding these consumption-related spatial frictions is vital for planning and has significant implications for welfare and spatial disparities.

However, identifying the degree of spatial frictions in retail consumption is complex due to the endogenous nature of store locations, which can render traditional gravity model estimates unreliable. Retailers often choose locations close to customer bases with a latent demand that are likely to spend more or have a preference for their products. Moreover, spatial frictions and the value of consumption access may vary significantly across different household groups, potentially obscuring valuable insights about diverse residential location choices. Factors such as varying transport costs, demand elasticity, and expenditure shares of consumption, particularly grocery consumption, can differ between household types. Despite their relevance, causal estimates are scarce, but various papers acknowledge their importance. Among them, Eizenberg et al. (2021) states that the location choice of shops is outside the scope of their paper, Marshall and Pires (2018) use weather shocks to identify distance parameters and Taylor and Villas-Boas (2016) instrument the distance to stores with the distance to the closest outlet of different types, while Miyauchi et al. (2022) rely on a model-based structural GMM.

In this paper, we follow a different approach and achieve a causal identification of spatial frictions by exploiting quasi-experimental variation from store openings. We collect information on hundreds of store openings, which we link to individual-level data on detailed consumption spending and sociodemographic characteristics such as income, age, and household size. The expenditure data includes expenditures for food 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 Migros, the largest Swiss retailer, for the period 2019Q1-2021Q2.[1] Households live in 315,000 grid cells, measuring 100 $\times$ 100 meters, and we have coordinate-level precision for stores. Together with hand-collected data on store openings for all major retail chains and administrative individual-level data, we are able to estimate consumption decay functions at a high spatial resolution.

[1]Our result are still valid if we exclude the COVID-19 pandemic.

To this end, we apply a staggered difference-in-differences approach to the geo-referenced household-store-linked consumption data. This allows us to isolate expenditure shifts to the new stores from incumbent stores within the same retail chain and from different chains. The *expenditure shift* within the chain is fully caused by distance reductions as, for a given size, stores of the same chain offer the same product variety at the same price. The *competitor shift* reflects variety substitutions as well as distance reductions. Variations in these two types of expenditure shifts enable us to estimate flexible distance gradients of consumption. In the second step, we estimate the shop-specific attraction parameters. These estimates from the store-opening experiments provide insights into the parameters of distance frictions, substitution elasticities, and quality-adjusted prices of stores in a spatial model of consumption activities. Building on the model structure and parameter estimates, we compute local and type-specific measures of consumption access. Finally, we demonstrate that our local measures of consumption access exhibit significant variation across and within cities and explain a substantial portion of regional variation in housing rents, consistent with spatial equilibrium theory.

Our results show that conventional gravity estimates yield biased estimates of distance frictions. This is not surprising as residential choice and store locations are highly interdependent. Correcting for the endogenous nature of distances between stores and consumers, we find a distance elasticity of about 15 percent. Non-parametric estimates show that the marginal effect of distance ceases to be significant at around 14 minutes of travel time on average. Using detailed sociodemographic and location data, we document that distance frictions vary across heterogeneous households and locations. Based on the distance gradients and observed expenditures, we can recover shop attraction terms and compute consumption access measures. Consumption access varies significantly across regions and also within urban areas. Comparing the degree of disparities in income to the one in market access, we find that market access displays a much more pronounced variation. Combined with the observed positive correlation between income and market access, this underscores the relevance of consumption access for spatial disparities in real income. We further link the estimated market access measures to local rents. Consistent with spatial equilibrium theory, better market access capitalizes in higher rents. We further learn from event studies that households adjust their spatial consumption pattern quickly after the opening of a new store. For same-chain openings close to a customer's home, expenditures at incumbent 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.

This paper contributes to a recent strand of research that examines the role of consumption in space. Previous literature has documented a positive link between store openings and house prices, which suggests that households value consumption access positively (Pope and Pope, 2015; Hausman et al., 2023). 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. Hoelzlein and Miller (2024) study openings of Whole Foods Markets and document capitalization effects in house prices as well changes in neighborhood dynamics. Handbury and Weinstein (2015) show that price levels for food products fall with city size. In line with these results, we document that market access for grocery products improves significantly with population density. We relate to these papers by identifying consumption areas conditional on geographical and sociodemographic characteristics, where we employ an identification strategy that allows for quantification of the causal distance gradient.

A second line of research explores spatial consumption at the store level. For example, 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, restaurants in Milan cluster close to each other (Leonardi and Moretti, 2023) 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 expenditures 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 Domınguez-Iino, 2024), 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., 2024).

The structure of the paper is as follows. First, Section 2 introduces the data sources and shows summary statistics before we present our conceptual framework on spatial grocery shopping in Section 3. Section 4 then discusses the empirical identification strategy to causally estimate the model's key parameter, and Section 5 examines these empirical findings (followed by robustness checks in Section 6). Finally, we bring the model and estimation results together in Section 7 and discuss the spatial distribution in market access as well as potential individual-level heterogeneities in spatial consumer behavior. Section 8 concludes.

2 Data

We combine (i) individual transaction data from the largest Swiss retailer with (ii) administrative data from the Swiss Federal Statistical Office on a high spatial resolution of 100 $\times$ 100 meters. To introduce the data, we refer to individuals in the grocery data as *customers* and those in the administrative data as *residents*. This section introduces the different data sets, explains the matching procedure based on residential location and age, and presents corresponding summary statistics of the final data set.

Transaction Data – The consumption data stems from the loyalty program of the largest Swiss grocery retailer *Migros* (holding a market share of 32.7% in 2020). We observe expenditures on 41 product groups for the universe of 1.5 billion customer-store-linked purchases between 2019Q1 and 2021Q2, and customer characteristics include their residence location, age, and household type. Locations are coded on a grid of 350,000 100 $\times$ 100 meter cells with a mean population of 25 residents.[2] In this program, participants identify themselves at the checkout with their loyalty cards in exchange for exclusive offers and discounts. The program has substantive coverage, tracking expenditures of 2.1 million active users (32% of all Swiss residents above legal age), spending on average at least 50 Swiss francs monthly (USD 56 on July 29, 2024), and capturing 79% of the retailer's total sales. Importantly, the chain 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.

Administrative Data – We enrich this unique consumption data with administrative records for the entire Swiss population (8.7 million inhabitants in 2020). Pseudo social security numbers allow linking residents across three different administrative data sets. The *Population and Households Statistics* provides socio-demographic characteristics for each resident for the years 2016–2021. This includes, among others, information on gender, age, marital status, residence location, and household identifiers. The residence locations are coded on the same 100 $\times$ 100 meter grid as in the grocery transaction data. The *Old-Age and Survivors Insurance* dataset contains annual gross labor market income for every resident for the years 2016 to 2021.[3] We average annual household income for the years 2016–2021 to reduce biases in permanent income from transitory shocks and adjust, in most cases, average household income by the square root of household size.[4] Finally, the *Structural Survey* gives information on the highest completed education in a household for the years 2010–2021.[5]

Supermarket Entries – Finally, we collect data on supermarket openings between 2019Q1 and 2021Q2. To this end, we use a web-scraped and geo-coded monthly panel on supermarkets' locations and define a store's emergence in the panel as a potential opening. We observe the true openings for a subset of chains – including our data provider *Migros*, their discounter *Denner*,

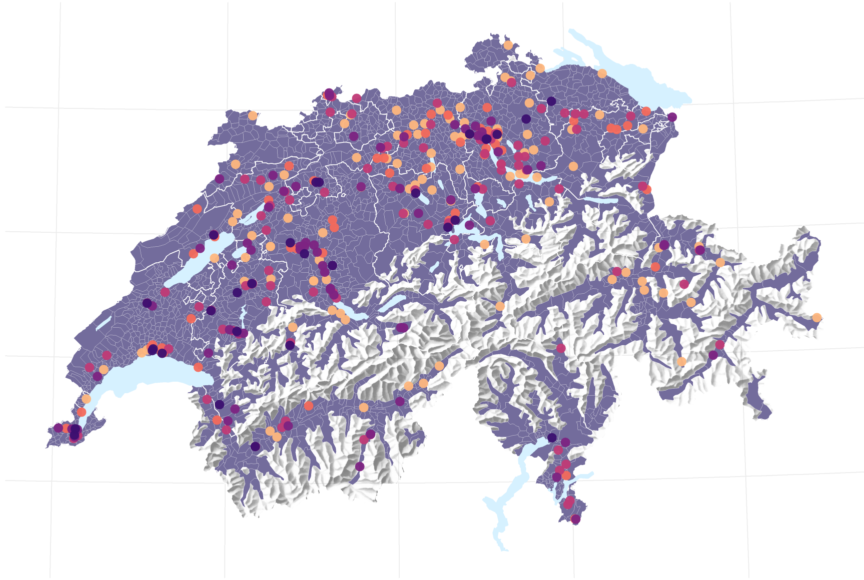
[2]The major product groups include, among others, *fruits and vegetables*, *meat and fish*, *milk products and eggs*, and *bakery and convenience*. The household types include the categories *small households*, *young families*, *established families*, *golden agers*, and *pensioners*. To be a family, consumers have to register their children. This registration gives access to additional benefits related to family products.

[3]Contribution to this insurance is mandatory for everyone except for individuals younger than 25 with an annual income below 750 Swiss francs. The contributions amount to a fixed share of the gross labor market income, including official awards, gifts, and bonuses, and are also mandatory for self-employed individuals.

[4]The calculation is $income\_adjusted = \frac{income\_total}{\sqrt{\#household\_members}}$, where we consider all household members, including small children. The adjustment follows one of the equivalence scales suggested by the OECD. We compute *income_total* as the household's annual income by summing the income of all household members but excluding grown-up children who still live with their parents, as they likely do not contribute to the household's budget.

[5]The survey questions a representative sample of 200,000 people above age 15 every year on housing, employment, mobility, and education. Participation is mandatory. Education is categorized as either primary, secondary, or tertiary education. Primary (or compulsory) education ends at the latest after eleven mandatory school years (including kindergarten). Individuals who completed high school or an upper-secondary specialized school have a secondary education. The completion of any degree at a university, university of applied sciences, or university of teacher education results in a tertiary degree. As education stabilizes for most individuals after a certain age, we use educational variables only for individuals above age 25 at the time of the survey.

Figure 1: Spatial Distribution of Grocery Shop Openings



Notes: The figure shows the spatial distribution of 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 chains operating mostly in rural areas.

and one of the competitors – to validate the high accuracy of the scraped data and cross-check the scraped opening dates with newspaper announcements on *Factiva*, a global database of more than 400 news agencies. Finally, we manually exclude gas stations and stores that are too small to matter in their neighborhood and select 351 entries between 2019Q1 and 2021Q2 as treatments.[6] Figure 1 shows the geographical distribution of all 351 openings across Switzerland. Seventy-five stores entered the market in urban areas (corresponding to 21% of entries for 30% of the population), and all administrative regions, except for two, received at least one new supermarket.[7] The correlation between the regional number of entrants and the population is 0.91.

Sample Construction – We determine the closest supermarket entry for each household in terms of car travel time and concentrate on households who receive a new supermarket within less than 30 minutes.[8] Our analysis focuses on *customers* that we can uniquely match to a *resident* based on the common variables of age and location. Section 1 describes the individual steps of the matching procedure. We focus on treated customers who did not move during

[6] Our analysis will mostly focus on the 31 same-chain openings by Migros. Additionally, we identify 69 openings for the main competitor Coop, 159 for discounters, and 96 for smaller chains that mainly operate in rural areas.

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

[8] We calculate car travel times in minutes and road distance in meters between stores and customers using the API of *search.ch*, a Swiss mapping service.

Table 1: Transactions Summary Statistics

	Spending		No. of Visits		Road Dist.		Car Travel	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Overall	146	189	10.3	10.9	8.80	13.9	14.2	13.2
By Age Group								
<34	108	137	8.3	8.7	10.6	15.8	15.8	14.6
35–44	156	199	9.8	10.3	9.5	14.2	14.8	13.4
45–54	165	217	10.0	10.7	9.5	14.1	14.9	13.4
55–64	146	194	9.8	10.5	9.6	14.7	15.1	13.9
65-74	134	170	10.3	11.0	8.5	13.9	13.9	13.2
75+	137	160	11.9	12.0	6.6	11.6	11.8	11.5
By Income Quintile								
< 4,530	128	156	10.9	11.5	7.4	12.6	12.6	12.2
4,530–6,717	127	164	9.6	10.4	9.1	14.1	14.4	13.4
6,718–9,288	145	185	9.9	10.6	9.5	14.1	14.8	13.5
9,289–12,855	162	206	10.1	10.7	9.7	14.2	15.1	13.5
12,856+	175	229	9.8	10.4	9.9	15.2	15.5	14.2
By Education								
Primary	125	154	11.1	11.8	7.1	11.8	12.2	11.6
Secondary	146	183	10.5	11.0	8.8	13.3	14.1	12.8
Tertiary	162	212	10.0	10.7	9.5	15.1	15.0	14.0
By Household Size								
1	103	123	9.8	10.1	7.8	13.5	13.1	13.0
2	140	170	10.4	11.0	8.7	13.8	14.0	13.2
3–4	169	217	10.3	11.1	9.4	14.2	14.9	13.4
5+	192	250	10.5	11.3	9.5	14.2	14.9	13.5
Number of Monthly Visits	23,155,515							
Number of Households	780,429							

Notes: The table shows summary statistics for the 23 million monthly shopping trips in the final data: monthly expenditures, number of visits, and travel distances across different groups of household characteristics. *Spending* is measured in Swiss francs, *Road Dist.* in kilometers, and *Car Travel* in minutes.

the sample period and whose average monthly grocery expenditures lie between CHF 20 and 1,000 per capita in the year before the treatment (between 23 and 1,126 USD on June 18, 2024). This restriction is important because too-small monthly baskets might not accurately capture the overall consumption, while too-large monthly baskets are unlikely to suit personal use but are from business customers. Eventually, we aggregate the remaining transactions into monthly expenditures and visits per household, which yields 23 million observations for 780,000 households.

Summary Statistics – Table 1 shows summary statistics for the 23 million shopping trips. First, individuals visit a store ten times a month on average, and the number of visits is relatively stable across income, age groups, education, and household size. Second, the average household spends 150 Swiss francs a month (169 USD on July 29, 2024). Although these expenditures increase monotonically with income, the share of grocery expenditure relative to income declines. This observation suggests the presence of non-homothetic preferences, and we incorporate this in our theoretical framework. Finally, shopping tends to be quite local, with an average road distance of about 9 minutes and only minor variation across household characteristics.

Table 2: Summary Statistics for Households

	Final sample		Population	
	Mean	SD	Mean	SD
Age	61.00	15.19	54.84	17.53
Income Total	94.05	127.23	88.63	119.73
Income Adjusted	57.60	78.39	59.22	77.03
Panel b)	Pct.	N	Pct.	N
Gender		780,429		3,991,230
Female	40.4	315,233	39.6	1,578,660
Male	59.6	465,196	60.4	2,412,570
Marriage		780,429		3,991,230
Married	62.0	483,780	46.8	1,866,832
Not Married	38.0	296,649	53.2	2,124,398
Highest Education		514,297		2,311,993
Primary	10.9	56,036	13.4	308,754
Secondary	46.2	237,460	45.2	1,045,440
Tertiary	42.9	220,801	41.4	957,799
Language Region		779,407		3,987,127
French	23.5	183,343	25.3	1,007,039
German	70.8	551,637	67.9	2,705,434
Italian	5.7	44,427	6.9	274,654
Pop. Density		779,407		3,987,127
Rural	18.0	140,168	17.4	693,093
Suburban	56.3	438,614	51.1	2,038,383
Urban	25.7	200,625	31.5	1,255,651
Household Size		780,429		3,991,230
1	23.2	180,694	37.0	1,475,101
2	38.5	300,839	32.7	1,306,748
3-4	31.2	243,496	24.8	991,735
5+	7.1	55,400	5.5	217,646
Observations		780,429		3,991,230

Notes: The table shows summary statistics for the characteristics of households in the final sample and compares them to the households in the population. *Income Total* is the total sum of annual labor market income in a household, and *Income Adjusted* adjusts this by the square root of household size.

Table 2 presents summary statistics for household characteristics. Our matched data includes more than a quarter of Swiss households and is highly representative of the total population. Notably, average income, gender composition, and education levels are very close to the corresponding population values. Households in our final data are slightly larger, live more often in suburban areas, and have older household heads.[9]

[9] See further discussion of the data and its representativeness in Kluser and Pons (2024), analyzing the intergenerational persistence of consumption, and Kluser (2024), studying cross-border shopping.

3 Conceptual framework

To inform our empirical analysis, we use a simple model of store choice: Household ω resides in location i and shops at store $s \in n$.[10] We assume non-homothetic preferences of the form:

$$U_{\omega i} = \left(\frac{G_{\omega i} - \bar{G}}{\alpha}\right)^{\alpha} \left(\frac{h_{\omega i} - \bar{h}}{\beta}\right)^{\beta} \left(\frac{x_{\omega i}}{1 - \alpha - \beta}\right)^{1-\alpha-\beta}, \tag{1}$$

where $G_{\omega i} = \left[\int_0^n g_{\omega i}(s)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$ is a composite good of store-specific grocery varieties, and $\bar{G}$ denotes subsistence consumption. $h_{\omega i}$ represents housing consumption with $\bar{h}$ being the subsistence level and $x_{\omega i}$ captures the consumption of all other freely tradable goods. The latter goods specify a numéraire with the price of $x_{\omega i}$ being unity, and we denote housing cost (rents) by r_i. This yields utility-maximizing demands $G_{\omega i} = \bar{G} + \alpha \tilde{w}_{\omega i}/P_{\omega i}$, $h_{\omega i} = \bar{h} + \beta \tilde{w}_{\omega i}/r_i$, and $x_{\omega i} = (1 - \alpha - \beta)\tilde{w}_{\omega i}$, where $\tilde{w}_{\omega i} = w_{\omega i} - P_{\omega i}\bar{G} - r_i \bar{h}$. The location- and household-specific price index for groceries is

$$P_{\omega i} = \left[\int_0^n (p(s)\tau_{\omega i s})^{1-\sigma}\right]^{\frac{1}{1-\sigma}}, \tag{2}$$

where $p(s)$ is the producer price (optimally chosen as a fixed markup over marginal cost) and $\tau_{\omega i s}$ are the distance costs, which may vary with the household type and location.
With this setting, indirect utility is given by $V_{\omega i} = \frac{w_{\omega i} - P_{\omega i} G_{\omega i} - r_i h_{\omega i}}{P_{\omega i}^{\alpha} r_i^{\beta}}$, the price index $P_{\omega i}$ is decreasing in n and increasing in $p(s)$ and $\tau_{\omega i s}$, such that the relative indirect utility between locations is decreasing in the relative price index. Note that even with price indices being not individual-specific (i.e., $P_{\omega i} = P_i \ \forall \omega$), the relative indirect utility within locations between a high-income (w_{1i}) and a low-income (w_{2i}) household is increasing in P_i:

$$\frac{\partial (V_{1i}/V_{2i})}{\partial P_i} = \frac{\bar{G}\,(w_1 - w_2)}{(\tilde{w}_2)^2} > 0.$$

Ceteris paribus, better consumption access is more valuable for low-income households. Solving for the expenditure per variety we obtain

$$p(s) g_{\omega i s} \tau_{\omega i s} = \frac{(\tau_{\omega i s} p(s))^{1-\sigma}}{P_{\omega i}^{1-\sigma}} \left(P_{\omega i} G_{\omega i} + \alpha \tilde{w}_{\omega i}\right). \tag{3}$$

In the following, we estimate this expression to identify the role of distance frictions. The distance costs to travel to the store are specified as a function of distance, which we either

[10] Note that we can restrict the choice-set of stores for each household ω in location i, meaning, n_i can be i-specific and include all stores within, for example, a half-hour car drive, s.t. $Distance_{is} \leq 30$ minutes.

measure in minutes of travel time or kilometers of road distance: $ln(\tau_{\omega is}) \equiv \kappa_\omega ln(Distance_{is})$.

In the empirical analysis, producer prices are captured by a store (or chain) fixed effect, and the remaining components of Equation (3) are collected in a location-household-type fixed effect. Accordingly, this yields the following estimation equation:

$$\ln(Y_{\omega ist}) = \gamma_{\omega i} + \gamma_t + \lambda_s - \beta ln(Distance_{is}) + \epsilon_{ist}, \tag{4}$$

where $Y_{\omega ist}$ captures either expenditures $p(s)g_{\omega is}\tau_{\omega is}$ or the number of shop visits. The gravity coefficient β is identified from is-specific variation and reflects the product of distance costs (κ) and the elasticity of substitution (σ).

With consistent estimates of β and λ_s as well as the set of all store locations, we can compute the individual and location-specific market access measure:[11]

$$\Phi_{\omega i} = \sum_{s \in n} \left[\exp(\lambda_s) \times Distance_{is}^{-\beta} \right]. \tag{5}$$

This measure reflects the utility contributions of access to stores with different weights depending on the income groups and their expenditure shares. According to spatial equilibrium theory, we expect market access to be relevant for residential location choice and accordingly to be capitalized in local housing prices.

Isolating spatial friction parameters from the estimation of Equation (4) is complicated by the fact that stores choose their location according to the expected expenditures that they can attract at a certain location. This implies that the $\hat{\beta}$ is likely biased if the above equation is estimated. In the following, we discuss our empirical strategy addressing this endogeneity bias, and we compare the 'conventional estimates' of Equation (4) with our approach.

4 Empirical Strategy

To identify a causal effect β of distance on consumption patterns, we encounter three main identification challenges: (i) the endogeneity of location choices, (ii) an omitted variable bias, and (iii) a potential measurement error.

First, we have to deal with the endogeneity of non-random simultaneous store and residential location choices. Retailers strategically choose locations where they expect higher latent consumer demand, and households prefer living close to amenities like grocery stores. This simultaneity creates an upward bias in distance elasticities when using traditional gravity models. To ad-

[11] Note that $\Phi_{\omega i} = P_{\omega i}^{1-\sigma}$. Furthermore, β here is constant across all individuals. We relax this assumption in the last section.

dress this identification challenge, we use a staggered difference-in-differences (DiD) approach that leverages the quasi-experimental variation from close store openings by comparing treated households to not-yet-treated control units that receive an opening later. We then derive the logarithmic distance decay function through the treatment response at different distances. Our identification depends – next to the standard parallel trend assumption – on the key assumption that the exact opening date of a new store depends on administrative and bureaucratic delays rather than the latent household demand and the strategic planning of retailers. We argue that this is a sensible assumption within the short time span of two years we observe in our data. Focusing on households who do not move throughout this period, we exclude the possible response of short-term residential relocation in response to the changing shopping landscape.[12]

Second, we face an omitted variable bias. Households may choose stores for reasons unobserved by the econometrician, such as convenience, store promotions, or unrecorded variations in store pricing. These factors, if not accounted for, could bias our estimates. The DiD setting addresses potential unobserved store attributes through store fixed effects. These control for any time-invariant characteristics specific to individual stores. Additionally, household–location fixed effects capture heterogeneity in preferences, transportation costs, and other factors across different household types and geographic locations.

Third, there might be a measurement error in spatial frictions if the simple log-distance model oversimplifies the relationship between distance and consumption. To ensure we capture the true effect, we allow in the robustness section for flexible functional forms in the estimation of the distance gradients. Beyond a standard log-distance model, we implement log distance functions with a kink and non-parametric estimation results for distance decay to account for possible non-linearities, especially for longer travel times. This helps ensure that our model doesn't impose overly rigid structures on how distance affects shopping behavior, leading to more reliable estimates of distance elasticities.

Particularly, we are interested in two distinct explanatory variables. First, the change of weekly expenditures at the incumbent same-chain stores isolates the expenditure shift from incumbent stores to the new store in response to the opening. Second, the change in total weekly expenditures at all stores of the grocery chain measures the expenditure shift from competitors to the new store induced by the opening.[13] Taken together, these two channels reflect the overall change in consumer behavior.

To estimate the model's key Equation (4), we rely on a staggered difference-in-differences design where the treatment interacts with a logarithmic distance function. This model isolates

[12] One remaining concern might be that although we correctly identify the treated households' response to new supermarket openings, this does not correspond to the correct parametric distance decay function because the distance between treated households and their corresponding opening depends again on the latent grocery demand. We eliminate this concern with a robustness check where we add binned distance–period fixed effects. This compares treated households to control units that receive treatment later on in the same bin, therefore ensuring that the treatment and control groups have the same latent grocery demand.

[13] This effect also includes a general income effect, which may change grocery spending. For groceries, this effect is likely much less relevant than the shift from competitors, so we refer to this part as the competition shift.

the causal effects of interest if the parallel-trend assumption holds. Yet, as the probability of receiving a treatment likely depends on location characteristics, untreated households may not be a valid comparison. Therefore, we exploit the variation in the exact timing of openings and use not-yet-treated control units, as 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 time span are comparable.

We report our main findings for a conventional TWFE model but also take into account the recent advances in the theoretical difference-in-differences literature, considering the potential heterogeneity of treatment effects across periods and cohorts.[14] For our context, we require an estimator that allows the treatment effect to vary with a distance covariate. Furthermore, weekly expenditures have a mass point at zero, and we follow Chen and Roth (2024) by estimating a Quasi-MLE Poisson model in this case to recover the proportional treatment effect. Wooldridge (2022) and Wooldridge (2023) proposes a robust staggered difference-in-differences estimator fulfilling these requirements – allowing for (i) a Poisson model and (ii) interacted covariates – that will complement our conventional estimates and assure their validity.

Staggered DiD: Average Effect of Entry

To start with, we estimate a baseline parametric specification of the following form:[15]

$$Y_{it} = \exp\left(\alpha_i + \gamma_t + \beta(T_{it} \times ln(Dist_i)) + \delta T_{it}\right)\epsilon_{it}, \tag{6}$$

where Y_{it} is either the sum of incumbent same-chain expenditures (number of visits) or total chain expenditures (number of visits) for the incumbent and competitor shifts, respectively. The treatment indicator T_{it} equals one if the store assigned to household i as a treatment opened in period $z \leq t$. In particular, we are interested in the distance gradients for both expenditure shifts (*incumbent* and *competitor*), captured by β. We control for unobserved time-invariant household-specific characteristics α_i. These fixed effects capture idiosyncratic characteristics such as workplace location, school location of children, or other routine trips. The period fixed effect γ_t absorbs common time trends and seasonality. While β in Equation (6) is constant across all households, we provide household-type specific estimates of the distance gradient by allowing β to vary with income, age, and household size in Section 7.3, allowing for heterogeneities in our model.

Our baseline approach in Equation (6) estimates a conventional two-way fixed effects (TWFE)

[14]See, for example, de Chaisemartin and D'Haultfœuille (2020) and Callaway and Sant'Anna (2021). In our context, our results may be biased if an opening affects the same household differently depending on the shock's timing. 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. 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.

[15]We run a robustness check where we allow for non-parametric bins of car travel time to assess the validity of the parametric form the model imposes.

model with a QMLE-Poisson regression. Following Chen and Roth (2024), we report in our tables and figures the proportional treatment effects $\hat{\beta}_{\%} = \exp(\hat{\beta}) - 1$, allowing for a percentage change interpretation of the coefficients, and calculate standard errors of $\hat{\beta}_{\%}$ using the Delta method.

Staggered DiD: A Robust Approach (Wooldridge, 2022)

Alternatively, we use a robust estimator accounting for the recent advances in difference-in-differences models. Wooldridge (2022) suggests the following flexible extension of the TWFE estimator, allowing the coefficient of interest to vary across periods and cohorts:[16]

$$Y_{it} = \exp\left(\alpha_i + \gamma_t + \delta_{g,t}(T_{it} \times g_i \times \gamma_t \times ln(Dist_i)) + \beta_{g,t}(T_{it} \times g_i \times \gamma_t) + \xi_t(\delta_t \times ln(Dist_i))\right)\epsilon_{it}, \tag{7}$$

where the time-constant g_i denotes the period household i is treated (meaning, it indicates which cohort or group household i belongs to). Hence, $\beta_{g,t}$ reflects the average treatment effect and $\delta_{g,t}$ the parametric distance coefficient for the respective cohort-period combination. We aggregate the weighted coefficients for $\beta_{g,t}$ and $\delta_{g,t}$ to get an average marginal treatment and interaction effect for all period-cohort pairs:[17]

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

Dynamic DiD: An Event-Study Style Approach

Additionally, we report dynamic event-study style estimates in the robustness section. 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 due to an incremental adaptation of consumer behaviors. Second, the dynamic estimation results 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:

$$Y_{it} = \exp\left(\alpha_i + \gamma_t + \sum_{\substack{k=-12 \\ k \neq -1}}^{12} \beta_k T_{i,t}^k\right)\epsilon_{it}, \tag{8}$$

[16] Wooldridge (2023) discusses the extension to Poisson regressions in more detail.

[17] It is unclear whether the suggestions of Chen and Roth (2024) to recover proportional treatment effects recover an ATT in the staggered intervention case. To make the obtained marginal effects (in Swiss francs) comparable to the proportional treatment effects from Equation (6), we relate the estimates to the average expenditures in the data. Standard errors can be obtained by bootstrapping. This approach is computationally very expensive, so we estimate this robust estimator with quarterly data (instead of monthly) to reduce the number of coefficients. The point estimates remain almost unaffected by this change. We use the Wooldridge (2022) approach as a robustness check for the conventional TWFE main results and stick to the conventional method for all other analyses.

where $T_{i,t}^{k}$ is a set of dummies indicating that at time period t household i got a treatment $k \in [-12, 12]$ months ago. The exclusion of $k = -1$ normalizes the coefficients to the period preceding the treatment, and we stick here again to the standard TWFE estimator.[18]

5 Empirical Results

We next present our empirical results. We first investigate the role of distance frictions in conventional gravity-type specifications. Then, we estimate the impact of a store entry on shifts of average expenditures and the number of shopping trips from same-chain incumbent stores as well as from competitor shops. Based on these results, we quantify the geographical size of consumption areas and the distance gradients in consumption by exploiting the distances between households' residences and store entries. Most of our discussion focuses on car travel times as our preferred measure of distance.

5.1 Conventional Gravity Estimates

In the first step, we run conventional gravity regressions to estimate the decline of shopping activity with distance, ignoring the potential endogeneity of β. Since we are interested in the combination of the extensive and intensive margin effects, we estimate the Poisson QMLE model in Equation (4) and report proportional effects in Table 3 for total expenditures and the number of visits.[19] We study parametric log functions of distance as measured by Euclidean distance, road travel distances in kilometers, and car travel times in minutes. The estimates indicate a significant decline in expenditure by 6.9 to 8.7 percent for a ten percent increase in distance. The number of visits responds very similarly to distance changes. Overall, distance frictions implied by the conventional gravity model are substantial. The linearized coefficients of the Poisson model imply that expenditures fall to zero at a distance of only about 4 to 5 minutes of travel time.

5.2 Store-Opening Effects

Distance between stores and households is an endogenous variable that may partly but not fully be addressed by including store and household fixed effects as in the specification in Table 3.

[18]We assign the event periods of 12 and -12 to any observation lying outside this window. To consider an alternative approach, we can aggregate the estimated coefficients from model Equation (7) in an event-study fashion. However, Wooldridge (2022) does not compute pre-treatment coefficients, and therefore, the visual check for the parallel trend assumption is not possible. Yet, the post-treatment coefficients provide very similar estimates to the TWFE results.

[19]We include zero-values for all stores household ω every visited within the sample period. Additionally, we perform robustness checks including 'irrelevant alternatives', meaning we sample ten shops that each household has never visited. The results remain qualitatively unchanged.

Table 3: Conventional Gravity (Poisson Model)

Proportional Effects	Expenditures			No. of Visits		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(Euclid. Dist. in km)	-0.683***			-0.665***		
	(0.000)			(0.000)		
ln(Road Dist. in km)		-0.813***			-0.796***	
		(0.000)			(0.000)	
ln(Car Dist. in min)			-0.877***			-0.861***
			(0.000)			(0.000)
Household and Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Store FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.54	0.55	0.55	0.48	0.48	0.48
Observations	1.62e+08	1.62e+08	1.62e+08	1.62e+08	1.62e+08	1.62e+08

Notes: The table shows conventional two-way gravity regression results, estimating Equation (4). The coefficients are Poisson estimates where we report the exponentiated Poisson coefficients $exp(\beta) - 1$, following Chen and Roth (2024). We focus on households with average monthly expenditures between 20 and 10,000 Swiss francs with full information on income and household size who did not move during our sample period. We use the same sample as in the following opening experiments, where we focus on households who live within 30 minutes of a store opening. The panel includes all shops ever visited by a customer, including month-shop observations with zero expenditures/visits.

Table 4: Incumbent Expenditure Shift (Poisson Model)

Proportional Effects	Expenditures			No. of Visits		
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	-0.073***	-0.098***	-0.226***	-0.068***	-0.091***	-0.224***
	(0.003)	(0.003)	(0.006)	(0.008)	(0.003)	(0.005)
Treat × ln(Euclid. Dist. in km)	0.037***			0.039***		
	(0.002)			(0.003)		
Treat × ln(Road Dist. in km)		0.045***			0.049***	
		(0.002)			(0.002)	
Treat × ln(Car Dist. in min)			0.099***			0.104***
			(0.003)			(0.003)
Marginal Effect at Mean	-0.017***	-0.015***	-0.016***	-0.003	-0.001	-0.003
	(0.002)	(0.002)	(0.002)	(0.006)	(0.002)	(0.002)
Observations	2,599,180	2,601,098	2,601,098	2,599,180	2,601,098	2,601,098
Mean Distance	5.27	7.30	12.64	5.27	7.30	12.64
Mean ln(Distance)	1.66	1.99	2.54	1.66	1.99	2.54
Squared Correlation	0.757	0.757	0.757	0.754	0.754	0.754

Notes: The table shows difference-in-differences estimates for the effect of a store opening on expenditures at incumbent stores, estimating Equation (6). This captures expenditures shifted from incumbent stores to the new store. The coefficients are Poisson estimates where we report the exponentiated Poisson coefficients $exp(\beta) - 1$, following Chen and Roth (2024). We focus on households with average monthly expenditures between 20 and 10,000 Swiss francs with full information on income and household size who did not move during our sample period. Households are treated if they live within 30 minutes of a store opening.

Therefore, we exploit the store openings as quasi-experimental shocks to identify causal distance frictions. The total expenditures at a new store consist of two parts: (i) the expenditure shift from same-chain incumbent stores (*incumbent shift*) and (ii) the expenditure shift from competitor stores (*competitor shift*).[20] We first analyze both shifts individually and discuss then the implications for the distance parameter β in our model. We estimate the role of distance costs separately for both parts, where we use the expenditures at the incumbent same-chain stores as the dependent variable to measure the incumbent shift and the total chain expenditures as the dependent variable to measure the competitor shift. In both cases, we estimate the difference-in-differences model in Equation (6) with a Poisson QMLE model and report the exponentiated proportional treatment effects. As robustness checks, we complement our findings with conventional specifications using logarithmic dependent variables instead of Poisson models in Section 3.1 (This approach ignores the mass point at zero in the dependent variables).

Incumbent Expenditure Shift – Table 4 reports the results for the incumbent shift, estimating the effect of a store opening on a household's expenditures at the incumbent stores. Note that the *incumbent shift* is the inverse of the estimated coefficients. Table 4 shows that the more distant the new store is, the lower the household's response. Accordingly, the more distant the new store, the smaller the incumbent shift. An opening within one minute of car travel time leads to a 22.6% reduction in expenditures at incumbents and reduces the number of visits by 22.4%, leaving, therefore, the average spending per trip unchanged. We assume that the new store is comparable to the incumbents for all characteristics beyond location (and, thus, distance to the household's residence). This assumption seems plausible as the retailer charges the same prices throughout the country and offers similar products for a given store size. Additionally, the estimated slope coefficient shows how the household's response declines with distance to the new store. Namely, a doubling of distance corresponds to a ten percentage point lower reallocation of expenditures and store visits.

Competitor Expenditure Shift – Households shift a second part of their grocery expenditures from competing chains to the new store. To isolate the impact of distance on this *competitor shift*, we use the same empirical strategy with the total expenditure of household ω at the supermarket chain as a dependent variable (meaning, not only expenditures at incumbent stores but including the expenditures at the new store). Since we expect the supermarket chain to be profit-maximizing, a store opening should, on average, increase total expenditures for the chain. Thus, in contrast to the main effect of the incumbent shift, the main effect of the competitor shift should be positive. Table 5 reports the results, following the same structure as for the incumbent expenditure shift. Overall, we find that total expenditures at the chain increase by 13.4 percent if a new store opens in close proximity to a household. For the number of visits, the corresponding effect amounts to about 19.5 percent. Distance costs are significant, as a doubling of distance to the new store reduces the competitor expenditure shift by about 4 percent. Distance frictions are more pronounced for the number of visits, where the elasticity for travel times amounts to about 5 percent. The fact that the distance elasticity is smaller for the competitor shift than for the incumbent shift reflects imperfect substitutability between the product ranges of the different chains.

[20] Note that the latter part also includes potential income effects.

Table 5: Competitor Expenditure Shift (Poisson Model)

Proportional Effects	Expenditures			No. of Visits		
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	0.059***	0.070***	0.134***	0.081***	0.101***	0.195***
	(0.002)	(0.003)	(0.006)	(0.008)	(0.003)	(0.006)
Treat × ln(Euclid. Dist. in km)	-0.016***			-0.024***		
	(0.001)			(0.003)		
Treat × ln(Road Dist. in km)		-0.018***			-0.027***	
		(0.001)			(0.001)	
Treat × ln(Car Dist. in min)			-0.037***			-0.052***
			(0.002)			(0.002)
Marginal Effect at Mean	0.031***	0.031***	0.031***	0.042***	0.041***	0.043***
	(0.002)	(0.002)	(0.002)	(0.006)	(0.002)	(0.002)
Observations	2,599,180	2,601,098	2,601,098	2,599,180	2,601,098	2,601,098
Mean Distance	5.27	7.30	12.64	5.27	7.30	12.64
Mean ln(Distance)	1.66	1.99	2.54	1.66	1.99	2.54
Squared Correlation	0.760	0.760	0.760	0.752	0.752	0.752

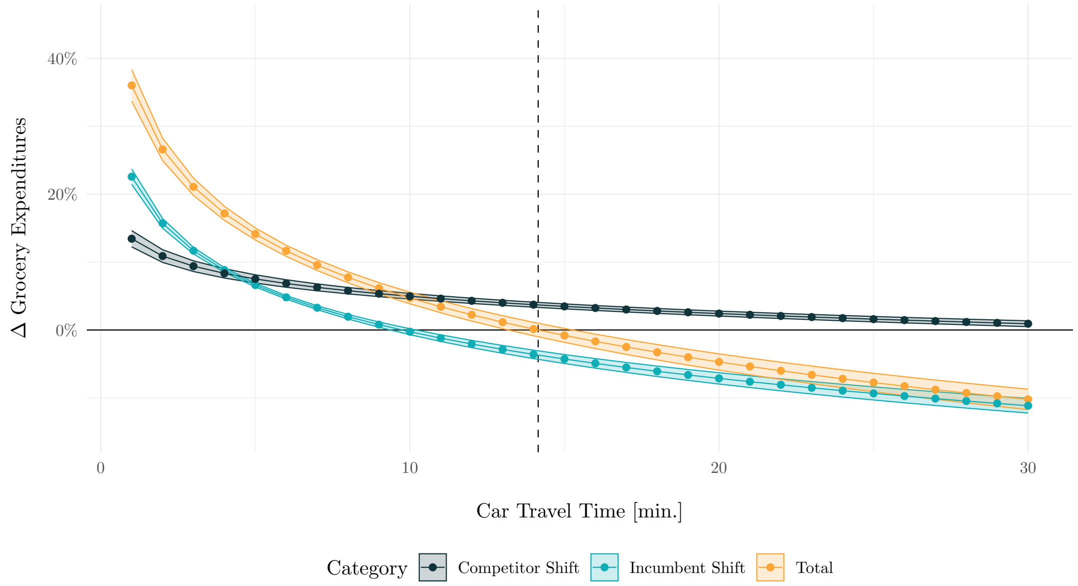
Notes: The table shows difference-in-differences estimates for the effect of a store opening on expenditures at all same-chain stores, estimating Equation (6). This captures expenditures shifted from competitors to the new store. The coefficients are Poisson estimates where we report the exponentiated Poisson coefficients $exp(\beta) - 1$, following Chen and Roth (2024). We focus on households with average monthly expenditures between 20 and 10,000 Swiss francs with full information on income and household size who did not move during our sample period. Households are treated if they live within 30 minutes of a store opening.

Total expenditure shift – With the expenditure shifts from the same chain incumbents and competitor shops at hand, we can compute the total distance gradient. For a new shop opening at a one-minute distance to the customer, Table 4 and Table 5 imply that 22 percent of the previous same-chain incumbent expenditures are shifted to the new store and 15.1 percent of the total same-chain expenditures are shifted from competitor stores. As distance increases, expenditures shifted to the new store via both channels decline according to the corresponding slope coefficients.

Figure 2 depicts graphically the marginal effects of both parametrically estimated distance gradients as well as the total distance gradient. We observe a steep decline for the total gradient, which, however, is much less pronounced than for the conventional gravity specifications. The marginal effect of distance starts to become insignificant at a distance of 14 minutes of car travel time. We interpret this point as the maximum spatial scope of average consumption areas as a household's consumption behavior is not significantly impacted by an entry of a shop at a distance beyond that.

Robust Estimator (Wooldridge, 2022) – Accounting for the recent advances in the theoretical difference-in-differences literature on staggered interventions, we apply the novel approaches suggested by Wooldridge (2022) and Wooldridge (2023), which seem to be best-suited for our case. Figure A3 shows the estimation results for the distance decay functions analogously to the main results in Figure 2. The point estimates are slightly higher compared to the conventional

Figure 2: Distance Gradients



Notes: The figure shows distance gradient functions, indicating how the treatment effects from the difference-in-difference analyses decline over time. The *incumbent shift* is based on the results in Table 4 (mirrored along the horizontal axis) and the *competitor shift* in Table 5. We calculate standard errors for the individual fitted points using the delta method. The *total expenditure shift* is the sum of the two curves, and the corresponding confidence bands are the aggregate of the two other bands. The vertical dashed line indicates the insignificance of the total shift.

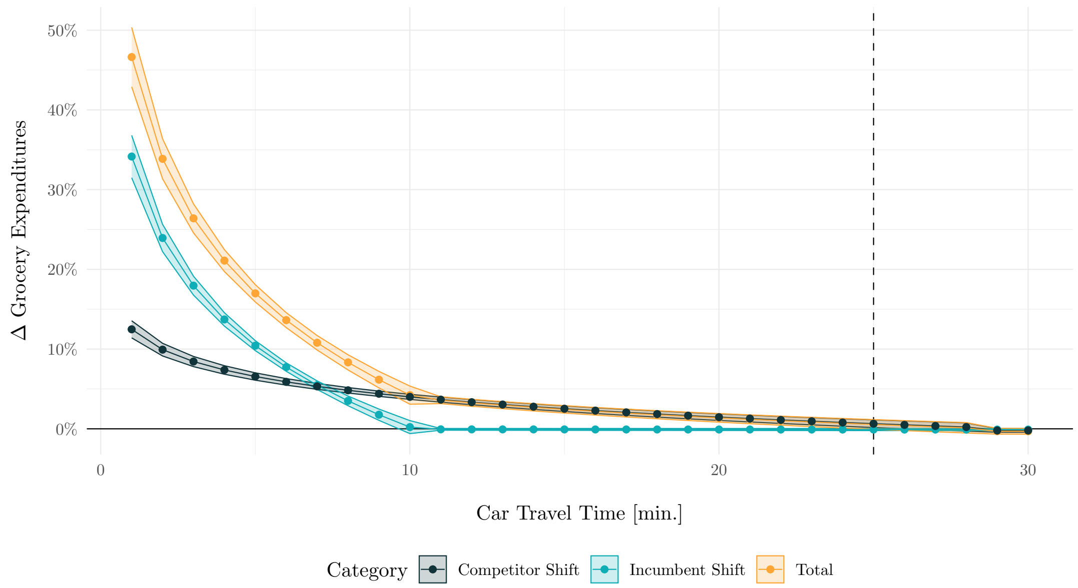
estimator but support qualitatively all our previous statements. As the competitor effect seems more persistent, the average customer will respond to an opening for up to 24 minutes of car travel time.

Non-parametric estimation and distance gradients with a kink – While the log-specification of the distance decay derived in our model section follows the standard approach for gravity models, Figure 2 displays a function that might potentially be misspecified as the coefficients become negative instead of converging to zero. One explanation might be that the log specification fits well for short-distance shopping trips but may be an inappropriate measure for longer-distance traveling. Then, the log-specification of distance may put a too rigid structure on the distance frictions. Such non-linearities are, for example, documented by Hillberry and Hummels (2008) for shipments of manufacturing firms in the United States.

Therefore, we assess the suitability of our baseline specification and display in Figure A4 and Figure A5 a non-parametric function where we estimate a coefficient for travel time bins with a width of two minutes. The logarithmic specification and non-parametric alternative are very similar for the competitor shift. Yet, although the logarithmic specification captures the non-parametric alternative initially very well for the incumbent shift at short distances, the curves diverge for longer-distance trips, consistent with our hypothesis (while the non-parametric specification converges to zero as expected).

Hence, we want to ensure the reliability of our estimates. To do this, we estimate a log function including a kink, meaning, we allow the slope to change after the baseline function crosses

Figure 3: Log-Kink Distance Gradients



Notes: The figure shows distance gradient functions, indicating how the treatment effects from the difference-in-difference analyses decline over time. Compared to the baseline results in Figure 2, we add a kink in the parametric functions once the *incumbent shift* and the *competitor shift* turn insignificant. The *incumbent shift* is based on the results in Table 4 (mirrored along the horizontal axis and adding the kink) and the *competitor shift* on Table 5 (with the additional kink). We calculate standard errors for the individual fitted points using the delta method. The *total expenditure shift* is the sum of the two curves, and the corresponding confidence bands are the aggregate of the two other bands. The vertical dashed line indicates the insignificance of the total shift.

the zero line. Figure A4 and Figure A5 show that this functional form follows closely the non-parametric estimation, therefore likely capturing the true decay more accurately.[21] Yet, choosing the kink in this way is an arbitrary choice by the authors, and we show in Table A5 and Table A6 that the estimated slopes of the left part of the function only change slightly for different values of the kink within a reasonable distance range.

Figure 3 then shows the incumbent and competitor shift as well as the total distance gradient for our preferred kink-cutoffs, complementing the baseline results in Figure 2 and providing qualitatively identical results. Nonetheless, the added flexibility allows for an initially stronger household response and a steeper decline of the decay function.

6 Robustness and Sensitivity

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

[21] Non-linear gravity specifications are widely used in the trade literature (see, for example, Eaton and Kortum, 2002, Henderson and Millimet, 2008, or Hillberry and Hummels, 2008).

Dynamic Responses to Store Openings – Figure A6 shows the results for the dynamic difference-in-differences model outlined in Equation (8) for the store-opening experiment on household expenditures. The pre-treatment coefficients show no apparent pre-trend and violation of the parallel trend assumption. In a distance of less than two minutes, households reduce their expenditures by more than 40%, while the response quickly decreases with distance below 20% and 10% for distances bins of 2-5 minutes and 5-10 minutes, respectively. Furthermore, the reaction is immediate, and we do not observe a dynamic build-up of the effect.

COVID-19 Pandemic – Additionally, we might worry that the COVID-19 pandemic led to a fundamental shift in grocery shopping behavior that our empirical strategy cannot capture. We address these concerns by restricting our analysis to a sub-sample that only includes observations before the start of the pandemic in Switzerland (namely, for the period January 2019 to February 2020). Table A7 and Table A8 show the corresponding estimation results. We find qualitatively identical results across all distance bins that further ensure the credibility of our findings.

Multiple-Treated Units – We focus in Section 5 on a binary treatment and ignore multiple ones, and we might be concerned that additional openings bias our coefficients. To analyze this potential bias, we focus on a sub-sample of individuals who were only once treated during the observed sample period. Table A9 and Table A10 show these estimation results, which are again qualitatively identical to our previous findings.

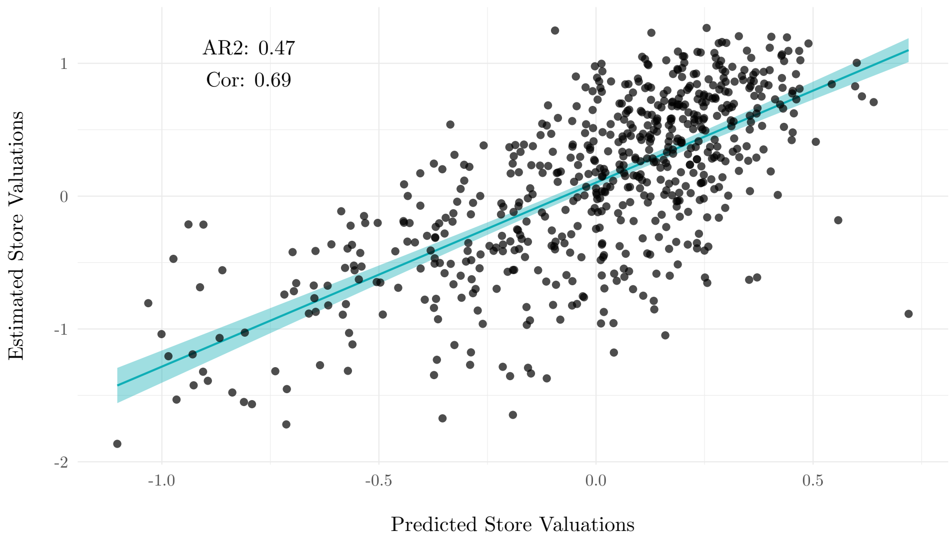
7 Consumption Areas

Next, we bring together our causal estimates of the distance decay functions with our model of spatial shopping. This section first discusses how we recover the fixed effects of unobserved stores to calculate a utility-based value for access to grocery shopping across different household locations. Then, we present our resulting market access measures and relate them to spatial equilibrium theory.

7.1 Recovering Store Valuations

Observed supermarkets (Constrained gravity regressions) – First, we recover the average store valuations λ_s for all the stores we observe according to Equation (4), where we use the causal estimates of the distance gradient. Since the kinks in the distance costs turn out significant and relevant, we use our preferred kink specifications shown in Figure 3 to calculate the market access measures. Specifically, we denote by $\overline{dist}$ the critical distance level beyond which an opening does not yield any significant expenditure shifts. Up to the distance level $dist_k$ at kink k, we identify a steeper gradient β_1, whereas, for higher distance levels, the gradient flattens to β_2. Accordingly, the distance costs are $dist^{\beta_1}$ for $dist <= dist_k$ and $(dist^{\beta_2}/dist_k^{\beta_2})dist_k^{\beta_1}$ for $dist_k < dist <= \overline{dist}$. Following Table A5 and Table A6, we set $\beta_1 = 0.2$, $\beta_2 = 0.05$, $dist_k = 14\ min$, and $\overline{dist} = 30\ min$. Hence, all stores beyond a distance of 30 minutes receive

Figure 4: Estimated vs. Predicted Store Fixed Effects



Notes: The figure plots the estimated store valuations for our main retailer against the predicted store valuations from the Lasso regression as a cross-check of Lasso's predictive power. The store valuations are recovered as the fixed effects λ_s from Equation (4) using the estimated distance gradients.

no expenditures and are not considered for recovering the store valuations.

Unobserved Supermarkets (Lasso Regressions) – As we have only data for one chain, we need to impute the store valuations of other chains by implementing a second-step regression inferring the store valuations of other supermarkets. If a set of observed characteristics sufficiently determines the valuation of the observed stores, then we can use these variables to infer the value of unobserved competing stores. Characteristics that might be useful include, first, the store size and quality that we approximate with review counts and average ratings from Google Maps. Second, the store's value likely also depends on the surrounding neighborhood in terms of the neighborhood's residents, the local labor market, and local amenities, including other potentially complementary stores. Hence, we infer the residents' characteristics using our administrative data sets to calculate local averages of income, household size, education, age, etc., as well as counts of sector-specific employees and firms around the supermarkets. Regarding local amenities, we use additional administrative data measuring the walking distance in meters to the closest store, pharmacy, bank, restaurant, etc.

To learn which of these 716 observed variables determine store valuations without overfitting the model, we apply a Lasso variable selection approach. Specifically, we use ten-fold cross-validation and feed the model with the above determinants that explain the variation in store valuation. Then, we let the algorithm choose the best predictors for store valuations of the retail chain.[22] Figure 4 depicts the store valuations estimated from Equation (4) for the stores we observe against the recovered store valuations from the Lasso regression for the same stores.

[22] Alternatively, we use a Ridge regression and different versions of elastic nets. Our results remain qualitatively unchanged.

We observe a high correlation of 0.69 between the recovered and the predicted values, and the model explains about 50 percent of the variation.

7.2 Spatial Consumption Access

Therefore, we can now derive a measure for market access. In order to compute the local values of consumption access, we need to combine the locations of stores, their valuations in terms of quality-adjusted prices, and the estimated distance frictions. We compute market access according to Equation (5) at a granular level of 100×100 meter grid cells across the whole country. Figure 5 shows the spatial distribution of market access for the city of Zurich and the entire country (note that we focus only on inhabited grid cells that are within the construction areas). We observe substantial differences in market access, with a mean of 40 and a standard deviation of 46. The interquartile range for the total country ranges from 21 to 66. Across the largest 10 Swiss cities, we observe a range between 55 and 98.[23] Even within the city of Zurich, the differences are pronounced with an interquartile range between 113 and 160. Hence, we observe substantial variations in market access both within cities and across the country.

Furthermore, Figure A7 maps, in addition to our measure of grocery market access, graphically the spatial distribution of income and population and the distance to the closest supermarket in the city of Zurich. Looking at correlations between these variables, we see that access correlates positively with population density with a value of 0.22 and negatively with income and the distance to the closest supermarket (-0.22 and -0.11, respectively). This means that grocery market access within the city is higher in denser and lower-earning neighborhoods with faster access to supermarkets.

Population Density and Rents

In order to relate our access measures to the spatial equilibrium, we depict in Figure 6 market access against the percentiles of population density as well as against hedonic market-rate rents. The figure shows a strong correlation in both cases (0.83 and 0.90, respectively). Notably, the correlation with population density is very strong among the densest areas, while we observe way more variation for less dense areas. Similarly, neighborhoods with higher rents typically have better grocery market access, with the weakest link observed in the most expensive areas. Note that the strong link between rents and market access also holds when population density is conditioned out (the slope coefficient declines from 0.040 to 0.037). These observations suggest that grocery market access represents an important amenity that capitalizes into local housing rents.

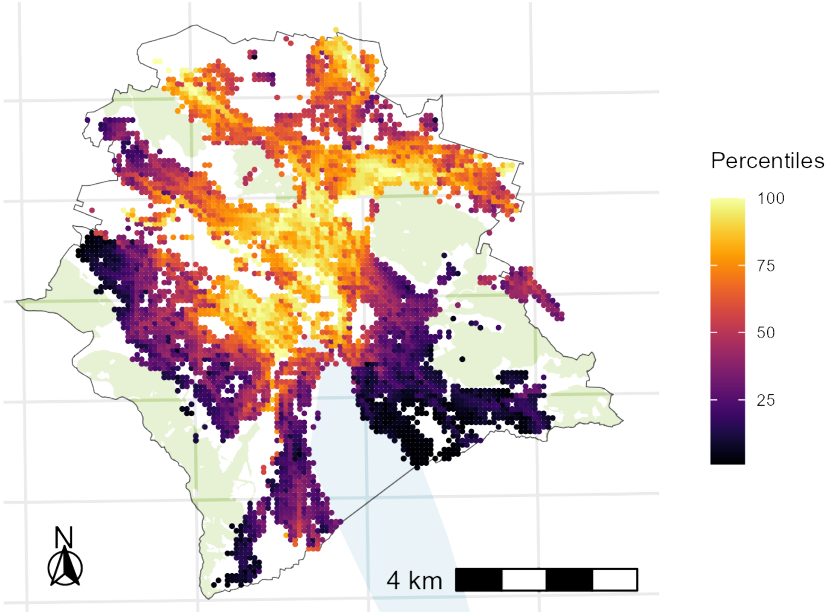
Market Access Across Different Groups and Locations

As evident from the summary statistics in Table 1, the households' expenditure shares vary with income levels such that higher market access might, *ceteris paribus*, be more valuable

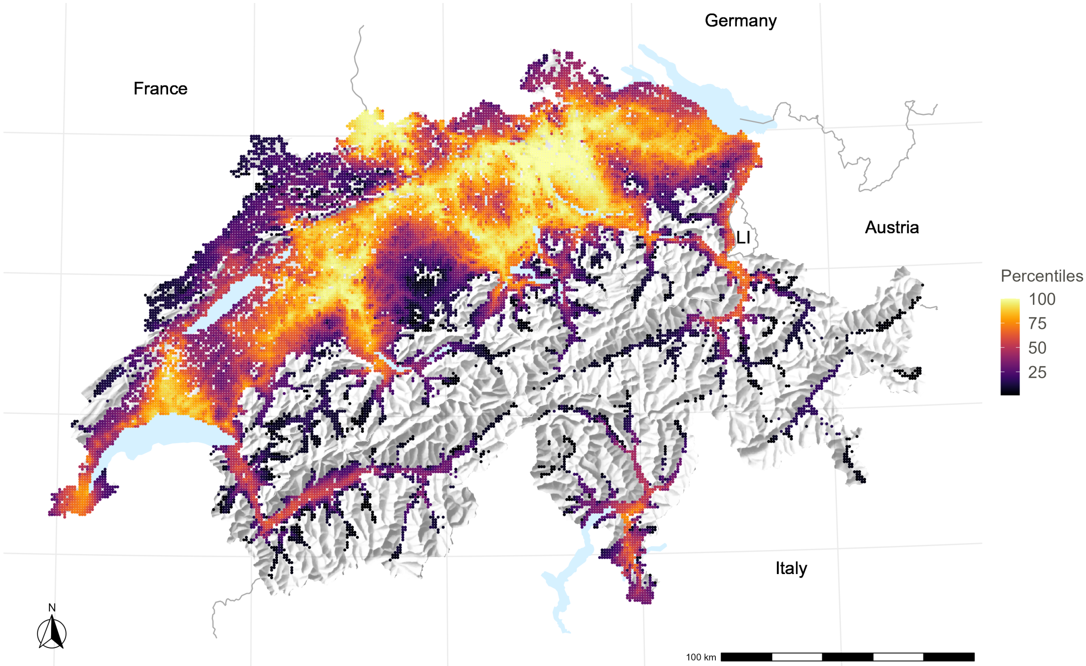
[23] Zurich, Geneva, Basel, Lausanne, Bern, Winterthur, Lucerne, St. Gallen, Lugano, Biel/Bienne.

Figure 5: Spatial Distribution of Grid-Level Retail Market Access

(a) Percentiles of Market Access in the City of Zurich



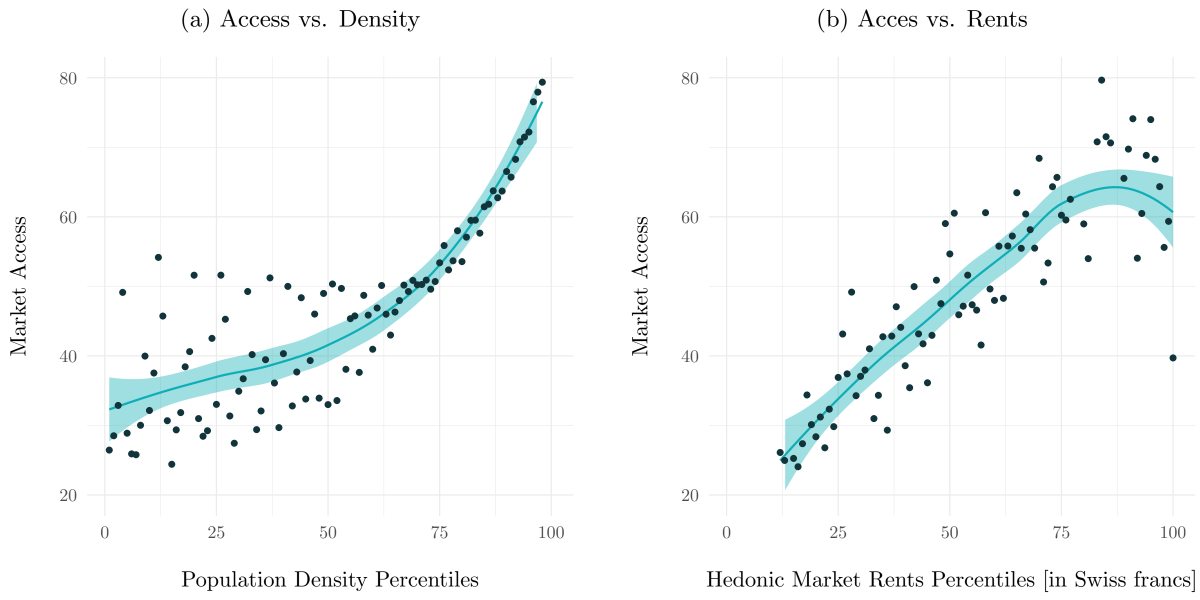
(b) Percentiles of Market Access in Switzerland



Notes: The figure plots for each populated 100 × 100 meter grid cell in Switzerland our utility-based valuation of market access as in Equation (5). We consider all stores of major grocery retailers in Switzerland, recover the unobserved store valuations with a Lasso approach, and use our causal estimates of travel costs. Travel distances between households and stores are measured as car travel times in minutes. Figure 5a zooms into the market access for the city of Zurich, while Figure 5b shows the market access for the entire country (aggregated to 1,000 × 1,000 meter cells).

for lower-income groups and for larger household sizes. Therefore, we next analyze patterns in market access based on household-level characteristics, and Table 6 shows the variation in

Figure 6: Relating to the Spatial Equilibrium



Notes: The figure plots the average cell-level market access (as in Equation 5) against the percentiles of the cell-level population count in Figure 6a and against hedonic market rents

market access across major household variables, including income, age, and household size. We report estimation results for the entire country as well as for urban, suburban, and rural regions separately. First, we observe considerable differences across income quintiles, where higher-income households typically benefit from better market access. This is especially the case in rural and suburban areas. Second, we document that market access is especially advantageous for young households in urban areas, with only minor patterns for other regions. Third, smaller households across the country live, on average, in places with better market access, a pattern that reverses in rural municipalities. Note that, so far, this dispersion in market access is calculated with distance decay functions and costs that are identical across different household characteristics, and we will discuss this assumption in the following subsection.

Spatial Variation in Market Access vs. Income

Finally, we relate the spatial variation in market access to spatial income disparities and observe that market access displays much higher variation. Across the entire country, the ratio of the 75th to the 25th percentile is 3.05 for local market access and 1.83 for local household income. Similarly, the coefficients of variation (meaning the ratio of the standard deviation to the mean) are 1.43 for market access and 1.06 for household income. In urban areas, the coefficient of variation in market access is even twice as high as that for income. Given the positive correlation between income and market access, this underscores the importance of price variation in measuring real income disparities across different regions.

Table 6: Grocery Market Access Across Household Characteristics

Dependent Variable	Market Access			
	Total (1)	Urban (2)	Suburban (3)	Rural (4)
Household Income				
Q1	63.427***	81.123***	52.391***	28.022***
	(0.049)	(0.085)	(0.063)	(0.083)
Q2	65.175***	83.789***	56.516***	31.998***
	(0.058)	(0.085)	(0.063)	(0.083)
Q3	64.981***	84.72***	58.056***	33.462***
	(0.055)	(0.085)	(0.063)	(0.083)
Q4	64.545***	84.305***	58.982***	35.79***
	(0.053)	(0.085)	(0.063)	(0.083)
Q5	68.017***	81.972***	60.836***	38.513***
	(0.05)	(0.085)	(0.063)	(0.083)
Age				
<34	69.228***	85.208***	57.693***	32.517***
	(0.050)	(0.078)	(0.064)	(0.089)
35-44	67.724***	84.226***	58.545***	34.178***
	(0.046)	(0.075)	(0.058)	(0.079)
45-54	63.545***	81.751***	57.13***	33.968***
	(0.044)	(0.075)	(0.054)	(0.071)
55-64	61.542***	81.653***	56.356***	33.328***
	(0.043)	(0.075)	(0.053)	(0.068)
65-74	60.554***	81.561***	56.053***	31.688***
	(0.05)	(0.089)	(0.061)	(0.078)
75+	61.219***	81.272***	55.565***	30.576***
	(0.047)	(0.079)	(0.058)	(0.078)
Household Size				
1	65.364***	83.23***	55.646***	30.123***
	(0.031)	(0.049)	(0.040)	(0.054)
2	63.672***	83.244***	57.808***	33.779***
	(0.033)	(0.058)	(0.041)	(0.053)
3-4	62.76***	81.297***	57.283***	34.487***
	(0.038)	(0.066)	(0.047)	(0.061)
5+	60.586***	80.549***	57.13***	34.205***
	(0.081)	(0.146)	(0.100)	(0.122)
n	3,989,077	869,932	1,711,803	570,697

Notes: The table shows the dispersion of our market access measure in Equation (5) across all 4 million Swiss households and grouped by the degree of urbanization. Across the three panels, we regress in three independent regressions market access on household income quintiles, the age of the household's head, and household size. Income quintiles are recalculated for each urbanization group.

7.3 Type-Specific Spatial Frictions

So far, we have estimated and used a distance decay parameter β that is constant across locations and different household characteristics. However, if distance costs vary across an important dimension that is spatially segregated, this might imply significant welfare costs for the disadvantaged group that we would miss so far. Therefore, we re-estimate the incumbent and competitor shift as well as the total distance gradient for different groups of household characteristics – income, age, household size, and population density – allowing β to vary across the groups.

Table 7 shows the estimation results. We display the intercepts and slopes of the incumbent and

Table 7: Heterogeneous Distance Costs

	Incumbent Shift		Competitor Shift		Total Shift				
Group	Intercept	Slope	Intercept	Slope	Intercept	Slope	Mean Dist	Cons. Area	n
Household Income									
<4,530	-0.234***	0.107***	0.101***	-0.028***	0.335***	-0.135***	12.3 min.	11.9 min.	1,053,897
	(0.009)	(0.005)	(0.009)	(0.003)	(0.013)	(0.006)			
4,530-6,717	-0.176***	0.071***	0.146***	-0.043***	0.323***	-0.114***	12.7 min.	17.0 min.	266,912
	(0.018)	(0.009)	(0.020)	(0.007)	(0.027)	(0.011)			
6,717-9,288	-0.242***	0.104***	0.128***	-0.034***	0.369***	-0.137***	13.1 min.	14.8 min.	357,721
	(0.015)	(0.008)	(0.019)	(0.006)	(0.024)	(0.010)			
9,289-12,855	-0.230***	0.097***	0.162***	-0.046***	0.392***	-0.143***	13.1 min.	15.5 min.	438,179
	(0.014)	(0.008)	(0.014)	(0.005)	(0.020)	(0.009)			
12,856+	-0.205***	0.088***	0.191***	-0.055***	0.397***	-0.143***	12.6 min.	16.0 min.	484,389
	(0.013)	(0.007)	(0.014)	(0.004)	(0.019)	(0.008)			
Age									
<34	-0.184***	0.070***	0.156***	-0.055***	0.340***	-0.125***	12.1 min.	15.2 min.	84,625
	(0.033)	(0.017)	(0.027)	(0.011)	(0.042)	(0.021)			
35-44	-0.209***	0.083***	0.166***	-0.057***	0.375***	-0.140***	12.6 min.	14.6 min.	321,972
	(0.017)	(0.009)	(0.015)	(0.006)	(0.023)	(0.011)			
45-55	-0.241***	0.106***	0.141***	-0.042***	0.382***	-0.148***	12.8 min.	13.2 min.	542,698
	(0.012)	(0.007)	(0.012)	(0.005)	(0.017)	(0.008)			
55-64	-0.195***	0.082***	0.150***	-0.045***	0.345***	-0.128***	12.9 min.	14.8 min.	585,039
	(0.013)	(0.007)	(0.011)	(0.004)	(0.017)	(0.008)			
65-74	-0.224***	0.100***	0.113***	-0.032***	0.336***	-0.132***	12.7 min.	12.7 min.	494,905
	(0.012)	(0.007)	(0.012)	(0.005)	(0.017)	(0.008)			
75+	-0.243***	0.115***	0.088***	-0.023***	0.332***	-0.138***	12.3 min.	11.0 min.	571,859
	(0.012)	(0.007)	(0.012)	(0.004)	(0.017)	(0.008)			
Household Size									
1	-0.210***	0.096***	0.110***	-0.034***	0.320***	-0.130***	11.9 min.	11.7 min.	610,431
	(0.012)	(0.007)	(0.012)	(0.005)	(0.016)	(0.008)			
2	-0.234***	0.105 ***	0.107***	-0.030***	0.341***	-0.135***	12.8 min.	12.5 min.	970,711
	(0.009)	(0.005)	(0.009)	(0.003)	(0.013)	(0.006)			
3-4	-0.218***	0.092***	0.148***	-0.047*	0.366***	-0.139***	12.8 min.	13.9 min.	833,765
	(0.010)	(0.005)	(0.009)	(0.004)	(0.013)	(0.006)			
5+	-0.157***	0.061***	0.159***	-0.047***	0.316***	-0.108***	13.2 min.	18.7 min.	43,500
	(0.050)	(0.025)	(0.034)	(0.013)	(0.060)	(0.028)			
Pop. Density									
Rural	-0.503***	0.269***	0.410***	-0.100***	0.913***	-0.369***	16.3 min.	11.8 min.	658,270
	(0.014)	(0.013)	(0.023)	(0.005)	(0.020)	(0.018)			
Suburban	-0.236***	0.102***	0.132***	-0.039***	0.368***	-0.141***	12.9 min.	13.6 min.	1,214,021
	(0.008)	(0.004)	(0.009)	(0.003)	(0.011)	(0.006)			
Urban	-0.249***	0.134***	0.069***	-0.021*	0.318***	-0.155***	9.0 min.	7.8 min.	728,807
	(0.011)	(0.007)	(0.010)	(0.004)	(0.015)	(0.010)			

Notes: The table shows for different characteristics heterogeneous difference-in-differences estimates for the effect of a store opening on expenditures at incumbent stores and all stores, estimating in both cases Equation (6). This captures the *incumbent shift* and *competitor shift* respectively. The coefficients are Poisson estimates where we report the exponentiated Poisson coefficients $exp(\beta)-1$, following Chen and Roth (2024). We focus on households with average monthly expenditures between 20 and 10,000 Swiss francs with full information on income and household size who did not move during our sample period. Households are treated if they live within 30 minutes of a store opening.

competitor effects for each group, respectively, as well as the total expenditure shift. Across the household-level socioeconomic and sociodemographic characteristics, we find rather little variation in the two coefficients of interest. Yet, looking at the implied consumption area measured in minutes – reflecting the distance beyond which expenditures are predicted to decline to zero – interesting patterns emerge. With regard to income, there is no clear pattern, as the smallest consumption area is predicted for the lowest income quintile and the largest consumption area for the second quintile. This suggests that spatial frictions are rather homogeneous across different income groups. Yet, looking at age, we observe more pronounced patterns as consumer areas decline with age, and accordingly, spatial frictions increase with age. Similarly, consumption areas grow more extensive as household size increases, especially for households with at least five members. Lastly, we observe substantial differences in spatial frictions across different locations. The distance elasticity in rural areas is more than twice as large as the distance elasticity in urban areas. Accordingly, we observe a significantly smaller consumption area in urban than in rural areas. This seems logical, as newly constructed supermarkets in areas with potentially insufficient grocery supply likely attract customers from further away. In principle, variable coefficients for any combination of attributes are possible, but the computational burden increases substantially. Additionally, Table A12 and Table A13 in the Appendix consider the influence of sociodemographic attributes for urban and rural locations separately.

8 Conclusions

This paper provides causal estimates of distance costs in grocery shopping. We exploit the quasi-random variation induced by openings of new supermarkets with a unique and large representative data set of households' transaction records from the largest retailer in Switzerland (1.5 billion transactions of more than 2 million households). Our empirical results show parametric distance elasticities of expenditure of roughly 0.15, while conventional gravity regressions suggest an elasticity of 0.85. Therefore, conventional estimates are largely biased upwards because stores locate endogenously close to households with high potential sales. Including our causal estimates into a simple conceptual framework of spatial grocery shopping, we show that grocery market access strongly varies in space – between regions as well as within cities. Our measure of grocery market access is consistent with predictions from standard spatial equilibrium theory, and better access correlates with higher population density and housing rents. Analyzing potential heterogeneities in the distance decay parameter, we find evidence for differences between socioeconomic and sociodemographic groups and particularly strong differences between rural and urban areas as consumption areas appear much larger in rural areas with worse store access.

References

Agarwal, S., Jensen, J.B., Monte, F., 2022. Consumer Mobility and the Local Structure of Consumption Industries. NBER Working Paper 23616. doi:10.3386/w23616.

Ahlfeldt, G.M., Bald, F., Roth, D., Seidel, T., 2022. Quality of Life in a Dynamic Spatial Model. Working Paper doi:10.2139/ssrn.3751857.

Ahlfeldt, G.M., Nitsch, V., Wendland, N., 2019. Ease vs. noise: Long-run changes in the value of transport (dis)amenities. Journal of Environmental Economics and Management 98, 102268. doi:10.1016/j.jeem.2019.102268.

Almagro, M., Domınguez-Iino, T., 2024. Location Sorting and Endogenous Amenities: Evidence from Amsterdam. Working Paper doi:10.2139/ssrn.4317074.

Arcidiacono, P., Ellickson, P.B., Mela, C.F., Singleton, J.D., 2020. The Competitive Effects of Entry: Evidence from Supercenter Expansion. American Economic Journal: Applied Economics 12, 175–206. doi:10.1257/app.20180047.

Brueckner, J.K., Zenou, Y., 1999. Why is central Paris rich and downtown Detroit poor? An amenity-based theory. European Economic Review 43, 91–107. doi:10.1016/S0014-2921(98)00019-1.

Caliendo, L., Dvorkin, M., Parro, F., 2019. Trade and Labor Market Dynamics: General Equilibrium Analysis of the China Trade Shock. Econometrica 87, 741–835. doi:10.3982/ECTA13758.

Callaway, B., Sant'Anna, P.H., 2021. Difference-in-Differences with Multiple Time Periods. Journal of Econometrics 225, 200–230. doi:10.1016/j.jeconom.2020.12.001.

de Chaisemartin, C., D'Haultfœuille, X., 2020. Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects. American Economic Review 110, 2964–2996. doi:10.1257/aer.20181169.

Chen, J., Roth, J., 2024. Logs with Zeros? Some Problems and Solutions. The Quarterly Journal of Economics 139, 891–936. doi:10.1093/qje/qjad054.

Couture, V., Handbury, J., 2020. Urban revival in America. Journal of Urban Economics 119, 103267. doi:10.1016/j.jue.2020.103267.

Diamond, R., 2016. The Determinants and Welfare Implications of US Workers' Diverging Location Choices by Skill: 1980–2000. American Economic Review 106, 479–524. doi:10.1257/aer.20131706.

Eaton, J., Kortum, S., 2002. Technology, Geography, and Trade. Econometrica 70, 1741–1779. doi:10.1111/1468-0262.00352.

Eizenberg, A., Lach, S., Oren-Yiftach, M., 2021. Retail Prices in a City. American Economic Journal: Economic Policy 13, 175–206. doi:10/gnp9vb.

Han, L., Heblich, S., Timmins, C., Zylberberg, Y., 2024. Cool Cities: The Value of Urban Trees. NBER Working Paper 32063. doi:10.3386/w32063.

Handbury, J., 2021. Are Poor Cities Cheap for Everyone? Non-Homotheticity and the Cost of Living Across U.S. Cities. Econometrica 89, 679–2715. doi:10.3982/ecta11738.

Handbury, J., Weinstein, D.E., 2015. Goods Prices and Availability in Cities. Review of Economic Studies 82, 258–296. doi:10.1093/restud/rdu033.

Hausman, J., Leibtag, E., 2007. Consumer Benefits from Increased Competition in Shopping Outlets: Measuring the Effect of Wal-Mart. Journal of Applied Econometrics 22, 1157–1177. doi:10.1002/jae.994.

Hausman, N., Samuels, P., Cohen, M., Sasson, R., 2023. Urban Pull: The Roles of Amenities and Employment. Working Paper doi:10.2139/ssrn.3670974.

Heblich, S., Trew, A., Zylberberg, Y., 2021. East-Side Story: Historical Pollution and Persistent Neighborhood Sorting. Journal of Political Economy 129, 1508–1552. doi:10.1086/713101.

Henderson, D.J., Millimet, D.L., 2008. Is gravity linear? Journal of Applied Econometrics 23, 137–172. doi:10.1002/jae.974.

Hillberry, R., Hummels, D., 2008. Trade responses to geographic frictions: A decomposition using micro-data. European Economic Review 52, 527–550. doi:10.1016/j.euroecorev.2007.03.003.

Hoelzlein, M., Miller, S., 2024. The Gentrification Effect of Retail Amenities: Evidence from Whole Foods Market. Working Paper .

Kluser, F., 2024. Cross-Border Shopping: Evidence from Household Transaction Records. CRED Research Paper 42.

Kluser, F., Pons, M., 2024. The Apple Does Not Fall Far From the Tree: Intergenerational Persistence of Dietary Habits. Working Paper .

Leonardi, M., Moretti, E., 2023. The Agglomeration of Urban Amenities: Evidence from Milan Restaurants. American Economic Review: Insights 5, 141–57. doi:10.1257/aeri.20220011.

Marshall, G., Pires, T., 2018. Measuring the Impact of Travel Costs on Grocery Shopping. The Economic Journal 128, 2538–2557. doi:10.1111/ecoj.12523.

Miyauchi, Y., Nakajima, K., Redding, S.J., 2022. The Economics of Spatial Mobility: Theory and Evidence Using Smartphone Data. Working Paper doi:10.3386/w28497.

Monte, F., Redding, S.J., Rossi-Hansberg, E., 2018. Commuting, Migration, and Local Employment Elasticities. American Economic Review 108, 3855–3890. doi:10.1257/aer.20151507.

Pope, D.G., Pope, J.C., 2015. When Walmart comes to town: Always low housing prices? Always? Journal of Urban Economics 87, 1–13. doi:10/f7ch8d.

Roback, J., 1982. Wages, Rents, and the Quality of Life. Journal of Political Economy 90, 1257–1278. doi:10.1086/261120.

Rosen, S., 1979. Wage-Based Indexes of Urban, Quality of Life. Current issues in urban economics , 74–104.

Schuetz, J., 2015. Why are Walmart and Target Next-Door neighbors? Regional Science and Urban Economics 54, 38–48. doi:10.1016/j.regsciurbeco.2015.07.002.

Taylor, R., Villas-Boas, S.B., 2016. Food Store Choices of Poor Households: A Discrete Choice Analysis of the National Household Food Acquisition and Purchase Survey (FoodAPS). American Journal of Agricultural Economics 98, 513–532. URL: https://onlinelibrary.wiley.com/doi/10.1093/ajae/aaw009, doi:10.1093/ajae/aaw009.

Wooldridge, J., 2023. Simple approaches to nonlinear difference-in-differences with panel data. The Econometrics Journal 26, C31–C66. doi:10.1093/ectj/utad016.

Wooldridge, J.M., 2022. Two-Way Fixed Effects, the Two-Way Mundlak Regression, and Difference-in-Differences Estimators. Working Paper doi:10.2139/ssrn.3906345.

1 Data: Matching Procedure

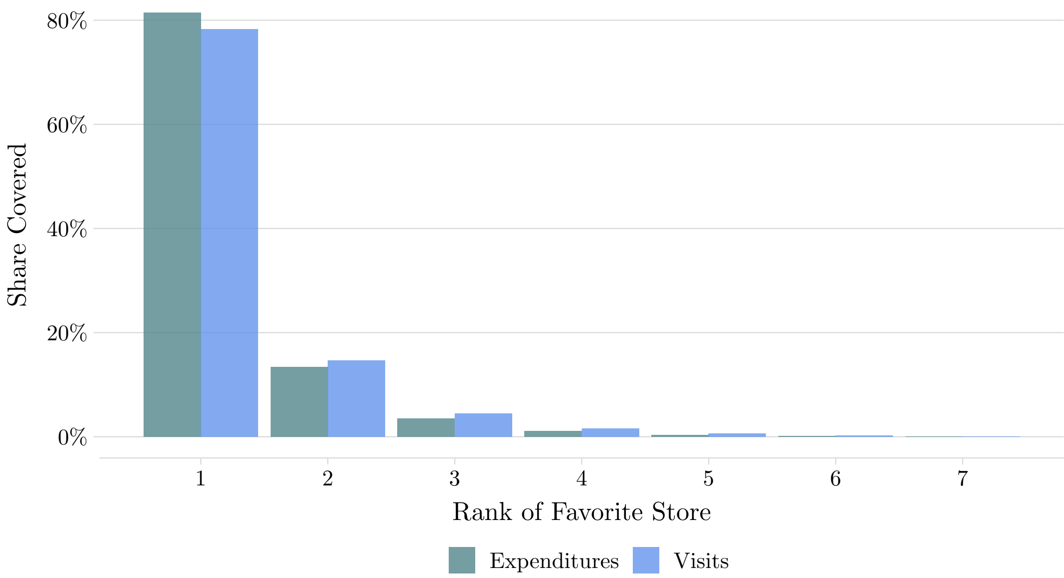
This section describes how we match the *customers* in the grocery transaction data with the *residents* in the administrative data. To begin with, we select all combinations of residents and customers with the same location grid cells and age. This generates 4.5 million matches between customers and residents, and we refer to them as *pairs*.[24] We take some additional steps to isolate the unique matches between *residents* and *customers*, proceeding as follows.

1. First, we want to exclude pairs where the customer's shopping behavior does not fit the resident's past locations of residence, as these residents are likely not the owners of the loyalty card they link to. So, we calculate the median annual road distance traveled between a resident's home location and the stores visited by the customer (weighted by trip expenditures). Then, we exclude customer-resident pairs with median shopping trips exceeding 20 kilometers in any year. This step excludes 191,000 pairs.
2. Customers can register in the loyalty program as a family if they have at least one child younger than 25. Hence, we delete all pairs where the customer is registered as a family, and the resident does not fulfill this criterion. This excludes 355,000 pairs.
3. Then, we select all customers that link to exactly one household (multiple residents can live in this household). This gives 1,585,204 unique customer-resident matches.
4. Although households can own multiple loyalty cards, the minimum age to register is 18. Hence, we exclude pairs with more customers than adult residents, eliminating 77,935 pairs.
5. We recover some additional unique matches by identifying consumers who have moved recently without notifying the retailer. To this end, we check whether these movers uniquely match a resident at their old location. This procedure identifies 47,571 additional unique pairs.
6. Removing the customers and residents matched in the previous step, we find an additional 3,845 unique matches at current locations. Steps (1) to (6) result in 1.55 million customers uniquely linked to a resident, accounting for 73% of active customers and 21% of Swiss adult residents.
7. For households owning multiple loyalty cards, we then aggregate expenditures within the household.
8. We assign the aggregated transaction data to all adult residents in the household. This provides grocery expenditures for 2,248,059 million residents living in 1.17 million different households.

[24] Note that some customers do not match any resident, which is most likely because their addresses in the grocery data are outdated. This is the case for 380,000 of the 2.8 million customers (13.5%), of which 260,000 are active customers (spending more than 50 Swiss francs monthly over our sample period).

2 Summary Statistics

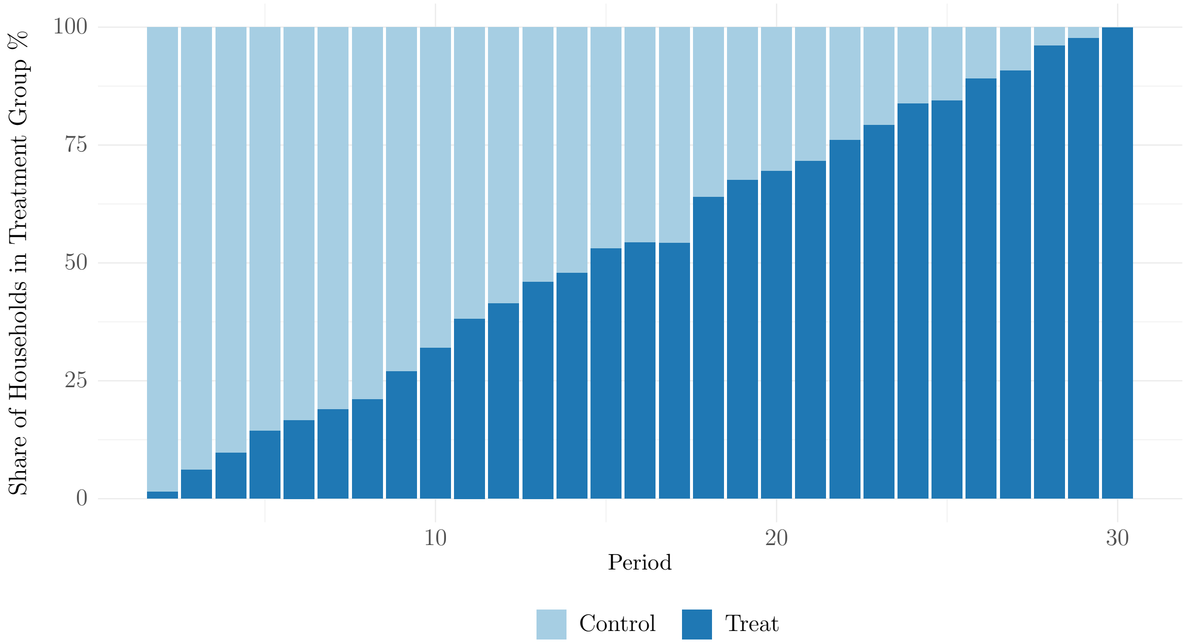
Figure A1: Ranking of Favorite Stores



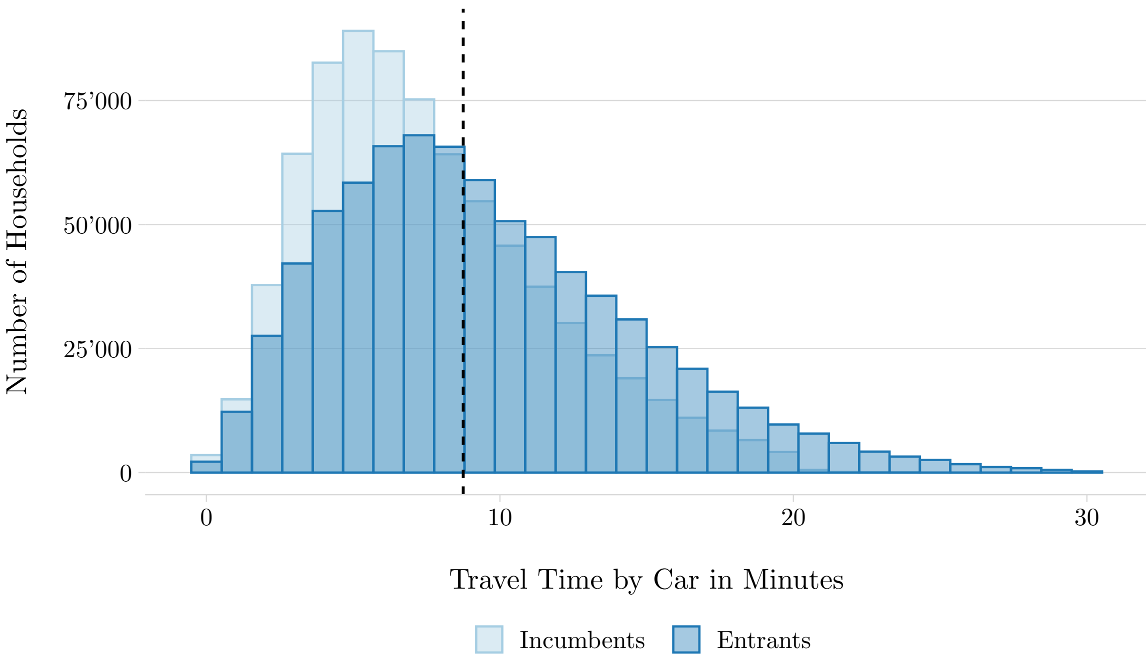
Notes: The figure shows the share of households' visits and expenditures at their ranked favorites. The figure aggregates all 1.5 billion transactions between 2019Q1 and 2021Q2 that have non-negative amounts and are at supermarkets within 30 minutes by car from the household's residence.

Figure A2: Descriptives of the Treatments

(a) Composition of Treatment and Control Groups



(b) Distance to Closest Treatment



Notes: Figure A2a shows how the composition of the treatment and control groups changes over time as more and more households switch to the treatment group. Figure A2b 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.

3 Additional Results

3.1 Staggered DiD: OLS With log(expenditures) Instead of Poisson

In the paper, we report the treatment effect for store openings using a QMLE-Poisson model – see Equation (6) – to take into account the mass point at zero in the dependent variable. Here, we ignore this mass point and estimate a more standard TWFE model with OLS, where we take the logarithm of the dependent variables. Therefore, we ignore all weekly expenditures with a value of zero:

$$log(Y_{it}) = \alpha_i + \gamma_t + \beta(T_{it} \times ln(Dist_i)) + \delta T_{it} + \epsilon_{it}, \tag{9}$$

where Y_{it} will again be (i) the expenditures at incumbent stores, capturing the incumbent shift, and (ii) total expenditures at any same-chain store, capturing the competitor shift. Therefore, we focus on the intensive margin of the store opening intervention, and zero-valued observations drop out in this case.

As a naive alternative, trying to incorporate the zero-valued observations, we report additional estimation results by adding the value 1 to expenditures Y_{it} in Equation (9). In this way, zero-valued observations do not drop out, and we use the entire balanced panel. However, note that Chen and Roth (2024) show that the resulting coefficients cannot be interpreted as a proportional treatment effect (meaning, a proportional change in percentage points).

Table A1: Incumbent Expenditure Shift – Intensive Margin (Log Model)

	log(Expenditures)			log(No. of Visits)		
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	-0.098***	-0.129***	-0.307***	-0.077***	-0.105***	-0.264***
	(0.003)	(0.004)	(0.008)	(0.008)	(0.003)	(0.007)
Treat × ln(Euclid. Dist. in km)	0.043***			0.041***		
	(0.002)			(0.004)		
Treat × ln(Road Dist. in km)		0.053***			0.049***	
		(0.002)			(0.002)	
Treat × ln(Car Dist. in min)			0.111***			0.100***
			(0.003)			(0.003)
Observations	2,333,704	2,335,343	2,335,343	2,333,704	2,335,343	2,335,343
Squared Correlation	0.664	0.664	0.665	0.659	0.659	0.660

Notes: The table shows difference-in-differences estimates for the effect of a store opening on expenditures at incumbent stores, estimating Equation (9). This captures expenditures shifted from incumbent stores to the new store. The dependent variable is log(expenditures). We focus on households with average monthly expenditures between 20 and 10,000 Swiss francs with full information on income and household size who did not move during our sample period. Households are treated if they live within 30 minutes of a store opening.

Table A2: Incumbent Expenditure Shift (Log+1 Model)

	log(Expenditures + 1)			log(No. of Visits + 1)		
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	-0.211***	-0.269***	-0.602***	-0.123***	-0.162***	-0.376***
	(0.006)	(0.007)	(0.016)	(0.016)	(0.004)	(0.009)
Treat × ln(Euclid. Dist. in km)	0.080***			0.056***		
	(0.003)			(0.006)		
Treat × ln(Road Dist. in km)		0.098***			0.068***	
		(0.004)			(0.002)	
Treat × ln(Car Dist. in min)			0.208***			0.136***
			(0.006)			(0.004)
Observations	2,599,180	2,601,098	2,601,098	2,599,180	2,601,098	2,601,098
Squared Correlation	0.572	0.572	0.573	0.653	0.653	0.654

Notes: The table shows difference-in-differences estimates for the effect of a store opening on expenditures at incumbent stores, estimating Equation (9). This captures expenditures shifted from incumbent stores to the new store. The dependent variable is log(expenditures+1), where we add the value 1 to each household's expenditures. We focus on households with average monthly expenditures between 20 and 10,000 Swiss francs with full information on income and household size who did not move during our sample period. Households are treated if they live within 30 minutes of a store opening.

Table A3: Competitor Expenditure Shift – Intensive Margin (Log Model)

	log(Expenditures)			log(No. of Visits)		
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	0.058***	0.070***	0.137***	0.087***	0.103***	0.193***
	(0.003)	(0.003)	(0.006)	(0.008)	(0.003)	(0.006)
Treat × ln(Euclid. Dist. in km)	-0.020***			-0.027***		
	(0.002)			(0.004)		
Treat × ln(Road Dist. in km)		-0.022***			-0.031***	
		(0.002)			(0.001)	
Treat × ln(Car Dist. in min)			-0.043***			-0.059***
			(0.003)			(0.002)
Observations	2,380,182	2,381,977	2,381,977	2,380,182	2,381,977	2,381,977
Squared Correlation	0.673	0.673	0.673	0.662	0.662	0.662

Notes: The table shows difference-in-differences estimates for the effect of a store opening on expenditures at all same-chain stores, estimating Equation (9). This captures expenditures shifted from competitors to the new store. The dependent variable is log(expenditures). We focus on households with average monthly expenditures between 20 and 10,000 Swiss francs with full information on income and household size who did not move during our sample period. Households are treated if they live within 30 minutes of a store opening.

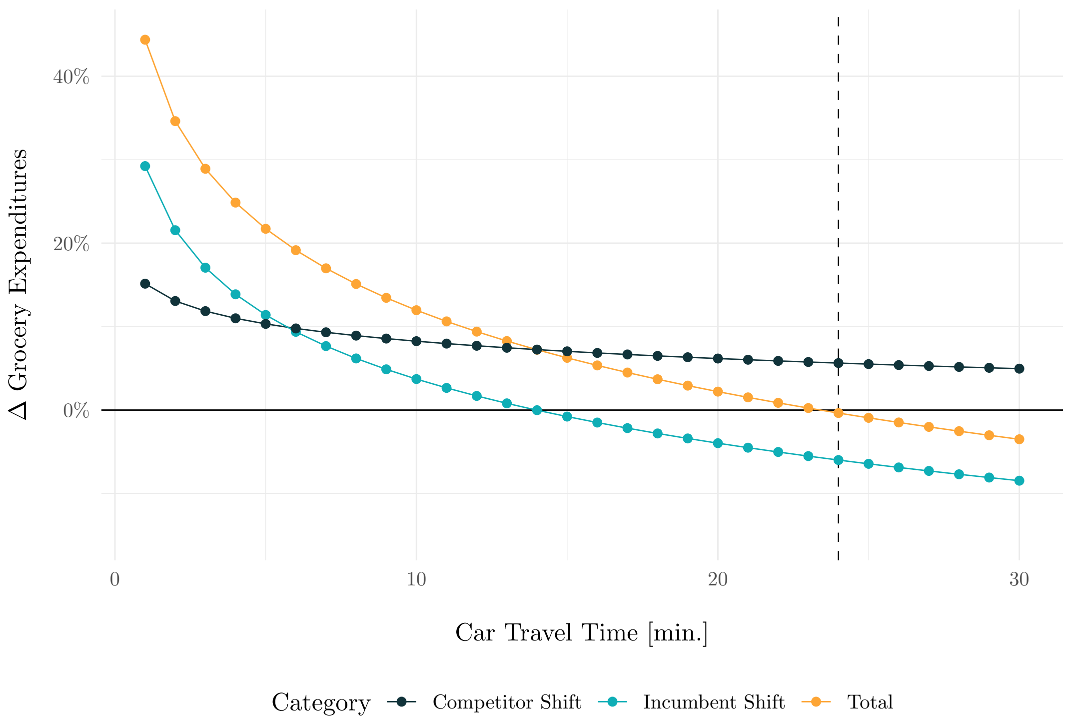
Table A4: Competitor Expenditure Shift (Log+1 Model)

	log(Expenditures + 1)			log(No. of Visits + 1)		
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	0.131***	0.162***	0.352***	0.111***	0.134***	0.272***
	(0.006)	(0.007)	(0.014)	(0.015)	(0.004)	(0.009)
Treat × ln(Euclid. Dist. in km)	-0.046***			-0.035***		
	(0.003)			(0.005)		
Treat × ln(Road Dist. in km)		-0.055***			-0.042***	
		(0.004)			(0.002)	
Treat × ln(Car Dist. in min)			-0.118***			-0.087***
			(0.006)			(0.003)
Observations	2,599,180	2,601,098	2,601,098	2,599,180	2,601,098	2,601,098
Squared Correlation	0.557	0.557	0.557	0.639	0.639	0.640

Notes: The table shows difference-in-differences estimates for the effect of a store opening on expenditures at all same-chain stores, estimating Equation (9). This captures expenditures shifted from competitors to the new store. The dependent variable is log(expenditures), where we add the value 1 to each household's expenditures. We focus on households with average monthly expenditures between 20 and 10,000 Swiss francs with full information on income and household size who did not move during our sample period. Households are treated if they live within 30 minutes of a store opening.

3.2 Robust DiD Estimator and DiD With Kinks in the Log-Distance

Figure A3: Distance Gradients (Robust Estimator)



Notes: The figure shows distance gradient functions, indicating how the treatment effects from the difference-in-difference analyses decline over time. Compared to Figure 2, this figure uses the robust DiD estimator proposed by Wooldridge (2022) and Wooldridge (2023) as in Equation (7).

Table A5: Log Specifications With Kinks (Incumbent Shift)

	Expenditures					
Kink at Travel Time Distance	10 min.	11 min.	12 min.	13 min.	14 min.	15 min.
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	-0.2893***	-0.2846***	-0.2723***	-0.2688***	-0.2640***	-0.2621***
	(0.0096)	(0.0091)	(0.0082)	(0.0079)	(0.0076)	(0.0073)
Treat × log(Car Dist) × 1(Below Kink)	0.1588***	0.1527***	0.1383***	0.1347***	0.1299***	0.1281***
	(0.0083)	(0.0075)	(0.0062)	(0.0057)	(0.0053)	(0.0050)
Treat × log(Car Dist) × 1(Above Kink)	0.0003***	0.0003***	0.0005***	0.0005***	0.0006***	0.0005***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	2,601,098	2,601,098	2,601,098	2,601,098	2,601,098	2,601,098
Squared Correlation	0.75687	0.75686	0.75684	0.75684	0.75683	0.75682

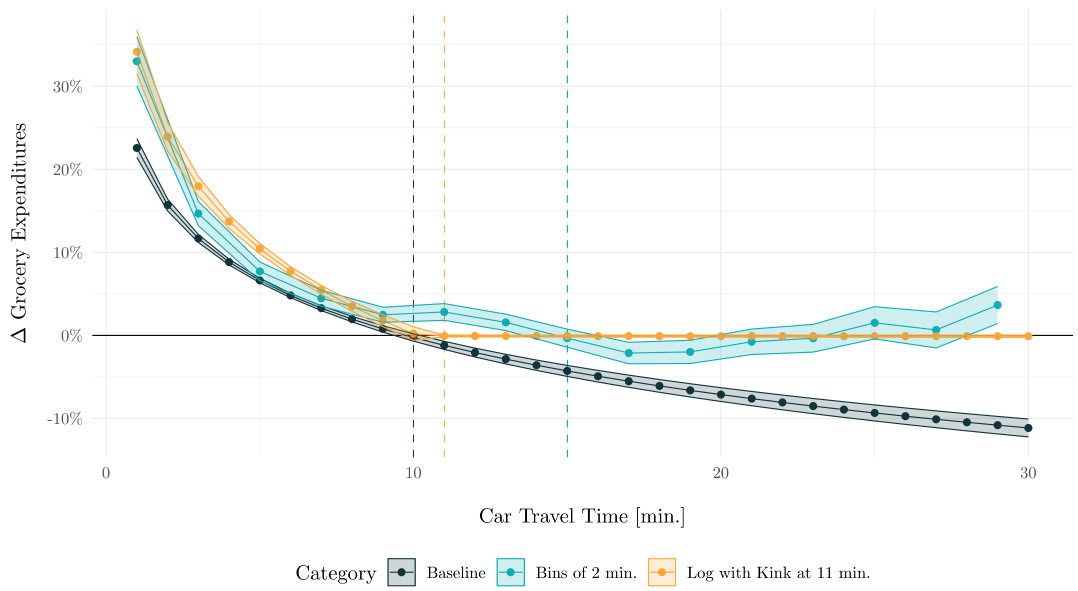
Notes: The table shows alternative model estimates for the distance decay functions in Figure A4 with a kink in the logarithmic specifications. Compared to Figure A4, the table displays intercepts and slope-coefficients of interest for kinks between 10 and 15 minutes.

Table A6: Log Specifications With Kinks (Competitor Shift)

Kink at Travel Time Distance	23 min. (1)	24 min. (2)	25 min. (3)	26 min. (4)	27 min. (5)	28 min. (6)
	Expenditures					
Treat	0.1315***	0.1316***	0.1329***	0.1325***	0.1329***	0.1329***
	(0.0065)	(0.0064)	(0.0063)	(0.0063)	(0.0062)	(0.0062)
Treat × log(Car Dist) × 1(Below Kink)	-0.0355***	-0.0355***	-0.0361***	-0.0359***	-0.0361***	-0.0361***
	(0.0023)	(0.0022)	(0.0022)	(0.0022)	(0.0021)	(0.0021)
Treat × log(Car Dist) × 1(Above Kink)	-0.0001	-0.0002	-0.0001	-0.0003	-0.0004	-0.0006**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)
Observations	2,601,098	2,601,098	2,601,098	2,601,098	2,601,098	2,601,098
Squared Correlation	0.76008	0.76008	0.76008	0.76008	0.76008	0.76008

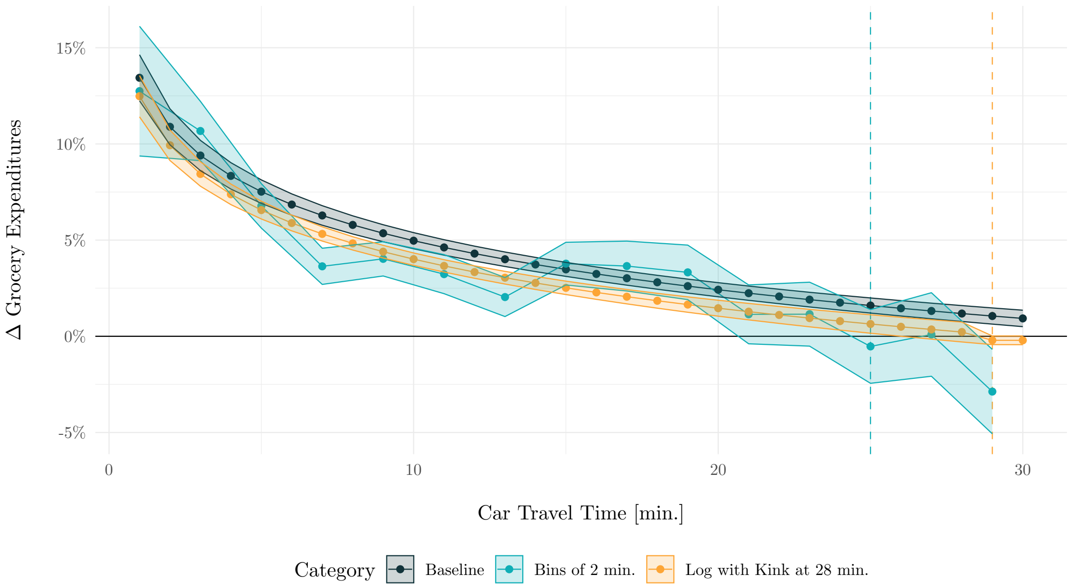
Notes: The table shows alternative model estimates for the distance decay functions in Figure A5 with a kink in the logarithmic specifications. Compared to Figure A5, the table displays intercepts and slope-coefficients of interest for kinks between 23 and 28 minutes.

Figure A4: Non-Parametric and Log-Kink Specification of the Incumbent Shift



Notes: The figure shows different specifications for the distance gradient functions, indicating how the treatment effects from the difference-in-difference analyses decline over time for the baseline *incumbent shift* estimates in Table 4 (mirrored along the horizontal axis). We calculate standard errors for the individual fitted points using the delta method. The dark *baseline* specification corresponds to the results displayed in Figure 2. The blue *bins of 2 min.* specification uses non-parametric travel time bins of 2 minutes. The orange *log with kink at 11 min.* estimates the baseline logarithmic model in Equation (6) but allows the slope to change after 11 minutes (when the baseline gravity function becomes insignificant).

Figure A5: Non-Parametric and Log-Kink Specification of the Competitor Shift

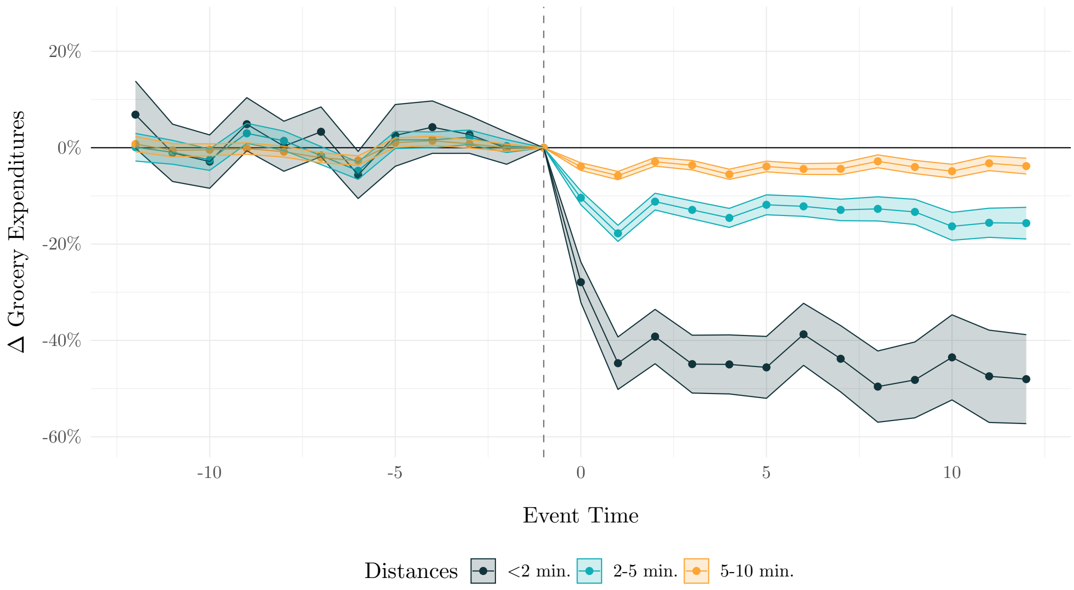


Notes: The figure shows different specifications for the distance gradient functions, indicating how the treatment effects from the difference-in-difference analyses decline over time for the baseline *competitor shift* estimates in Table 5. We calculate standard errors for the individual fitted points using the delta method. The dark *baseline* specification corresponds to the results displayed in Figure 2. The blue *bins of 2 min.* specification uses non-parametric travel time bins of 2 minutes. The orange *log with kink at 28 min.* estimates the baseline logarithmic model in Equation (6) but allows the slope to change after 28 minutes (when the baseline gravity function becomes insignificant).

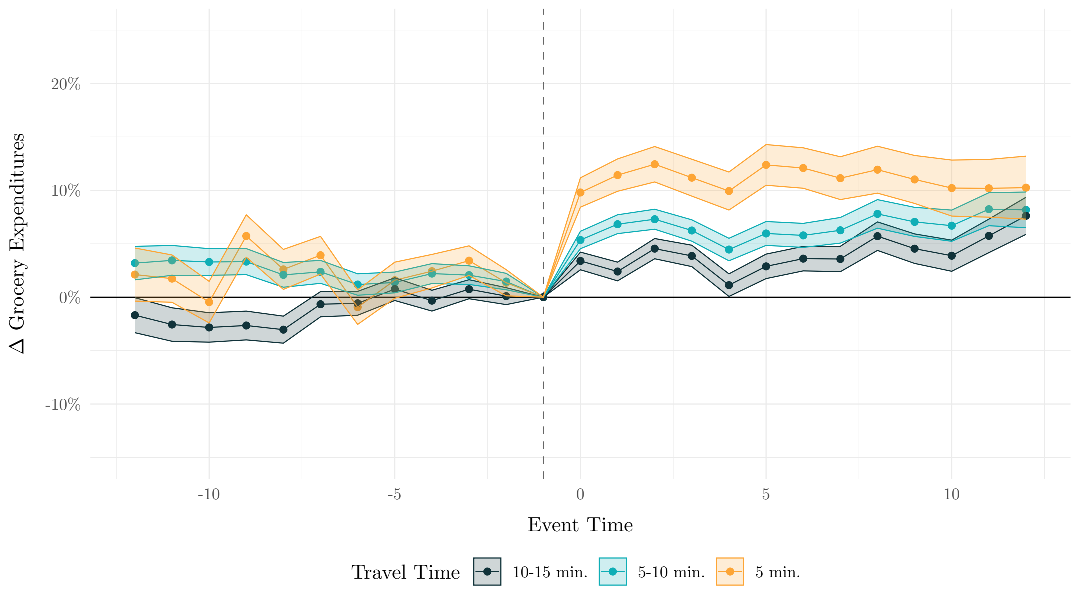
4 Robustness

Figure A6: Dynamic Treatment Effects

(a) Dynamic Effects: Incumbent Shift



(b) Dynamic Effects: Competitor Shift



Notes: The figure shows dynamic difference-in-differences estimates for the effect of a store opening on expenditures in an event-study fashion, estimating Equation (8). Figure A6a shows the incumbent shift and Figure A6b shows the competitor shift. As in the static results, coefficients are Poisson estimates where we report the exponentiated Poisson coefficients $exp(\beta) - 1$, following Chen and Roth (2024). We focus on households with average monthly expenditures between 20 and 10,000 Swiss francs with full information on income and household size who did not move during our sample period. Households are treated if they live within 30 minutes of a store opening.

Table A7: Incumbent Expenditure Shift Pre-COVID-19 (Poisson Model)

Proportional Effects	Expenditures			No. of Visits		
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	-0.068***	-0.089***	-0.202***	-0.061***	-0.079***	-0.188***
	(0.003)	(0.003)	(0.006)	(0.011)	(0.003)	(0.006)
Treat × ln (Euclid. Dist. in km)	0.034***			0.031***		
	(0.002)			(0.004)		
Treat × ln (Road Dist. in km)		0.040***			0.038***	
		(0.002)			(0.002)	
Treat × ln (Car Dist. in min)			0.085***			0.081***
			(0.003)			(0.003)
Observations	823,046	823,367	823,367	823,046	823,367	823,367
Squared Correlation	0.802	0.802	0.802	0.807	0.807	0.808

Notes: The table shows difference-in-differences estimates for the effect of a store opening on expenditures at incumbent stores, estimating Equation (6). This captures expenditures shifted from incumbent stores to the new store. Here, we focus on the period before the start of the COVID-19 pandemic, 2019/01 - 2020/02. The coefficients are Poisson estimates where we report the exponentiated Poisson coefficients $exp(\beta) - 1$, following Chen and Roth (2024). We focus on households with average monthly expenditures between 20 and 10,000 Swiss francs with full information on income and household size who did not move during our sample period. Households are treated if they live within 30 minutes of a store opening.

Table A8: Competitor Expenditure Shift Pre-COVID-19 (Poisson Model)

Proportional Effects	Expenditures			No. of Visits		
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	0.045***	0.052***	0.105***	0.058***	0.069***	0.141***
	(0.003)	(0.003)	(0.007)	(0.014)	(0.003)	(0.007)
Treat ln(Euclid. Dist. in km)	-0.007***			-0.014***		
	(0.001)			(0.004)		
Treat × ln(Road Dist. in km)		-0.009***			-0.016***	
		(0.001)			(0.001)	
Treat × ln(Car Dist. in min)			-0.026***			-0.037***
			(0.002)			(0.002)
Observations	823,046	823,367	823,367	823,046	823,367	823,367
Squared Correlation	0.803	0.803	0.803	0.804	0.804	0.805

Notes: The table shows difference-in-differences estimates for the effect of a store opening on expenditures at all same-chain stores, estimating Equation (6). This captures expenditures shifted from competitors to the new store. Here, we focus on the period before the start of the COVID-19 pandemic, 2019/01 - 2020/02. The coefficients are Poisson estimates where we report the exponentiated Poisson coefficients $exp(\beta) - 1$, following Chen and Roth (2024). We focus on households with average monthly expenditures between 20 and 10,000 Swiss francs with full information on income and household size who did not move during our sample period. Households are treated if they live within 30 minutes of a store opening.

Table A9: Incumbent Expenditure Shift, Only Once-Treated Households (Poisson Model)

Proportional Effect	Expenditures			No. of Visits		
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	-0.153***	-0.219***	-0.290***	-0.180***	-0.216***	-0.288***
	(0.029)	(0.033)	(0.048)	(0.060)	(0.028)	(0.039)
Treat × ln(Euclid. Dist. in km)	0.051***			0.067***		
	(0.014)			(0.023)		
Treat × ln(Road Dist. in km)		0.074***			0.084***	
		(0.016)			(0.014)	
Treat × ln(Car Dist. in min)			0.097***			0.106***
			(0.023)			(0.019)
Observations	198,354	198,354	198,354	198,354	198,354	198,354
Squared Correlation	0.735	0.735	0.735	0.755	0.755	0.755

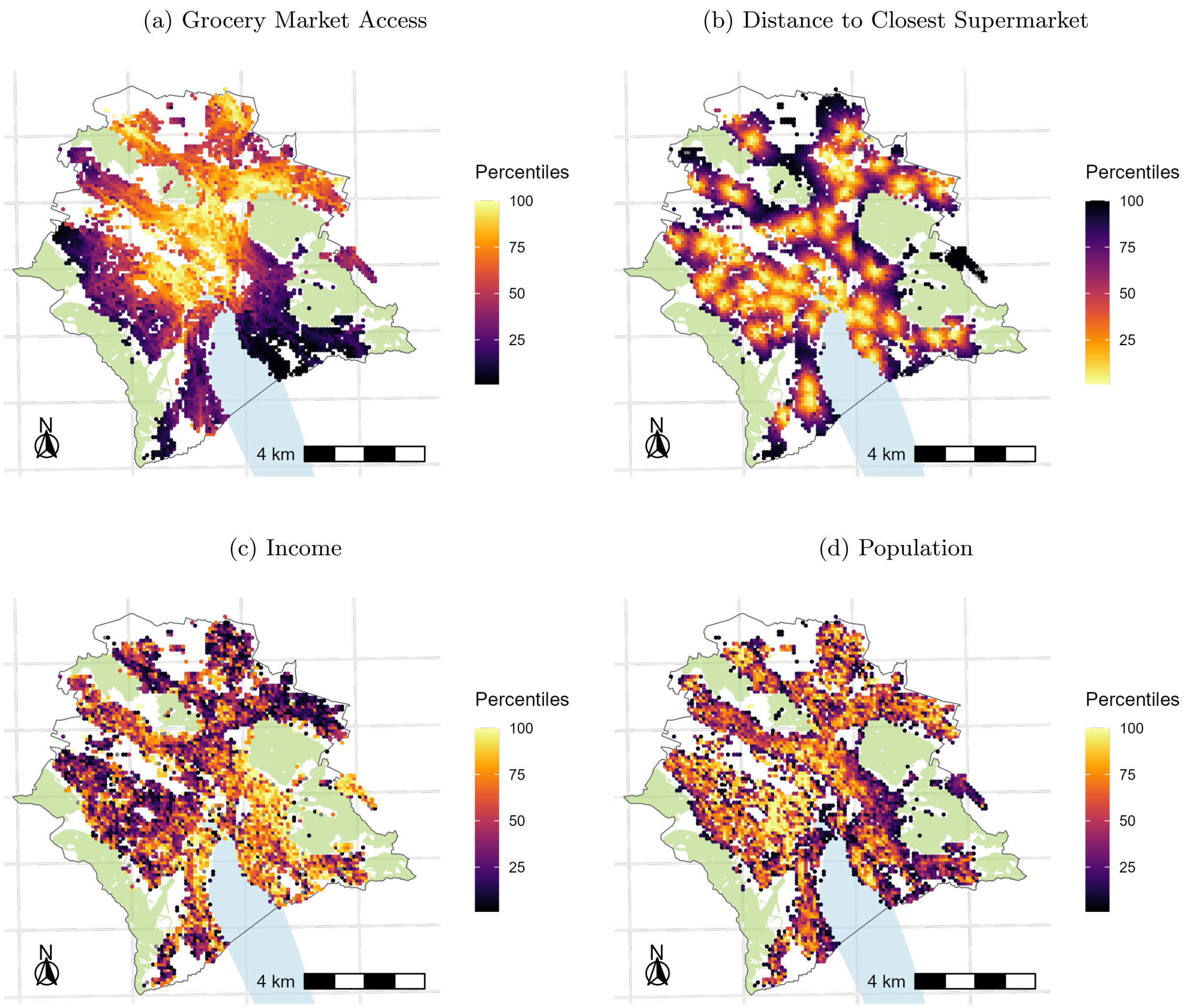
Notes: The table shows difference-in-differences estimates for the effect of a store opening on expenditures at incumbent stores, estimating Equation (6). This captures expenditures shifted from incumbent stores to the new store. Here, we focus on households who were only treated once, meaning they only received one opening within 30 minutes from 2019Q1 to 2021Q2. The coefficients are Poisson estimates where we report the exponentiated Poisson coefficients $exp(\beta) - 1$, following Chen and Roth (2024). We focus on households with average monthly expenditures between 20 and 10,000 Swiss francs with full information on income and household size who did not move during our sample period. Households are treated if they live within 30 minutes of a store opening.

Table A10: Competitor Expenditure Shift, Only Once-Treated Households (Poisson Model)

Proportional Effect	Expenditures			No. of Visits		
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	0.075**	0.144***	0.259***	0.080***	0.144***	0.193***
	(0.034)	(0.045)	(0.080)	(0.025)	(0.038)	(0.061)
Treat × ln(Euclid. Dist. in km)	-0.042***			-0.031***		
	(0.012)			(0.009)		
Treat × ln(Road Dist. in km)		-0.057***			-0.045***	
		(0.013)			(0.011)	
Treat × ln(Car Dist. in min)			-0.078***			-0.052***
			(0.018)			(0.015)
Observations	198,354	198,354	198,354	198,354	198,354	198,354
Squared Correlation	0.741	0.741	0.741	0.757	0.757	0.757

Notes: The table shows difference-in-differences estimates for the effect of a store opening on expenditures at all same-chain stores, estimating Equation (6). This captures expenditures shifted from competitors to the new store. Here, we focus on households who were only treated once, meaning they only received one opening within 30 minutes from 2019Q1 to 2021Q2. The coefficients are Poisson estimates where we report the exponentiated Poisson coefficients $exp(\beta) - 1$, following Chen and Roth (2024). We focus on households with average monthly expenditures between 20 and 10,000 Swiss francs with full information on income and household size who did not move during our sample period. Households are treated if they live within 30 minutes of a store opening.

Figure A7: Spatial Distribution: City of Zurich



Notes: The figure plots for each populated 100 × 100 meter grid cell in the city of Zurich the percentiles of (a) our utility-based valuation of market access, (b) the distance to the closest supermarket, (c) average household labor market income, and (d) population. The market access is based on Equation (5). We consider all stores of major grocery retailers in Switzerland, recover the unobserved store valuations with a Lasso approach, and use our causal estimates of travel costs. Travel distances between households and stores are measured as car travel times in minutes. Blue areas are water bodies, and green areas indicate forest areas.

Table A11: Correlations for Figure A7

	Access	Inc.	Pop.
Income	-0.22		
Pop.	0.22	-0.15	
Dist. Store	-0.11	0.06	-0.26

Notes: This table shows the correlation matrix for four spatial variables, shown in Figure A7 for the City of Zurich.

Table A12: Heterogeneous Distance Costs (Rural Areas)

	Incumbent Shift		Competitor Shift		Total Shift				
Group	Intercept	Slope	Intercept	Slope	Intercept	Slope	Mean Dist	Cons. Area	n
Household Income									
<4,530	-0.827***	0.283***	0.356***	-0.108***	0.991***	-0.430***	16.4	10.0	224,761
	(0.050)	(0.018)	(0.029)	(0.010)	(0.047)	(0.025)			
4,530-6,717	-0.599***	0.198***	0.369***	-0.114***	0.897***	-0.327***	16.4	15.5	66,028
	(0.119)	(0.042)	(0.059)	(0.021)	(0.108)	(0.055)			
6,718-9,288	-0.812***	0.272***	0.335***	-0.099***	0.954***	-0.406***	16.6	10.5	105,178
	(0.083)	(0.029)	(0.040)	(0.014)	(0.067)	(0.040)			
9,289-12,856	-0.734***	0.252***	0.391***	-0.122***	0.999***	-0.401***	16.3	12.1	141,209
	(0.050)	(0.018)	(0.032)	(0.011)	(0.053)	(0.025)			
12,856+	-0.530***	0.182***	0.278***	-0.088***	0.732***	-0.283***	15.8	13.3	121,094
	(0.049)	(0.018)	(0.033)	(0.012)	(0.052)	(0.024)			
Age									
<34	-0.790***	0.262***	0.363**	-0.114*	0.985***	-0.408***	15.7	11.2	19,747
	(0.162)	(0.057)	(0.128)	(0.046)	(0.198)	(0.085)			
35-44	-0.559***	0.184***	0.359***	-0.115***	0.859***	-0.311***	16.2	15.8	90,255
	(0.082)	(0.029)	(0.041)	(0.014)	(0.075)	(0.038)			
45-55	-0.698***	0.240***	0.344***	-0.105***	0.913***	-0.371***	16.1	11.7	150,839
	(0.047)	(0.017)	(0.032)	(0.011)	(0.050)	(0.023)			
55-64	-0.706***	0.239***	0.321***	-0.097***	0.885***	-0.363***	16.4	11.5	161,584
	(0.050)	(0.018)	(0.031)	(0.011)	(0.050)	(0.024)			
65-74	-0.768***	0.262***	0.325***	-0.098***	0.920***	-0.393***	16.4	10.4	124,419
	(0.058)	(0.021)	(0.038)	(0.013)	(0.059)	(0.029)			
75+	-0.781***	0.273***	0.398***	-0.121***	1.030***	-0.428***	16.5	11.1	111,426
	(0.071)	(0.025)	(0.043)	(0.015)	(0.071)	(0.036)			
Household Size									
1	-0.661***	0.226***	0.334***	-0.098***	0.880***	-0.347***	16.3	12.6	113,633
	(0.114)	(0.041)	(0.043)	(0.015)	(0.084)	(0.053)			
2	-0.719***	0.245***	0.335***	-0.102***	0.911***	-0.375***	16.5	11.4	254,463
	(0.042)	(0.015)	(0.027)	(0.010)	(0.043)	(0.021)			
3-4	-0.668***	0.226***	0.309***	-0.097***	0.850***	-0.345***	16.1	11.7	231,827
	(0.039)	(0.014)	(0.024)	(0.009)	(0.039)	(0.019)			
5+	-0.815***	0.288***	0.498***	-0.150***	1.203***	-0.473***	16.5	12.7	58,347
	(0.082)	(0.029)	(0.048)	(0.017)	(0.087)	(0.041)			

Notes: The table shows for different characteristics in rural areas heterogeneous difference-in-differences estimates for the effect of a store opening on expenditures at incumbent stores and all stores, estimating in both cases Equation (6). This captures the *incumbent shift* and *competitor shift* respectively. The coefficients are Poisson estimates where we report the exponentiated Poisson coefficients $exp(\beta) - 1$, following Chen and Roth (2024). We focus on households with average monthly expenditures between 20 and 10,000 Swiss francs with full information on income and household size who did not move during our sample period. Households are treated if they live within 30 minutes of a store opening.

Table A13: Heterogeneous Distance Costs (Urban Areas)

	Incumbent Shift		Competitor Shift		Total Shift				
Group	Intercept	Slope	Intercept	Slope	Intercept	Slope	Mean Dist	Cons. Area	n
Household Income									
<4,530	-0.326***	0.141***	0.028*	-0.009	0.307***	-0.161***	8.8	6.7	328,510
	(0.021)	(0.010)	(0.014)	(0.006)	(0.021)	(0.013)			
4,530-6,717	-0.205***	0.092***	0.088**	-0.031*	0.278***	-0.128***	8.6	8.8	71,365
	(0.039)	(0.018)	(0.028)	(0.013)	(0.044)	(0.023)			
6,718-9,288	-0.262***	0.119***	0.069*	-0.019	0.301***	-0.145***	8.8	8.0	85,111
	(0.042)	(0.019)	(0.028)	(0.013)	(0.045)	(0.025)			
9,289-12,856	-0.280***	0.124***	0.096***	-0.033**	0.346***	-0.165***	8.7	8.1	97,735
	(0.036)	(0.016)	(0.024)	(0.011)	(0.039)	(0.021)			
12,856+	-0.246***	0.109***	0.136***	-0.045***	0.364***	-0.159***	9.7	9.9	146,086
	(0.037)	(0.015)	(0.024)	(0.010)	(0.039)	(0.020)			
Age									
<34	-0.249***	0.093**	0.083·	-0.043*	0.306***	-0.140***	8.7	8.9	26,399
	(0.071)	(0.032)	(0.044)	(0.022)	(0.073)	(0.041)			
35-44	-0.243***	0.115***	0.107***	-0.033**	0.329***	-0.154***	8.8	8.5	86,220
	(0.044)	(0.020)	(0.026)	(0.012)	(0.045)	(0.025)			
45-55	-0.302***	0.132***	0.081***	-0.026**	0.345***	-0.167***	9.1	7.9	142,122
	(0.034)	(0.015)	(0.022)	(0.010)	(0.035)	(0.019)			
55-64	-0.250***	0.112***	0.077***	-0.023**	0.301***	-0.142***	9.0	8.3	150,992
	(0.033)	(0.015)	(0.019)	(0.009)	(0.033)	(0.019)			
65-74	-0.273***	0.123***	0.066**	-0.019*	0.308***	-0.149***	8.9	7.9	133,567
	(0.027)	(0.012)	(0.021)	(0.010)	(0.031)	(0.016)			
75+	-0.356***	0.150***	0.008	-0.003	0.308***	-0.165***	9.0	6.5	189,507
	(0.028)	(0.013)	(0.019)	(0.009)	(0.027)	(0.017)			
Household Size									
1	-0.266***	0.112***	0.054**	-0.022*	0.289***	-0.141***	8.7	7.8	210,790
	(0.025)	(0.011)	(0.019)	(0.009)	(0.028)	(0.015)			
2	-0.325***	0.145***	0.039**	-0.007	0.317***	-0.163***	9.0	7.0	257,345
	(0.022)	(0.010)	(0.015)	(0.007)	(0.022)	(0.013)			
3-4	-0.273***	0.121***	0.098***	-0.033***	0.342***	-0.161***	9.0	8.4	214,856
	(0.027)	(0.012)	(0.018)	(0.008)	(0.029)	(0.015)			
5+	-0.186**	0.084**	0.141***	-0.051**	0.321***	-0.137***	9.1	10.4	45,816
	(0.066)	(0.029)	(0.037)	(0.016)	(0.069)	(0.035)			

Notes: The table shows for different characteristics in urban areas heterogeneous difference-in-differences estimates for the effect of a store opening on expenditures at incumbent stores and all stores, estimating in both cases Equation (6). This captures the *incumbent shift* and *competitor shift* respectively. The coefficients are Poisson estimates where we report the exponentiated Poisson coefficients $exp(\beta) - 1$, following Chen and Roth (2024). We focus on households with average monthly expenditures between 20 and 10,000 Swiss francs with full information on income and household size who did not move during our sample period. Households are treated if they live within 30 minutes of a store opening.