Cross-Border Shopping: Evidence from Household Transaction Records*

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Abstract

Cross-border shopping allows purchasing comparable goods at lower prices abroad. At the same time, it can reduce domestic consumption, sales, or tax collection. During the COVID-19 pandemic, many countries restricted cross-border movements to mitigate the virus's spread, thereby also prohibiting cross-border shopping. I exploit the random timing of the Swiss border closure using administrative data and unique consumer-linked transaction data from the largest Swiss retailer on one million customers to study heterogeneities in the willingness to travel for lower prices. I find that grocery expenditures temporarily increase by 10-15% in border regions, and this effect declines linearly with distance for up to 40 minutes before flattening out. I show that the effect increases in household size, and decreases in age, income, education, and the cross-border locations' price index. I find evidence that citizens working close to the border combine their commuting trips with cross-border shopping, indicating strategic trip chaining.

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

JEL: R1, R2, L14

First Version: February, 2023

This version: October 24, 2023

Link to the newest version

*I thank Martina Pons and Maximilian von Ehrlich for all their support. I thank Dino Collalti, Costanza Naguib, and Tobias Seidel for their helpful comments. Support for this project from the Swiss National Science Foundation with grant ref. 187443 (NRP 77) is gratefully acknowledged. I thank the Migros Genossenschafts Bund and the Federal Statistical Office for sharing their data.

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1. Introduction

Cross-border shopping has been a growing phenomenon in many countries, particularly along national borders, where consumers can purchase goods and services at lower prices from neighboring countries. This activity increases product variety for households living close to the border and puts pressure on domestic prices but may have adverse effects on local employment, consumption, sales, or tax collection (see Leal, López-Laborda and Rodrigo, 2010, Knight and Schiff, 2012, or Baggs, Fung and Lapham, 2018). Yet, at many of these borders, cross-border shopping came to a sudden halt in the year 2020 as numerous countries imposed rigorous travel restrictions at national borders to contain the spread of COVID-19.

This paper analyzes the Swiss closure of all national borders during the COVID-19 pandemic in order to examine patterns and heterogeneities in consumer mobility. On March 16, 2020, the Swiss government mandated the immediate closure of all national borders to neighboring countries to mitigate the spread of COVID-19. This policy was then upheld until June 2020.[1] Additionally, the government announced the closing of all restaurants, bars, entertainment, and leisure facilities, with the exception of essential stores, including supermarkets and pharmacies.

Among countries introducing comparable policies, Switzerland is a unique case to study cross-border shopping because of two reasons. First, Switzerland is completely surrounded by countries with 28-39% lower grocery prices, allowing Swiss citizens to purchase comparable products at lower prices in Germany, Italy, Austria, or France.[2] These Eurozone countries share a common currency, facilitating comparisons for Swiss households by eliminating exchange rate differences.[3] Hence, the relative attractiveness of these countries for Swiss consumers depends solely on their variety and prices of grocery products. Second, the exact timing of the border closure was random for Swiss residents, and Burstein, Lein and Vogel (2022) show that the policy was stringent and effective in achieving its purpose, as cross-border shopping shares almost fell to zero during the intervention.

[1] The borders to Liechtenstein remained open while crossing between Lichtenstein and Germany or Austria was prohibited. Nonetheless, crossings remained possible for work-related reasons for the 370,000 workers commuting from neighboring countries into Switzerland and the 29,000 Swiss residents working abroad.

[2] Importation into Switzerland is exempt from VAT for a total value below 300 Swiss francs, as long as certain limits for meat, tobacco, etc., are met.

[3] The CHF/EUR exchange rate was stable throughout this period. Therefore, the border closure was the only shock at the time.

I identify the causal effect of the border closure on grocery expenditures within Switzerland by comparing households living close to a national border to households residing further inland within a difference-in-differences framework. The estimated increase in domestic grocery expenditures measures the magnitude of cross-border shopping during open borders as customers were forced by the shock to shift these expenditures to domestic retailers. I use this setting to analyze extensive heterogeneities across households' socioeconomic characteristics, cultural backgrounds, and commuting behavior. Ultimately, I calculate a distance decay function (the decline in cross-border shopping with distance). To conduct this analysis, I merge the universe of customer-linked transactions from the largest Swiss retailer for the year 2020 with administrative records on labor market income, commuting behavior, and household characteristics for the entire Swiss population. The final data set contains 62 million weekly shopping baskets for one million customers that I can uniquely link to residents in the administrative data.

My findings show that mobility patterns in consumption are persistent over time and vary strongly between different groups of customers. First, I find that the policy increases expenditures by 10-15% in border regions. This effect vanishes instantly and entirely once the border reopens. Therefore, behaviors in cross-border shopping are deeply rooted and resist temporary shocks. Second, I document various heterogeneities and observe that households combine their trips to work with cross-border shopping if they commute towards the border. Regarding socioeconomic characteristics, I find larger effects among poorer, younger, and larger households in response to the policy, while differences in cultural backgrounds are minor. Further, I assess the role of prices and find that cross-border shopping is more pronounced in areas with cheaper neighboring countries, suggesting an elasticity of 0.78. Third, the effect decays linearly with distance for up to 40 minutes before flattening out. This indicates an extensive margin effect of travel fixed costs, and most individuals having to drive more than 40 minutes avoid the trip altogether.

This paper contributes to the rich literature on cross-border shopping, where previous papers exploited either changes in exchange rates, taxes, or relative prices. For example, Chandra, Head and Tappata (2014) find that an appreciation of the US dollar increases the propensity to cross into Canada (and vice versa) and Campbell and Lapham (2004) analyze the retailers' response. Further, Asplund, Friberg and Wilander (2007) show that Danish tax cuts reduce alcohol sales in Sweden, and Baker, Johnson and Kueng (2021) find that customers in the United States use cross-border shopping to escape local sales taxes. Focusing on relative price changes, Friberg, Steen and Ulsaker (2022b) estimate a hump-shaped demand elasticity for the effect of foreign price changes on store sales in Norway. The findings of Friberg, Steen and Ulsaker (2022b) imply that the domestic reaction to changes in relative prices does not capture cross-border shopping accurately, as a large response to these shocks does not one-to-one imply a high level of cross-border shopping. Therefore, I contribute to this previous work by analyzing a natural experiment that restricts access to cross-border shopping completely rather than changing its financial costs.

At least two other papers tackle the topic of cross-border shopping through COVID-19-related border closures, answering, however, different questions. First, Friberg, Halseth, Steen and Ulsaker (2022a) use Norway's COVID-19-related border closure to show that cross-border shopping reduces national tax revenues by 3.6% nationally and 27% in border regions. In contrast to their work on tax revenues, I focus on the customers' expenditures and the heterogeneities therein to analyze consumers' mobility. Second, Burstein, Lein and Vogel (2022) also use the Swiss border closure in response to COVID-19. They derive empirical facts from the Nielsen Homescan data to motivate a model on spatial shopping, calculating the welfare benefits of cross-border shopping. They conclude that cross-border shopping lowers the cost of living by over 14% in some regions. Relative to their work, I study rich socioeconomic heterogeneities as well as trip chaining between shopping and work locations. This is made possible by the unique matching of large transaction data with administrative data. While Einav, Leibtag and Nevo (2008) demonstrate that the self-recorded Nielsen data contains reporting errors, this is likely not the case for my official transaction data. This may especially be essential to measure heterogeneities accurately as Einav, Leibtag and Nevo (2008) find that these reporting mistakes are correlated with demographic variables. Further, the novel data used in this paper covers 200 times more households, and measures addresses 3,000 times more granular than the Nielsen data.[4]

In a broader context, this paper also links to the research on spatial shopping in general and trip chaining, showing that customers deliberately plan and adapt their grocery expenditures and shopping trips. For example, Agarwal, Jensen and Monte (2022) show that customers use the products' storability strategically for their travel length decisions, while Agarwal, Marwell and McGranahan

[4]While the Nielsen data in Burstein, Lein and Vogel (2022) reports addresses for the 83 two-digit zip codes, my data does the same for 300,000 granular cells with a 100-meter precision.

(2017) show that sales tax holidays lead to substantial additional increases in spending. Connected to this strand of the literature, my analysis aims to shed light on spatial consumer mobility rather than analyzing a COVID-19 shock per se. Regarding the phenomenon of trip-chaining, previous work argues that customers incorporate their shopping trips consciously into their daily routine by analyzing trip-chaining between supermarkets and coffee shops (Relihan, 2021) or workplaces (Miyauchi, Redding and Nakajima, 2022). Here, my paper adds suggestive evidence on trip chaining, indicating that households strategically include their (cross-border) shopping trips into their daily work commutes.

The remainder of this paper is structured as follows. Section 2 introduces the grocery and administrative data. Section 3 discusses the empirical strategy, while Section 4 presents my findings. Section 5 concludes.

2. Data

I combine unique transaction data from the largest Swiss retailer with administrative data from the Federal Statistical Office on a 100 × 100 meter spatial resolution.

The grocery data provides information on every customer-linked purchase at the retailer *Migros* in 2020, collected through their loyalty program in which customers identify themselves at the check-out with their loyalty card in exchange for exclusive offers and discounts. This loyalty program captures 79% of the retailer's total sales, and 2.8 million customers participate in it (i.e., 42% of all Swiss residents above legal age). Furthermore, Migros charges the same prices throughout the country, independently of local purchasing power, wages, and costs. Hence, prices are not endogenously lower close to the border. Stores of similar size also generally offer similar goods, except for local products. The data set contains the universe of 600 million customer-linked purchases for the year 2020 and provides information on individual customer characteristics, including the location of their residence coded on a grid of 100×100–meter cells, their age, and household type.

The outcome of interest throughout this analysis is a household's total grocery expenditures in a given week. Hence, I aggregate the individual shopping trips into weekly baskets and exclude customers who moved in 2020 as well as those spending less than 100 Swiss francs a month before the shock (equalling 111 USD on October 18, 2023), as their baskets might not capture the overall consumption accurately. This procedure generates 129 million weekly baskets for 2.4 million customers.

I enrich the purchase data with individual-level administrative records for the entire Swiss population (8.7 million inhabitants in 2020). The *Population and Households Statistics* includes individual and household characteristics, including information on gender, age, and residence location on the same 100×100-meter grid. The *Old Age and Survivors Insurance* provides annual gross labor market income, which I adjust by the square root of household size.[5] Finally, the administrative *Structural Surveys* 2018-2021 add education and commuting behavior for individuals participating in the survey.[6] Education is categorized as either primary, secondary, or tertiary education, and the commuting behavior is characterized by travel times in minutes, means of transport, and the municipality of the work location.[7]

Both data sets measure addresses on the same spatial grid spanning 350,000 cells over the entire country with a median population of 11 residents. Therefore, I merge the two data sets by identifying unique pairs of customers and residents using the common variables grid cell and age. This approach matches one million customers in the grocery data uniquely to a citizen and her household in the administrative data. Hence, I can match 41% of the 2.4 million regular customers, corresponding to 25% of all Swiss households. The final data set used throughout this paper includes 62 million of the weekly consumption baskets.[8]

Table 1 shows summary statistics for the households. The average matched household has an income of 59,000 Swiss francs (adjusted for the square root of household size), and the mean cardholder is 56.6 years old, while 43.4% have a tertiary education, and 80% live in multi-person households. Comparing these statistics to the corresponding population values shows that the

[5] The calculation is income adjusted $= \frac{\text{income total}}{\sqrt{\#\text{household members}}}$, where I consider all household members, including small children. The adjustment follows one of the equivalence scales suggested by the OECD. I compute *income total* as the household's annual income by summing the income of all household members.

[6] This representative survey selects 200,000 people above age 15 every year, and participation is mandatory.

[7] Primary (or compulsory) education ends at the latest after around eleven mandatory years of school (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.

[8] See Kluser and Pons (2023) and Kluser, Seidel and von Ehrlich (2022) for additional information on the two data sources and the matching procedure.

Table 1: Household summary statistics

	Final Sample		Population	
Panel a)	Mean	SD	Mean	SD
Age	56.56	16.08	50.43	18.17
Income Total	99.20	128.15	106.01	132.48
Income Adjusted	59.73	78.57	64.90	78.96
Time to work	28.04	23.09	29.12	23.70
Time to border	56.63	24.71	54.54	25.03
Time to border from work	56.67	32.06	54.48	23.71
Panel b)	Pct.	N	Pct.	N
Education		662,644		4,413,173
Primary	10.4	68,867	11.3	498,292
Secondary	46.2	306,111	44.3	1,954,810
Tertiary	43.4	287,666	44.4	1,960,071
Household size		1,005,014		7,043,734
1	20.5	205,902	20.9	1,471,897
2	36.3	364,381	36.1	2,544,442
3-4	34.8	349,279	33.8	2,381,660
5+	8.5	85,452	9.2	645,735
Language		1,003,914		7,016,029
French	21.1	211,837	24.2	1,697,654
German	75.0	753,421	71.4	5,010,326
Italian	3.9	38,656	4.4	308,049
Pop. Density		1,003,914		7,036,484
Rural	21.0	210,762	18.0	1,264,699
Suburban	56.5	566,897	51.9	3,649,595
Urban	22.5	226,255	30.2	2,122,190
Nationality		1,004,927		7,042,341
Swiss	85.1	854,961	74.0	5,210,215
European	12.9	129,784	22.0	1,551,076
African	0.5	4,988	1.1	77,266
Asian	1.0	9,980	1.9	131,883
N.American	0.1	1,415	0.3	21,530
S.American	0.4	3,799	0.7	50,371
Commuting Mode		133,712		923,718
Car	60.4	80,739	55.4	511,779
Public Transport	23.6	31,546	27.8	256,869
Other	16.0	21,427	16.8	155,070
Observations		1,005,014		7,043,734

Notes: The table shows summary statistics for the customers uniquely matched to the administrative data and compares them to the entire Swiss population. *Income Total* equals the total annual labor market income of a household in Swiss Francs, *Income Adjusted* adjusts for the square root of household size. All *Time* variables measure the car travel time in minutes.

Table 2: Transactions summary statistics

Group	Mean	SD	p50	p1	p99
Overall					
Expenditures in Matched Sample	69.8	57.0	54.4	2.4	257.3
Expenditures in Complete Sample	63.4	83.4	34.8	0.0	352.4
Shop Visits in Matched Sample	4.7	3.3	4.1	0.2	15.1
Shop Visits in Complete Sample	4.4	4.8	4.0	0.0	20.0
Expenditures by household size					
1	44.3	34.6	36.8	1.7	163.6
2	62.8	47.7	52.1	2.3	213.8
3–4	85.6	63.9	71.3	3.3	276.8
5+	95.8	74.0	77.8	3.6	318.6
Expenditures by income quintile					
25–72	59.3	48.1	46.7	2.3	221.0
73–104	68.2	53.7	54.2	2.6	242.2
105–134	78.8	59.7	64.8	2.9	260.1
134–178	84.7	63.6	70.4	3.1	275.8
178+	89.9	70.5	73.3	2.8	306.3
Expenditures by age group					
20–34	58.9	47.3	46.2	2.1	211.7
35–44	80.8	62.3	65.3	3.0	269.4
45–54	83.9	66.4	66.7	2.9	290.2
55–64	72.0	57.6	57.3	2.7	260.5
65–74	61.0	47.2	49.6	2.4	216.3
74+	51.2	40.8	41.7	1.6	188.0
Expenditures by education					
1	52.5	43.6	41.2	1.9	203.8
2	69.3	54.5	55.5	2.6	246.8
3	81.6	63.9	65.9	2.8	281.4
Transactions in Matched Sampled			62,143,348		
Transactions in Complete Sampled			129,383,812		

Notes: The table shows summary statistics for the expenditures and trip frequency of customers that I can match to residents in the administrative data and compares these statistics to the complete grocery data. All statistics on subsamples are for the matched data. *Income* equals total household income adjusted by the square root of household size.

matched sample represents the population well. Further, Table 2 shows summary statistics for the transactions. The average household makes 4.7 transactions and spends 70 Swiss francs (77 USD on October 18, 2023) per week. This corresponds to roughly 48% of the average household's grocery expenditures based on administrative surveys. Looking at different subgroups, expenditures increase with household size and income, while they are hump-shaped for age. A comparison to the entire transaction data shows that the matched customers' shopping behavior matches expenditures in the full sample well.

Finally, I calculate car travel times to foreign shopping locations and workplaces as follows. First, I scrape the location and Google review counts of all foreign supermarkets within 20 km of the Swiss border from *Google Maps*. This results in 117 cross-border locations with 2 million inhabitants and a grocery supply featuring 1,787 stores, of which 691 have at least 100 Google ratings. Table A.1 lists the largest identified cross-border locations, showing the number of stores with a certain minimum amount of Google ratings. A municipality with a large number of stores typically also has many larger stores with more than 100 or 500 Google reviews, and all correlations between the population, the number of stores, and the number of stores with more than 100 and 500 Google ratings are very high, lying between 0.83 and 0.92. Second, as cross-border shoppers likely focus on larger stores, I define a cross-border location as a foreign municipality with at least one store that has more than 100 Google Ratings.[9] Third, I calculate the car travel time from every raster cell to all these locations from a national online mapping service (*search.ch*) and select the shortest trip for each cell. One-fifth of all households reaches the closest cross-border location within a 30-minute car drive, while the maximum distance is three hours. Following the same approach, I calculate distances to workplaces. Table 1 shows the average car travel time to the national border (56 minutes) and the work location (28 minutes). 60% commute to work by car, while 23.6% use public transportation.

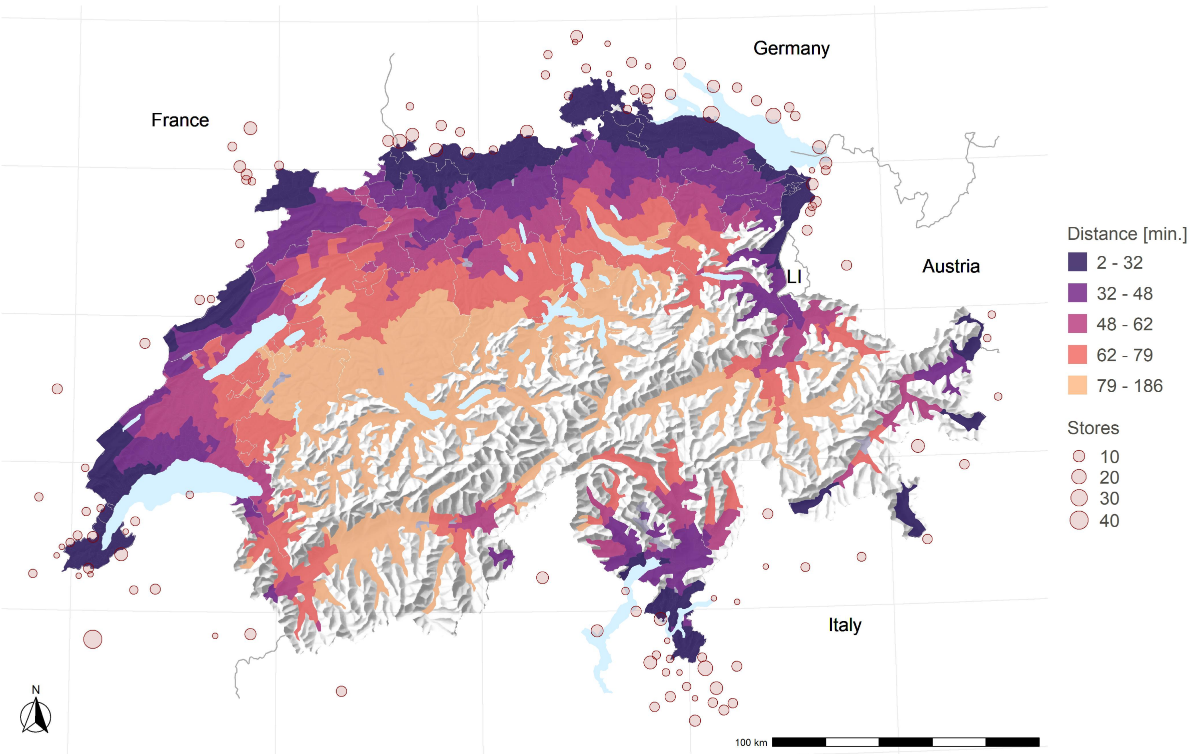
3. Empirical Strategy

I study the impact of the border closure on household expenditures by comparing households living within a 30-minute car drive from a cross-border location (the first quintile) to those living far enough inland such that they typically do not shop abroad. Hence, I choose a comparison distance of 80 minutes (the fifth quintile) and drop all individuals living within the doughnut area in between to ensure a clean control group.[10] Figure 1 shows these travel distance bins to the closest foreign location across Switzerland, resulting in roughly 240,000 treated and control

[9] My results are robust if I define cross-border locations alternatively as (i) locations with at least three stores with 100 Google Maps reviews or as (ii) locations with at least three stores with 500 Google Maps reviews.

[10] The results are robust if I use alternative comparison distances of 90 or 100 minutes. If a fraction of control units would still react to the border closure, my results would provide a lower bound of the effect.

Figure 1: Distance to the closest cross-border shopping location



Notes: The figure shows the quintiles of car driving times to the closest cross-border shopping location on the municipality level. The dots show all 117 cross-border locations within 20 kilometers of the Swiss border, and the dots' size indicates the number of supermarkets at this location.

households. The figure further illustrates the importance of explicitly using travel times to cross-border locations rather than the Euclidean distance to the border due to the dispersion of these shopping locations and the mountainous landscape of the area.

I use a difference-in-differences model to estimate the average treatment effect. Since all political regulations, grocery supply adaptations, and consumers' behavioral changes affect both the treatment and control group, I attribute any deviation after the intervention to cross-border shopping. As some households record zero expenditures in a given week, I follow the suggestions in Chen and Roth (2023) and Wooldridge (2023) to handle such data by estimating a QMLE-Poisson model.[11] Reporting the transformed coefficients $\hat{\beta}_{ATT\%} = exp(\hat{\beta} - 1)$ gives the average proportional treatment effect, allowing me to interpret the coefficients as percentage changes. I always report in the

[11] Chen and Roth (2023) show that using a linear model with $log(Y + 1)$ as a dependent variable does not allow interpreting the coefficients as percentage changes.

results section the transformed coefficients $\hat{\beta}_{ATT\%}$ and calculate the corresponding standard errors using the delta method. Therefore, I estimate the following model:

$$Y_{it} = \exp\left(\alpha_i + \gamma_t + \sum_{k=1}^{52} \beta_k (D_i \times T_k) + \tau z_{it}\right) \epsilon_{it}, \tag{1}$$

where Y_{it} are the grocery expenditures of household i in week $t \in 1, \ldots, 52$. α_i and γ_t are the household- and week-specific fixed effects, controlling for unobserved heterogeneity. D_i is an indicator variable that equals one if household i is in the treatment group, T_k indicates the weeks of the year 2020, and z_{it} are the time-varying cantonal reported cases of COVID-19. Controlling for the COVID-19 cases accounts for the differential exposure to the pandemic over time, as the first wave of COVID-19 hit Switzerland in 2020 from the South, with the largest initial number of cases in the Italian-speaking region (Ticino). Therefore, these households were sooner and stronger affected by the outbreak than people in the north, and z_{it} controls for these varying exposures, changing constantly over time. Finally, β_k are the associated pre- and post-treatment coefficients, estimating one coefficient for every week T_k of the year. Treatment starts in week twelve, and I normalize coefficients to the average in the pre-treatment period.

To analyze heterogeneities in the treatment effect, I use a static version of model (1) with additional dummies for the $k \in \mathcal{K}$ categories of a time-constant covariate x_i. The dummies x_{ik} equal one if $x_i = k$ and the model equation is

$$Y_{it} = \exp\left(\alpha_i + \gamma_{tk} + \sum_{k \in \mathcal{K}} \beta_k (D_i \times Post_t \times x_{ik}) + \tau z_{it}\right) \epsilon_{it}, \tag{2}$$

where β_k estimates the average treatment effect for group k. Note that in this specification, the time dimension of the treatment effect in model (1) collapses to a single post-treatment coefficient. I allow the time fixed effect to vary between the different groups k by including week-group fixed effects γ_{tk} as the pandemic might affect the individual groups differently.

Finally, I will use a third specification in which I add to model (2) a second set of dummies δ_{il} for travel time bins $l \in \mathcal{L}$, estimating in addition the decay of the treatment effect with distance for different household characteristics k:

$$Y_{it} = \exp\left(\alpha_i + \gamma_{tk} + \sum_{k\in\mathcal{K},l\in\mathcal{L}} \beta_{kl}(D_i \times Post_t \times x_{ik} \times \delta_{il}) + \tau z_{it}\right)\epsilon_{it}, \tag{3}$$

where β_{kl} estimates the average treatment effect for group k in distance bin l.

4. Results and Discussion

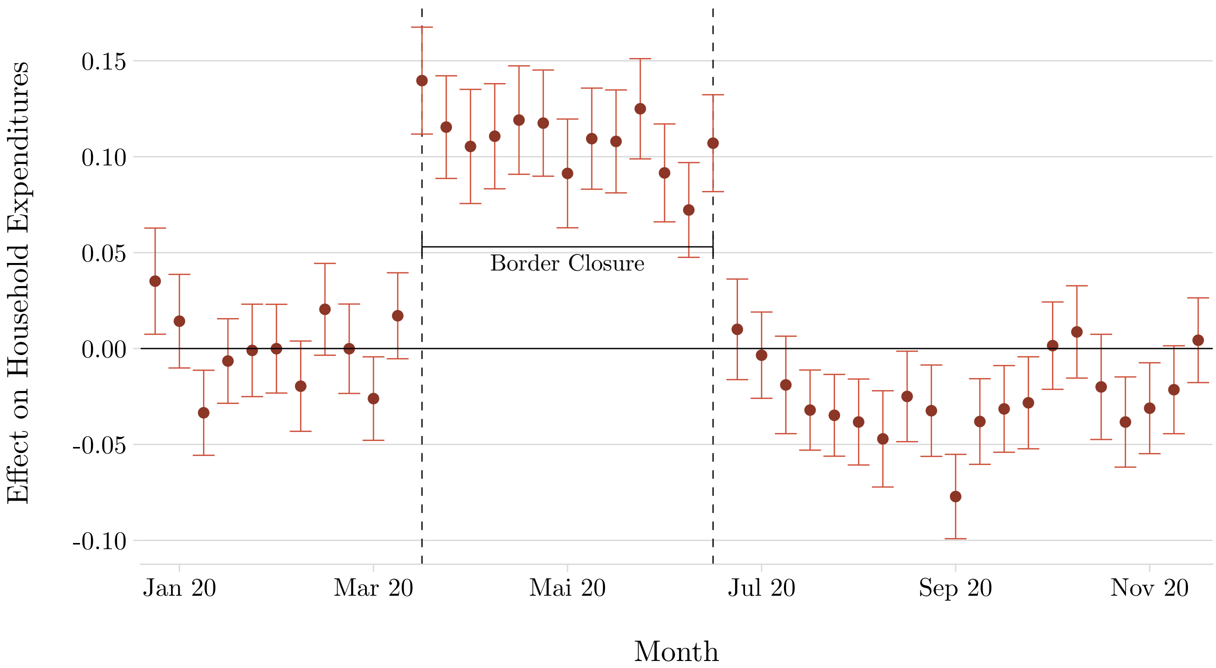
I report my empirical findings in three parts. I start by discussing (i) the treatment effects of the border-closing policy on grocery expenditures over time before analyzing (ii) diverse heterogeneities of the static average treatment effect, including socioeconomic household characteristics, culture, and commuting behavior, as well as foreign grocery prices. This provides rich insights into the varying patterns of consumer mobility in space in response to price differences. Ultimately, I document (iii) the effect's decay with distance, assessing how far customers are willing to travel for lower prices in addition to the estimated magnitude of the policy response. I cluster standard errors in the QMLE Poisson regressions on the zip-code level and report in all tables and figures the transformed $\beta_{ATT\%}$ with corresponding standard errors based on the delta method.[12]

4.1. Dynamic treatment effects

Figure 2 shows the results for the dynamic difference-in-differences outlined in model (1). The borders close in week 12 and reopen in week 25, and both events are indicated by vertical dashed lines. I find that the border closure temporarily increases domestic grocery expenditures by 10–15% at the border in comparison to households residing further inland. Figure 2 shows further that this shift is immediate and remains constant as long as the border is impassable. After the reopening, expenditures immediately drop to the previous level. Hence, although households in border regions temporarily increased their spending at domestic supermarkets, they did not adjust their cross-border shopping behavior through the COVID-19 pandemic and completely switched back to their old behavior as soon as possible. There may even be a temporary catch-up effect, as

[12] Alternatively, I calculate standard errors from 1,000 clustered bootstrap replications for the main results. The bootstrapped standard errors are lower, and I report the more conservative alternative.

Figure 2: Dynamic treatment effects



Notes: The figure shows the border closure's effect on household expenditures within a 30-minute car ride from a cross-border location compared to households living further away than 80 minutes. I indicate the period of border closure by vertical dashed lines. The regression estimates model (1) and uses 18 million observations. Coefficients are normalized to the pre-treatment periods' average, and standard errors are clustered at the zip code level.

most coefficients in the initial weeks after the reopening are below zero. This result suggests that cross-border shopping follows deeply rooted routines that withstand temporary shocks.

One concern might be that consumers adapted their shopping behavior before the actual introduction of pandemic restrictions, especially in strongly affected areas. Yet, the insignificant pre-treatment coefficients in Figure 2 do not indicate a potential violation of the parallel trend assumption between treated and control units, suggesting that households living in the border region and further inland did not react differently to the pandemic's onset. This conclusion remains unchanged (and pre-treatment coefficients insignificant) if I do not control for the local number of COVID-19 cases.

4.2. Variation across socioeconomic characteristics

Consumers may benefit differently from cross-border shopping based on their socioeconomic background. Hence, I analyze heterogeneities in the average treatment effect for different household

Table 3: Treatment effects by socioeconomic subgroups

Dep. Variable: log(Household Expenditures)							
a) Household size		b) Age		c) Income		d) Education	
Group	Coeff	Group	Coeff	Group	Coeff	Group	Coeff
1	0.061***	20–34	0.142***	Q1	0.147***	Primary	0.134***
	(0.007)		(0.011)		(0.009)		(0.010)
2	0.098***	35–44	0.151***	Q2	0.145***	Secondary	0.102***
	(0.008)		(0.009)		(0.008)		(0.007)
3-4	0.138***	45–54	0.133***	Q3	0.127***	Tertiary	0.103***
	(0.008)		(0.009)		(0.008)		(0.008)
>5	0.137***	55–64	0.118***	Q4	0.118***		
	(0.009)		(0.008)		(0.008)		
		65–74	0.125***	Q5	0.098***		
			(0.009)		(0.010)		
		75+	0.095***				
			(0.010)				
p-value	0.000	p-value	0.000	p-value	0.000	p-value	0.003
n	9,706,718	n	9,703,958	n	7,755,526	n	6,283,102

Notes: The table shows the border closure's average treatment effect on household expenditures within a 30-minute car ride from a cross-border location compared to households living further away than 80 minutes, separately for different household characteristics. These characteristics include the *household size*, *age* of the registered cardholder, household *income* adjusted by the square root of household size, and the highest *education* in the household. The regression estimates model (2), standard errors are clustered at the zip code level, and the reported p-values test the equality of all coefficients.

characteristics. This corresponds to the static model in Equation (2), interacting the treatment with the household characteristic x_i I am interested in. Note that for each heterogeneity, the individual fixed effects control for all other time-constant differences between households. Table 3 reports estimation results separately for each group of the socioeconomic variables household size, age, income, and education in the panels a) to d). The reported p-values test for the equality of all coefficients.

First, I find that the effect increases in household size. While a one-person household increases her expenditures by 6% in response to the border closure, I see an increase by 9.8% for two-person households, and by 14% for households with at least three members. Hence, larger households seem to engage in more cross-border shopping. Traveling abroad to shop at lower prices is particularly tempting if you buy large quantities, as it increases the trip's savings while the trip's traveling costs are fixed. Hence, relative costs decrease. Such economies of scale likely explain this finding, as the summary statistics in Table 2 show that larger households spend more money on groceries overall and consume larger quantities, making cross-border shopping more attractive for them.

Second, I find a life cycle in the response to the border closure. The estimated effect lies around 15% for young households between age 20 and 44 and decreases slowly as households become older. Yet, even retired households after age 65 show a relatively high response of roughly 12%, while their total expenditures are markedly lower (see Table 2). One explanation may be that their sharp decline in income after retirement induces them to still shop abroad at lower prices. Note that this life cycle can either be due to age or cohort effects, as the short sample period does not allow for disentangling them.

Third, I look at income, whose expected role is ambiguous. On the one hand, one should expect households with a lower income to engage in more cross-border shopping as they have higher import elasticities (see Auer, Burstein, Lein and Vogel, 2023) and spend a higher share of their income on groceries. In my data, high-income households (with a monthly income above 12,000 Swiss francs) spend 1.6% of their income on groceries compared to 3.5% for lower-income households (with a monthly income between 4,000 and 8,000 Swiss francs). On the other hand, lower car ownership might constrain the mobility of less affluent households. While 90% of high-income households (with a monthly income above 12,000 Swiss francs) own a car, this holds for only 77% of lower-income households (with a monthly income between 4,000 and 8,000 Swiss francs), according to the Federal Statistical Office. Furthermore, lower-income households are also less mobile and travel, on average, shorter distances on a given day (30.2 kilometers vs. 40.8 kilometers).
My results in panel c) show that the first argument dominates the narrative: the treatment effect decreases from 14.7% for the lowest-earning quintile to 9.8% for the highest-earning households. Hence, although they are less mobile, lower-income households still engage in more cross-border shopping activity.

Fourth, higher-educated individuals may have broader knowledge and access to more information to strategically optimize their consumption behavior while being in less need to do so. I observe that households with at least one member holding a tertiary education react less to the border

Table 4: Treatment effects by cultural and spatial subgroups

Dep. Variable: log(Household Expenditures)			
a) Nationality		b) Country	
Group	Coeff	Group	Coeff
African	0.181***	AT	0.077***
	(0.034)		(0.013)
Asian	0.156***	GER	0.121***
	(0.027)		(0.009)
European	0.154***	FR	0.108***
	(0.012)		(0.011)
N.American	0.182**	IT	0.235***
	(0.064)		(0.050)
S.American	0.134***		
	(0.038)		
Swiss	0.100***		
	(0.006)		
p-value	0.845	p-value	0.002
n	9,705,662	n	9,428,294

Notes: The table shows the border closure's average treatment effect on household expenditures within a 30-minute car ride from a cross-border location compared to households living further away than 80 minutes, separately for different household characteristics. These characteristics include the cardholders' *nationality* and the *country* of their closest cross-border shopping location. The regression estimates model (2), standard errors are clustered at the zip code level, and the reported p-values test the equality of all coefficients.

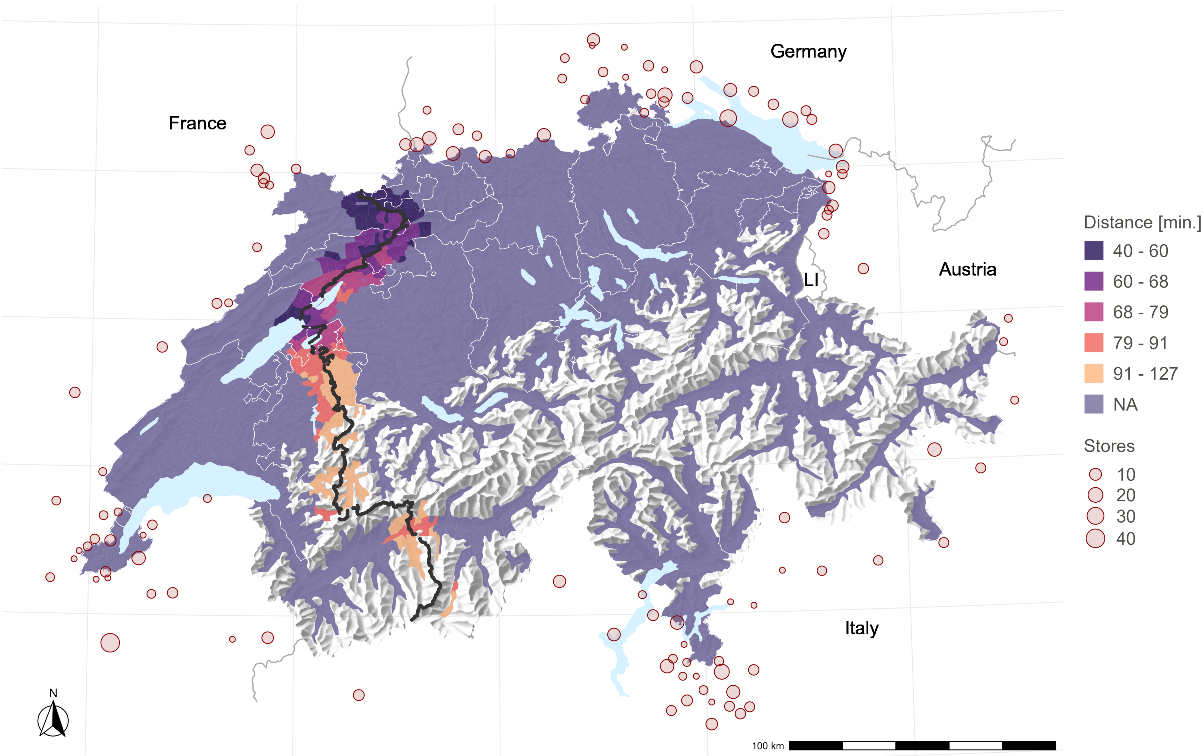
closure than comparable households further inland. While high-educated households increase their expenditures by 10.3%, I estimate a higher effect of 13.4% for low-educated households. This complements the results on income that households with an overall lower socioeconomic status shop more often abroad.

Overall, these socioeconomic heterogeneities suggest that many households engage in cross-border shopping either (i) out of an economic necessity because of large potential savings relative to their low income or (ii) because they have high overall grocery expenditures and can, therefore, save more money in absolute terms.

4.3. Culture

Beyond the socioeconomic background of households, I address the role of cultural differences as citizens from various cultural origins may prefer products offered abroad over Swiss products.

Figure 3: German-French language border



Notes: The figure shows the quintiles of car driving times to the closest cross-border shopping location in a 15-kilometer-band around the French-German language border on the municipality level. The dots show all 117 cross-border locations within 20 kilometers of the Swiss border. The dots' size indicates the number of supermarkets at this location, and the black line is the language border.

To this end, I analyze (i) a heterogeneity between customers of different nationalities and (ii) households living in close proximity but on opposite sides of the French-German language border within Switzerland.

To begin with, Panel a) in Table 4 shows the heterogeneous response of individuals from different aggregated nationalities, estimating again the regression model (2). I observe that Swiss households are relatively less likely to shop abroad compared to foreign citizens. A Swiss citizen in the border region spent 10% more in response to the border closure, while other Europeans and Asians increased their expenditures by 15%, South Americans by 13%, and Africans and North Americans by 18%.

Table 5: Cultural differences: effect at language border

	Dep. Var: log(HH Expenditures)		
Dist. to ntl. border	German	French	p-value
Treat × 30-45 min.	0.107***	0.024	0.000
	(0.013)	(0.014)	
Treat × 45-55 min.	0.054***	0.037*	0.395
	(0.015)	(0.015)	
Treat × 55-65 min.	0.026	0.040**	0.492
	(0.014)	(0.014)	

Notes: The figure shows the border closure's average treatment effect on household expenditures for households living within 10 kilometers of the German-French language border. I compare these treated units to same-language households living further away than 80 minutes from the closest cross-border location. The regression estimates model (3) using x million observations, and standard errors are clustered at the zip code level.

Furthermore, I use the intra-national Swiss language border between the French-speaking part of Switzerland in the West and the German-speaking part on the other side of this border to measure any cultural differences based on language. Figure 3 displays the language border crossing the entire country from North to South.[13] I use model (3) to estimate the treatment effect separately for French- and German-speaking households living within 10 kilometers of the language border compared to households further inland speaking the same language. I estimate treatment effects separately for households living between 30-45, 45-55, and 55-65 minutes from the national border compared to households farther away than 80 minutes. I do not report results for households living closer to the next cross-border location, as no household in the distance band around the language border can reach a cross-border location in less than 30 minutes. This empirical strategy relies on the testable assumption that households within this 20-kilometer band are comparable. Table 5 displays the estimation results for different distance bins to the border, and the reported p-value tests for equality of the coefficient in the two language regions. I find a stronger response for German-speaking households in the first distance bin but no significant difference for the other two bins further inland. One potential explanation for the difference in the first distance bin might be that Germany has lower grocery prices than France (see Table 7), and households may prefer to shop in the country speaking their own language.

[13] I exclude in this analysis the German-Italian border in the South because very few people on both sides have comparable access to cross-border locations as this language border lies in the mountains.

Table 6: Treatment effect for different commuting behaviors

	Dep. Var: log(HH Expenditures)		
Δ Border Access	Commute towards border	Commute away f. border	p-value
Treat × 5-15 min.	0.140***	0.086***	0.000
	(0.013)	(0.016)	
Treat × 15-25 min.	0.181***	0.084***	0.029
	(0.041)	(0.021)	
Treat × 25-35 min.	0.172***	0.083***	0.003
	(0.012)	(0.023)	

Notes: The table shows the border closure's average treatment effect on household expenditures within a 30-minute car ride from a cross-border location compared to households living further away than 80 minutes for different household commuting trips. These trips include commutes by car for 0-15 minutes, 15-25 minutes, and 25-35 minutes by car, either towards the national border (bringing the commuter closer to a cross-border location) or further away from the border in comparison to the household's home. The regression estimates model (3), using x observations. Standard errors are clustered at the zip code level.

4.4. Commuting and trip chaining

A key determinant of a household's shopping behavior may be her daily commute to work. First, households can combine commuting and shopping through trip chaining if their workplace is closer to the border than their home. Second, frequent commuting trips to work may alter a household's perception of traveling costs and influence her likelihood of traveling abroad. Hence, I use model (3) to estimate the treatment effect separately for households commuting either from home (i) towards foreign shopping locations or (ii) farther inland, away from cross-border locations. I focus on households that live 20 to 35 minutes from the border and report commuting by car.

Table 6 shows the estimation results. On the one hand, households with a commute bringing them 5 to 15 minutes closer to the border increase their cross-border shopping by 14% in response to the border closure. Yet, if households work even closer to the border, the coefficient increases to 17–18%. On the other hand, I observe for households commuting away from the border an almost constant effect around 8%, independent of the commuting time. Therefore, these two observations provide conclusive evidence that households combine work commutes with cross-border shopping trips in the form of trip chaining.

Table 7: Prices in neighboring countries 2015–2020

	Austria		France		Germany		Italy	
Category	PI	vs. CH	PI	vs. CH	PI	vs. CH	PI	vs. CH
Clothing and footwear	102.83	-20%	105.53	-18%	98.80	-23%	100.52	-22%
Consumer goods	106.37	-20%	107.02	-20%	103.12	-23%	105.18	-21%
Food and non-alcoholic beverages	120.47	-28%	112.38	-33%	102.52	-39%	109.30	-35%
Households appliances	95.08	-21%	105.37	-12%	101.18	-16%	101.50	-15%
Recreation and culture	113.27	-26%	107.28	-30%	104.57	-32%	100.10	-35%
Restaurants and hotels	108.67	-35%	119.73	-28%	105.88	-36%	104.02	-38%

Notes: The table shows prices in neighboring EU countries averaged over the six years before and during the first wave of the COVID-19 pandemic, 2015–2020. Prices are shown as price indices (PI) for different product categories and relative to the category's price index in Switzerland. In each year, the EU27 average is set to 100.

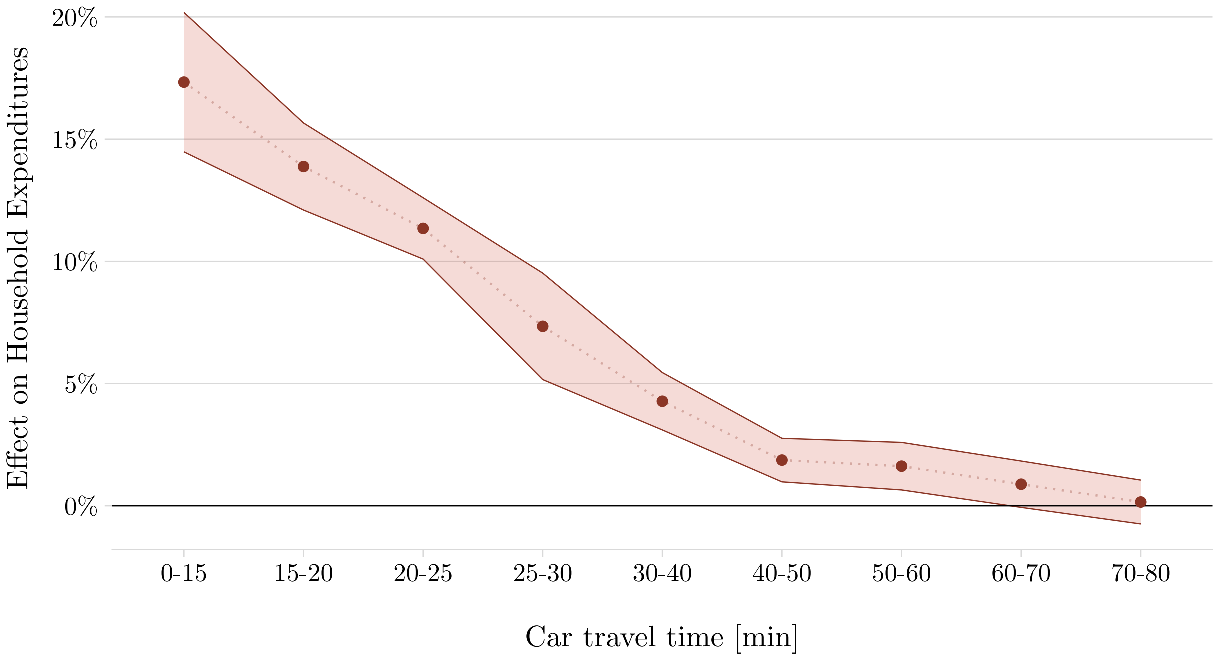
4.5. Variation across cross-border locations

Finally, I look at the role of neighboring countries and their grocery prices. Panel b) of Table 4 shows the spatial variation of the effect by estimating heterogeneous treatment effects for the four neighboring countries Austria, Germany, France, and Italy.[14] The results show a large estimate for households living closest to Italy (28%), with smaller values for France and Germany (11% and 15%, respectively) and no significant response to the shock for households living close to Austria. To assess the role of prices behind these findings, I show in Table 7 national price level indices averaged over the period of 2015 – 2020 for different major product categories and how much these products are cheaper compared to Switzerland. While each product category is in every country cheaper than in Switzerland, relative prices between these neighboring countries vary for different product categories.

Using the price level index for consumer goods, the heterogenous coefficients are negatively correlated with the price index of the neighboring countries, meaning that higher foreign prices correspond to less Swiss cross-border shopping. Based on a back-of-the-envelope calculation using the price indices for food and non-alcoholic beverages, a 1% increase in the price index of a neighboring country is associated with a 0.78% decline in cross-border shopping expenditures. Note that any interpretation of this as a price elasticity assumes that all households assigned to a given neighboring country face the same price difference at home and abroad, which seems plausible as our retailer

[14] For this spatial heterogeneity, I use week fixed effects compared to the week-group fixed effects in the case of socioeconomic variables.

Figure 4: Decay of the treatment effect



Notes: The figure shows the border closure's average treatment effect on household expenditures for households living within a certain distance bin. I compare these treated units to households living further away than 80 minutes from the closest cross-border location. Standard errors are clustered at the zip code level. The regression estimates model (3) and uses 23 million observations.

charges the same prices throughout the country. Additionally, this calculation assumes that residential location choice does not depend on the households' cross-border shopping preferences and that customers buy the same products at home and abroad. Also, not all foreign retailers charge the same prices across the entire country, and prices may be higher close to the Swiss border.

4.6. The distance decay function

Focusing on the role of distance behind these findings, I quantify the decay of cross-border shopping with distance by analyzing the effect for different distance bins from model (3). Figure 4 displays the distance decay function, plotting the average treatment effect for each distance bin separately.

Households living within a short distance of 15 minutes from a cross-border destination increase their expenditures by 17% during the border closure. The effect first declines linearly up to a distance of 40 minutes before flattening out and becoming negligible, although remaining significant for up to 70 minutes. This suggests an extensive margin effect due to the high fixed costs of the trip. Hence, most individuals having to drive more than 40 minutes avoid the trip altogether, leading to a strong kink in the decay function. Before hitting this threshold, the variable costs appear highly linear in travel time. Note that these distances are potentially lower bounds of the actual travel distance as customers might prefer to shop at other foreign stores further away. These findings are broadly in line with Burstein et al. (2022), who estimate that Swiss households close to the border spend roughly 8% of their expenditures abroad.

In addition, Figure A.1 to Figure A.4 display the distance decay for each socioeconomic characteristic separately. The general picture is consistent with the estimates in Table 3, suggesting that the variable costs of traveling longer do not depend on any of these variables. Larger households respond more to the shock across all distance bins, while rather old and young households engage in less cross-border shopping.

4.7. Robustness

This section adds robustness checks. In the main results of the dynamic treatment effect, I compare treated households living within 30 minutes from the closest cross-border location to control households living further than 80 minutes away. Figure A.5 displays the distribution of car travel times to the closest cross-border location for all households in the final data. Built on that, Figure A.7 reproduces the same results but uses a control group that lives at least 90 or 100 minutes from the closest cross-border location (resulting in a control group of 6% and 2.5% of the sample, respectively). In both cases, the average treatment effect remains between 10% and 15% percent, even as the comparison groups become small for these more restrictive doughnut bins. I also use another definition of cross-border locations where I only consider very large foreign stores that may be more attractive to travel to (Figure A.8). The changes in the coefficients are minimal. Finally, I report in Figure A.6 the dynamic estimates for the full sample of transaction data rather than focusing on the sub-sample of customers matched to residents in the administrative data. Also, in this case, the observed changes are negligible.

5. Conclusion

The phenomenon of cross-border shopping provides researchers with a precious setting to analyze the households' heterogeneous willingness to travel for lower prices through a sharp decline in relative prices at the border. While Friberg, Steen and Ulsaker (2022b) shows that the traditional study of cross-border shopping through changes in exchange rates, taxes, or relative prices does not capture cross-border shopping entirely, the Swiss COVID-19-related border closure (among others) provides a unique natural experiment that I exploit.

I find that cross-border shopping is a widespread and persistent phenomenon in Switzerland and that domestic sales would be 10-15% higher in border regions without it. I then dig into heterogeneities, revealing the willingness to travel for lower prices for different groups of households. My findings indicate that larger, poorer, less-educated, and younger households engage in more cross-border shopping, and that the response is larger if the neighboring country has relatively low grocery price indices. In addition, I provide novel evidence that households commuting towards the border combine their trip to work with shopping abroad.

These findings have important implications for urban research. While numerous spatial models in economics incorporate trips to the agents' workplaces and a broad empirical literature uncovers patterns in commuting behavior, household mobility for shopping remains largely understudied and insufficiently understood. One notably exception is Miyauchi, Redding and Nakajima (2022), who incorporate commuting and shopping trips jointly in a quantitative spatial model. Yet, as they cannot observe expenditures and focus on modeling the trips, they provide an incomplete picture, missing the intensive margin of spatial shopping. Future work could aim to bridge this gap, incorporating the empirical findings on shopping in this and other papers into theoretical models.

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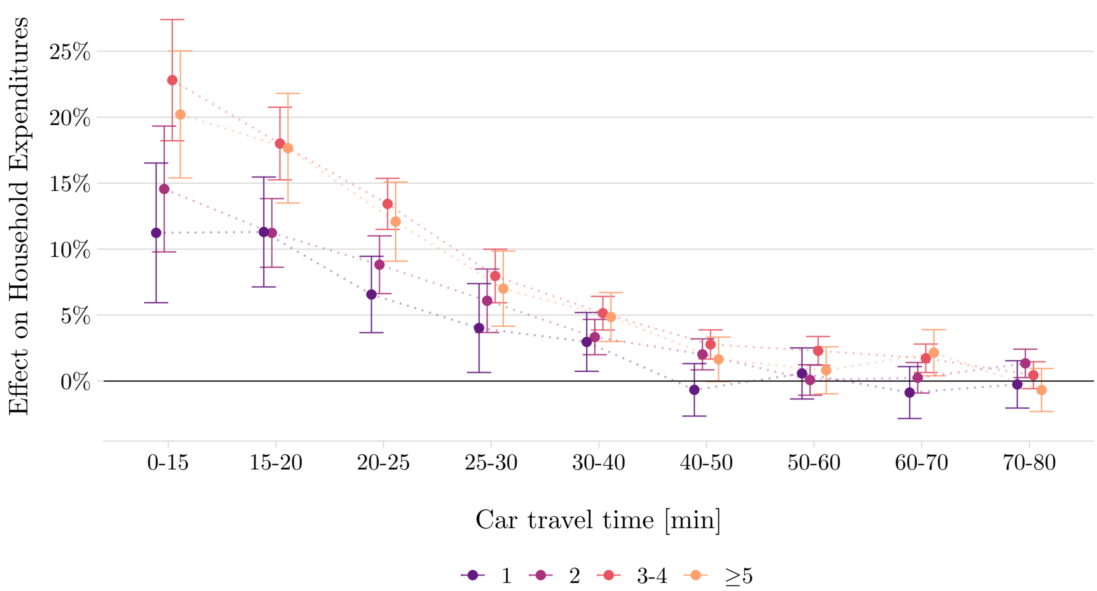
Appendix A. Supplementary Material

Table A.1: Cross-border locations

	Location	Country	Pop	Number of Stores			Rank		
				Google Reviews			*Google Reviews*		
				-	100	500	-	100	500
1	Annecy	FR	131’766	79	29	11	1	1	3
2	Como	IT	84’808	76	21	14	2	4	1
3	Konstanz	GER	84’446	71	29	14	3	1	1
4	Singen	GER	48’033	50	18	10	4	5	4
5	Annemasse	FR	36’582	49	13	5	5	13	15
6	Aosta	IT	34’052	47	7	3	6	30	34
7	Livigno	IT	6’363	47	14	5	6	12	15
8	Varese	IT	80’588	46	15	7	8	8	8
9	Friedrichshafen	GER	61’561	45	23	10	9	3	4
10	Sondrio	IT	21’457	40	3	1	10	67	67
11	Cantù	IT	40’031	39	12	6	11	16	10
12	Belfort	FR	45’458	37	15	4	12	8	22
13	Lindau	GER	25’547	36	15	9	13	8	6
14	Domodossola	IT	17’930	35	11	4	14	18	22
15	Lörrach	GER	49’295	33	15	7	15	8	8
16	Weil am Rhein	GER	30’009	31	18	9	16	5	6
17	Saronno	IT	39’332	30	9	6	17	24	10
18	Waldshut-Tiengen	GER	24’067	30	13	6	17	13	10
19	Stockach	GER	17’118	29	11	5	19	18	15
20	Radolfzell	GER	31’582	28	7	4	20	30	22
21	Überlingen	GER	22’684	27	13	4	21	13	22
22	Rheinfelden	GER	32’919	26	16	5	22	7	15
23	Bad Säckingen	GER	17’510	25	11	4	23	18	22
24	Bregenz	AT	29’806	25	12	5	23	16	15
25	Montbéliard	FR	25’806	25	10	3	23	22	34
			...						
Overall									
117			1’980’614	1’787	691	304			

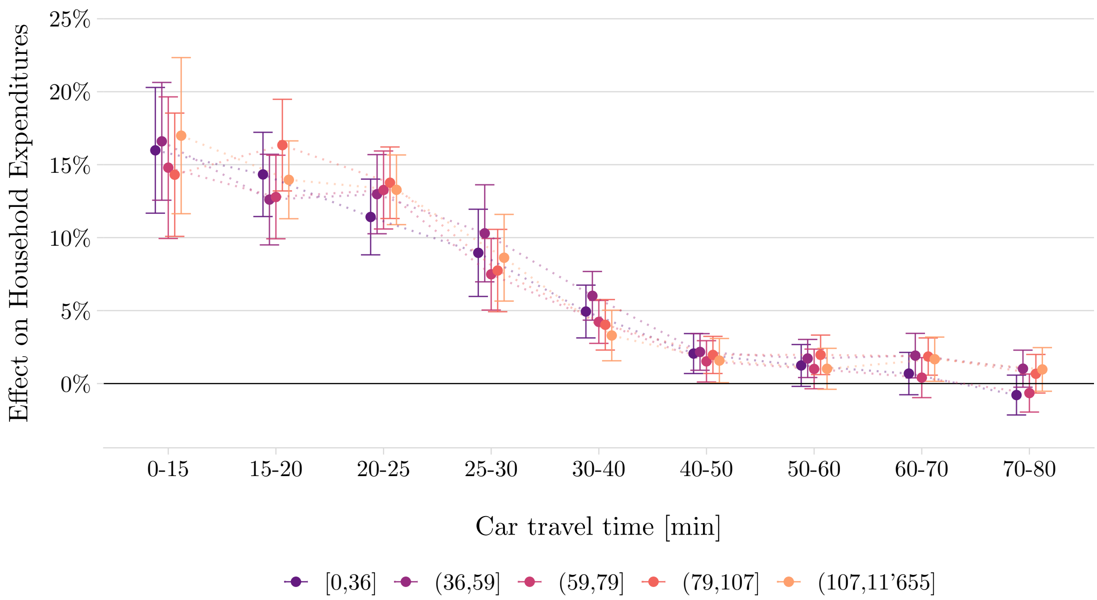
Notes: The table shows the 25 largest cross-border locations for grocery shopping. *Number of Stores* counts the municipality’s stores for a given minimum of Google reviews, while *Rank* ranks the locations according to the number of stores. All store locations are scraped from Google Maps.

Figure A.1: Decay of the treatment effect: by household size



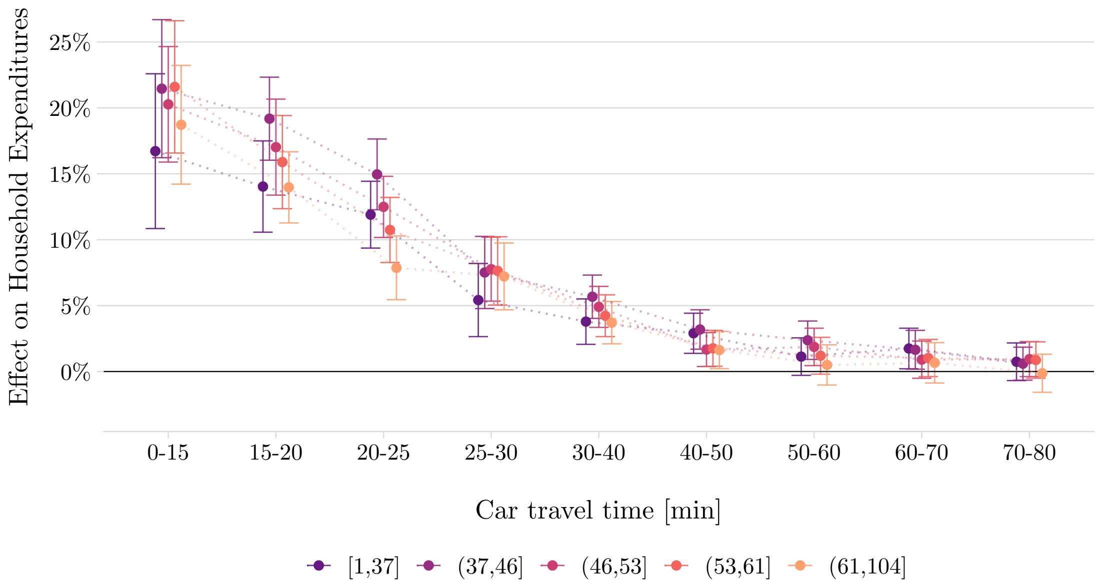
Notes: The figure shows the border closure's effect on household expenditures for different distance bins and household size quintiles compared to households living further away than 80 minutes. Household size is measured by the number of people living in this household according to administrative data. Standard errors are clustered at the zip code level. The regression estimates model (3) and uses 4.9 million matched observations.

Figure A.2: Decay of the treatment effect: by income



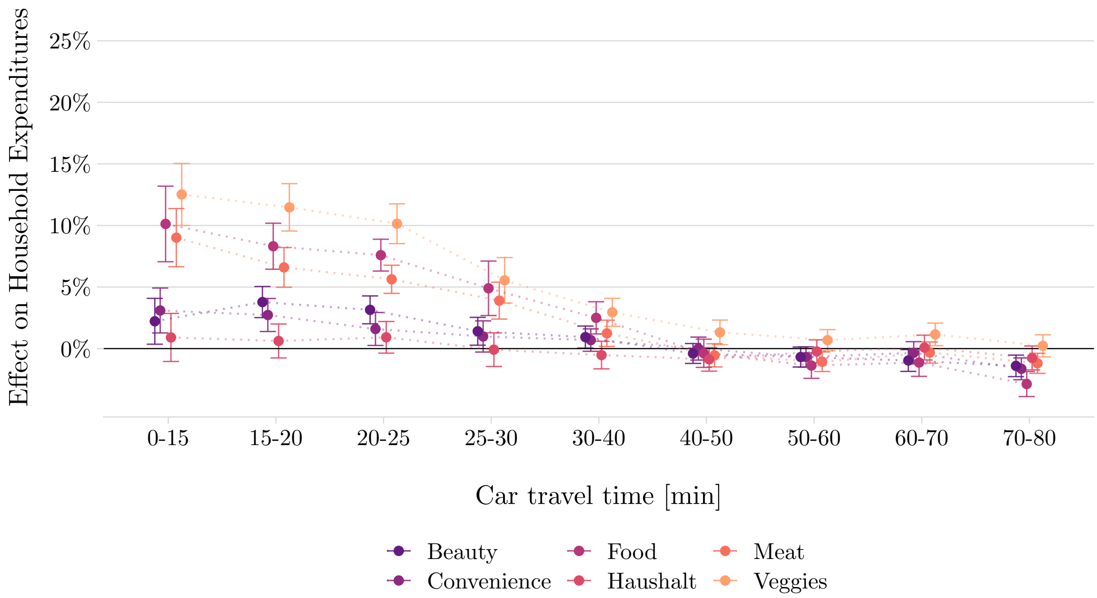
Notes: The figure shows the border closure's effect on household expenditures for different distance bins and income quintiles compared to households living further away than 80 minutes. Income is measured in 1,000 CHF. Standard errors are clustered at the zip code level. The regression estimates model (3) and uses 4.9 million observations.

Figure A.3: Decay of the treatment effect: by age



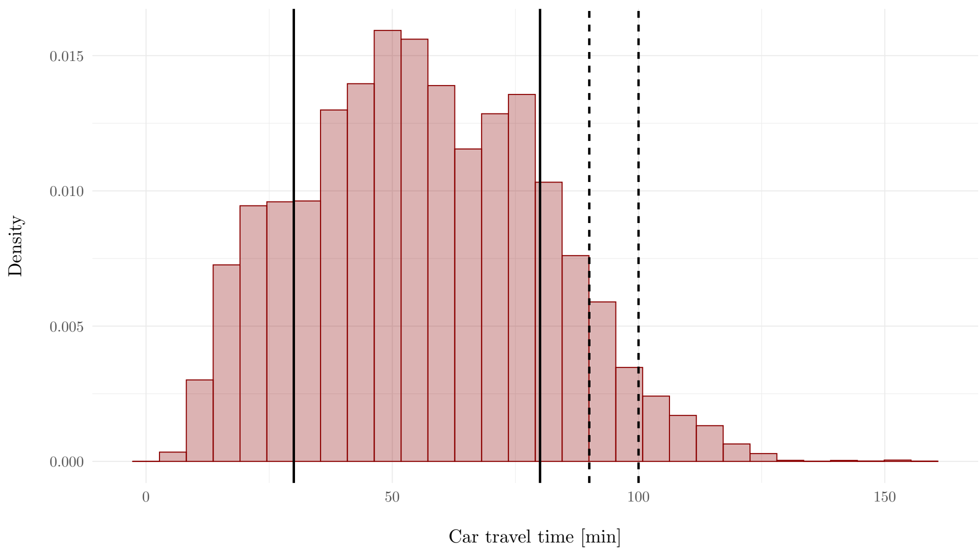
Notes: The figure shows the border closure's effect on household expenditures for different distance bins and age quintiles compared to households living further away than 80 minutes. Standard errors are clustered at the zip code level. The regression estimates model (3) and uses 4.9 million observations.

Figure A.4: Decay of the treatment effect: by product groups



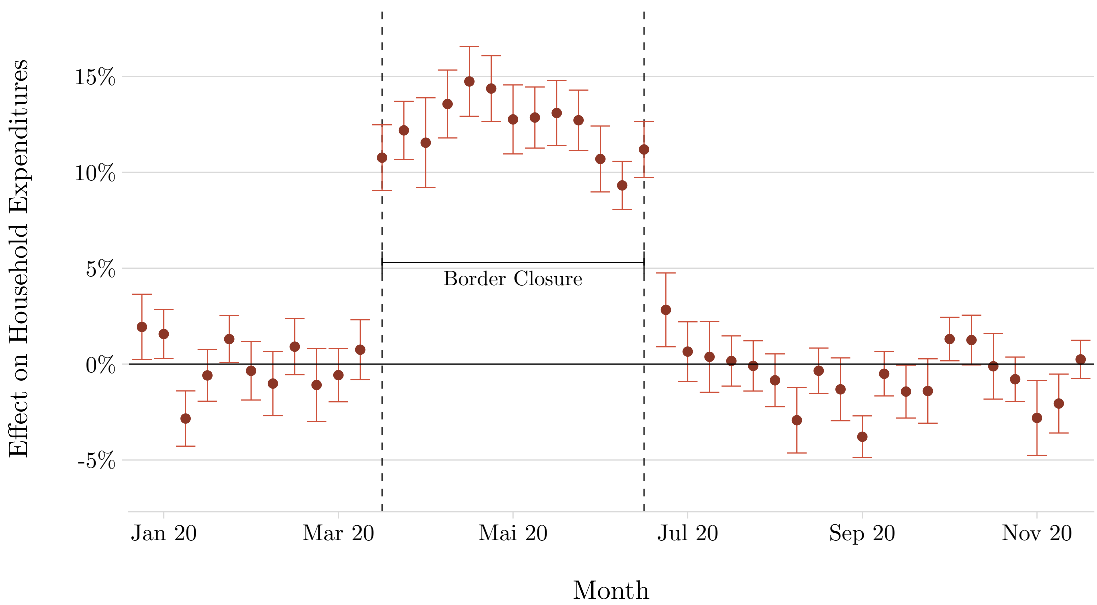
Notes: The figure shows the border closure's effect on household expenditures for different distance bins and product groups compared to households living further away than 80 minutes. Standard errors are clustered at the zip code level. The regression estimates model (3) and uses 67.6 million observations, where the transactions are aggregated to product categories.

Figure A.5: Distribution of travel times



Notes: The figure shows the distribution of car travel times from a household's home to the closest cross-border shopping location. The subsamples of control units used in the different robustness checks of the dynamic results are marked by vertical dashed lines.

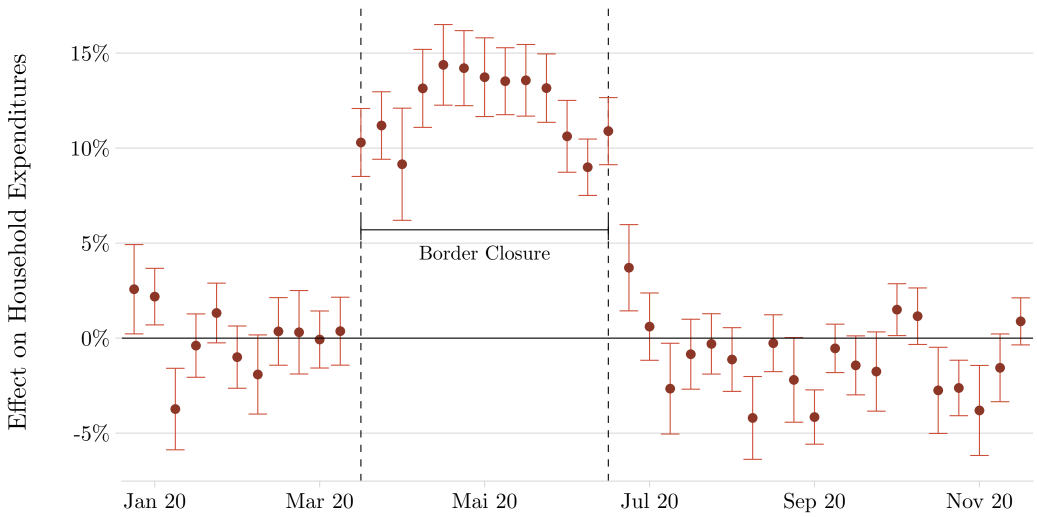
Figure A.6: Robustness of the dynamic treatment effects: the full grocery transaction data



Notes: The figure shows the border closure's effect on household expenditures within a 30-minute car ride from a cross-border location compared to households living further away than 80 minutes. Standard errors are clustered at the zip code level. The regression estimates model (1) and uses 16.6 million observations.

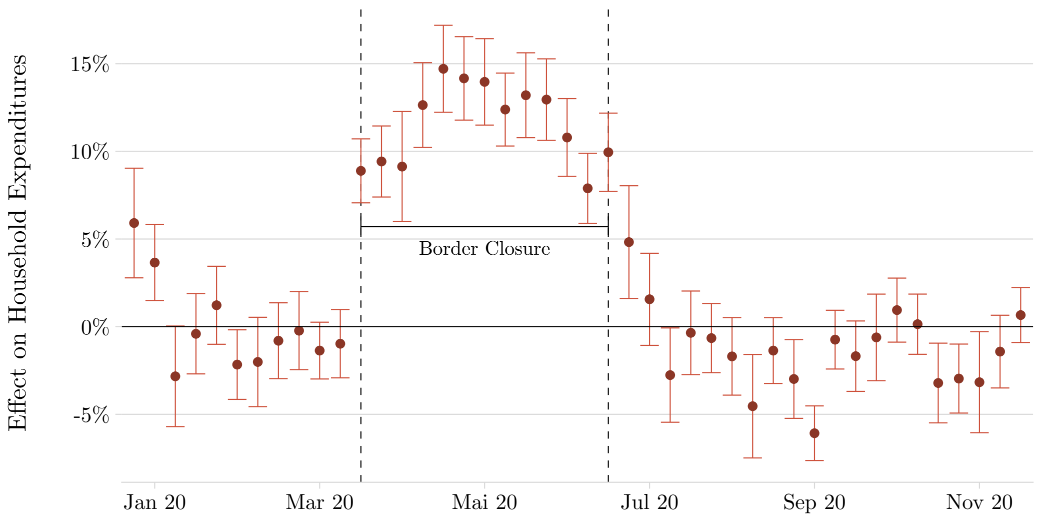
Figure A.7: Robustness of the dynamic treatment effects: different control distance

(a) Control group: more than 90 minutes distance



Month

(b) Control group: more than 100 minutes distance

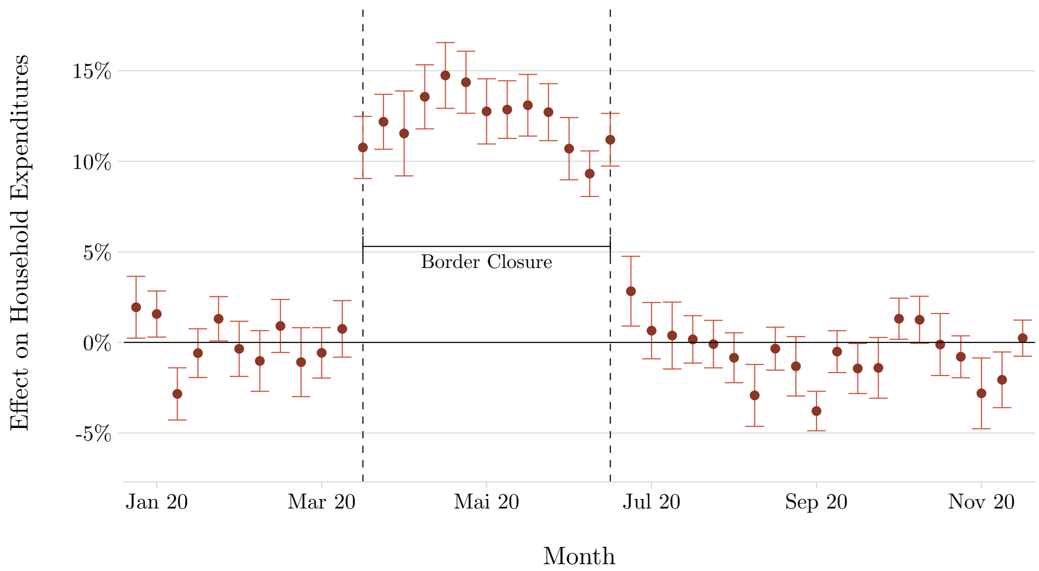


Month

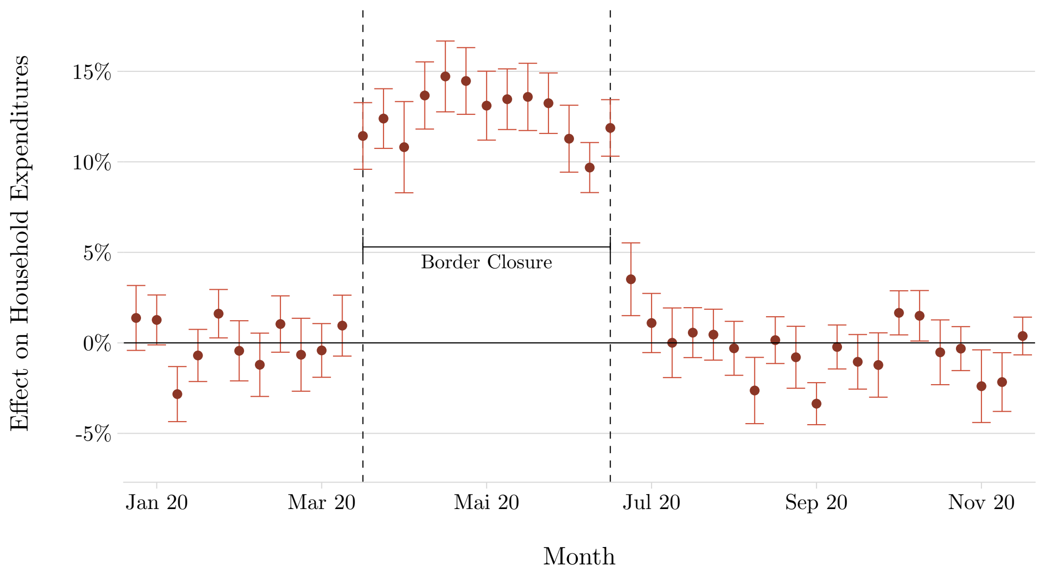
Notes: Figure A.7a shows the border closure's effect on household expenditures within a 30-minute car ride from a cross-border location compared to households living further away than 90 minutes. The regression estimates model (1) and uses 13.3 million observations. Figure A.7b also estimates model (1) for a distance of 100 minutes using 11.2 million observations. Standard errors are clustered at the zip code level.

Figure A.8: Robustness of the dynamic treatment effects: different definitions of cross-border locations

(a) At least three stores with more than 100 Google reviews



(b) At least three stores with more than 500 Google reviews



Notes: Figure A.8a shows the border closure's effect on household expenditures within a 30-minute car ride from a cross-border location compared to households living further away than 80 minutes. I consider all cross-border locations with at least three stores with more than 100 Google reviews. In comparison, Figure A.8b shows the same results but considers locations with at least three stores with more than 500 Google reviews. Both regressions estimate model (1) and use 16.6 million observations. Standard errors are clustered at the zip code level.