Cross-Border Shopping: Evidence from Household Transaction Records *

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Abstract

Cross-border shopping allows consumers from high-price countries to access a greater variety of goods at lower prices in nearby foreign markets. However, this activity can reduce domestic tax revenues, lower sales, and shift consumption away from local retailers. Leveraging the natural experiment of Switzerland's COVID-19-induced border closure, I explore the unequal socioeconomic benefits of cross-border shopping. Using rich transaction data for 750,000 households linked with administrative records, I find an additional temporary 10.9% increase in domestic grocery expenditures in border regions. Furthermore, the benefits of cross-border shopping are heterogeneous, with large households and those with lower incomes being particularly likely to shop abroad. I use these findings to calculate an annual reduction of domestic grocery sales of 1.5 billion Swiss frances due to cross-border shopping, equivalent to 3.8% of total sales. These findings underscore the need for nuanced policy approaches that address the spatial frictions and distributional impacts of cross-border shopping.

Keywords: economic geography, consumption, consumption access, consumption inequality, spatial competition *JEL-codes:* R1, R2, L14

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1 Introduction

Cross-border shopping is a significant economic activity in border regions, allowing consumers from high-price countries to access a greater variety of goods at lower prices in nearby foreign markets. While this raises purchasing power and choice near borders, it also reduces domestic tax revenues, shifts sales away from local retailers, and affects employment in border areas (see Leal, López-Laborda and Rodrigo, 2010, Knight and Schiff, 2012, or Baggs, Fung and Lapham, 2018). As such, cross-border shopping shapes consumer behavior and contributes to unequal economic impacts across socioeconomic groups and regions.

This paper quantifies cross-border shopping in Switzerland and examines heterogeneities across household backgrounds, offering new insights into cross-border shopping's role in exacerbating or mitigating inequality. In order to do so, I leverage Switzerland's border closure as a natural experiment to assess differences in consumer responses to restricted access to foreign markets. In 2020, many countries imposed travel restrictions to contain the spread of COVID-19 and on March 16, 2020, the Swiss government mandated the immediate closure of all national borders, along with domestic restaurants, bars, entertainment, and leisure facilities, with essential stores such as supermarkets and pharmacies as exceptions. This policy was upheld until June 2020.¹

Among countries introducing comparable policies, Switzerland is a unique case for studying cross-border shopping for two reasons. First, it is surrounded by countries where grocery prices are 28-39% lower, enabling Swiss citizens to shop for lower-priced goods in Germany, Italy, Austria, or France.² These countries share a common currency, facilitating price comparisons for Swiss households.³ Second, the exact timing of the border closure was random for Swiss residents, and Burstein, Lein and Vogel (2024) show that the policy was stringent and effectively reduced cross-border shopping nearly to zero during the intervention.

I identify the causal effect of the border closure on expenditures at grocery stores in Switzerland by comparing Swiss households living close to a national border to Swiss 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. To conduct this analysis, I merge unique grocery data featuring the universe of customer-linked transactions from the largest Swiss retailer for the year 2020 with individual-level administrative register records on labor market income, commuting behavior, and household characteristics for the entire Swiss population. The final data set contains 40 million weekly shopping baskets for 750,000 households that I can uniquely link to residents in the administrative data. I use

¹The borders to Liechtenstein remained open, although crossings between Liechtenstein and Germany or Austria were restricted. Nonetheless, the 370,000 workers commuting from neighboring countries into Switzerland and 29,000 Swiss residents working abroad were permitted to cross for work-related reasons.

 $^{^{2}}$ Imports into Switzerland are VAT-exempt for a total value below 300 Swiss francs, with additional limits on items like meat and tobacco. Switzerland also borders Liechtenstein (population 40,000), which uses the Swiss franc and has almost identical grocery prices.

³The CHF/EUR exchange rate remained stable throughout this period.

this setting to measure the decline in cross-border shopping with distance and analyze extensive heterogeneities across households' socioeconomic characteristics, cultural backgrounds, and commuting behavior to uncover the unequal costs and benefits of cross-border shopping.

My findings show that average mobility patterns in consumption are persistent over time and they vary strongly between different groups of customers. I find that the policy increases expenditures by 10.9% in border regions, but the effect vanishes instantly and entirely once the border reopens, suggesting that behaviors in cross-border shopping are deeply rooted and resist temporary shocks. The estimated effects decay with distance, indicating that a household's probability of engaging in cross-border shopping decreases with travel time. Studying the unequal socioeconomic and regional responses to the policy shock, I document the largest effects among poorer and larger households and in areas with cheaper neighboring countries. I combine these various insights and calculate a reduction in domestic grocery sales in Switzerland due to cross-border shopping of 1.5 billion Swiss frances (1.7 billion USD on December 10, 2024, corresponding to 3.8% of the total Swiss market volume), taking into account the heterogeneous customer responses as well as the role of distance. As an additional result, I provide novel evidence that households strategically combine their trips to work with cross-border shopping if they commute towards the border.

This paper relates to two strands of the literature. First, it contributes to the previous work on cross-border shopping, documenting that both consumers and retailers respond to changes in relative prices. For instance, a depreciation of the US dollar reduces the consumers' propensity to cross into Canada (Chandra, Head and Tappata, 2014) while increasing US employment and the number of establishments close to the border (Campbell and Lapham, 2004). Similarly, Asplund, Friberg and Wilander (2007) show that a cut in Danish spirits taxes reduces 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. Finally, Friberg, Steen and Ulsaker (2022) demonstrate that the marginal customer further inland reacts stronger to foreign price changes while households close to the border shop abroad anyway. This implies that the response to relative price changes is an incomplete measure of the level of cross-border shopping. Therefore, I follow an alternative approach and use a natural experiment that restricts access to cross-border shopping completely rather than changing relative prices.

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 (2024) investigate the effect on taxes and find that Norwegian cross-border shopping reduces national tax revenues by 3.6% nationally and 27% in border regions. Second, Burstein, Lein and Vogel (2024) study cross-border shopping in Switzerland using data from Nielsen and conclude that it lowers the cost of living by up to 14% in certain regions. In contrast to these papers, I focus on the customers' behaviors and the rich heterogeneities therein. My data – matching unique transaction records with administrative data – may be better suited for this analysis than the Nielsen data, whose self-recorded reporting errors are correlated with demographic variables (Einav, Leibtag and Nevo, 2008). 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) suggest that consumers purchase products with a low storability within a shorter distance. Additionally, previous work on spatial trip-chaining demonstrates that customers strategically visit multiple non-tradable services along their daily travels. This travel behavior generates consumption externalities that explain one-third of the spatial concentration in non-tradable services (Oh and Seo, 2023) and Miyauchi, Nakajima and Redding (2022) show that modeling trip-chaining is crucial to understanding the decreased demand for non-traded services following the shift to remote working during the COVID-19 pandemic. Furthermore, trip-chaining can cause complex adaptations in the spatial equilibrium with potentially winning and losing stores (Relihan, 2024). My paper contributes to this literature by showing that households strategically include their cross-border shopping trips into their daily commutes to work.

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 checkout with their loyalty card in exchange for exclusive offers and discounts. This loyalty program captures 79% of the retailer's total sales, and 2.4 million customers regularly participate in it (meaning, 33% 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.

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, household members, 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.⁴ Finally, the administrative *Structural Surveys* add education and commuting

⁴The calculation is income adjusted = $\frac{\text{income total}}{\sqrt{\#\text{household members}}}$, where I consider all household members, including

behavior for the sub-sample of customers participating in the survey.⁵ 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.⁶

Both data sets measure addresses on the same spatial grid spanning 350,000 cells over the entire country with a mean population of 25 residents. 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 1.3 million customers in the grocery data uniquely to a citizen and their household in the administrative data. Hence, I can match 54% of the 2.4 million regular customers, corresponding to 20% of all adult Swiss residents. The outcome of interest throughout this analysis is a household's total grocery expenditures in a given week. 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 per capita a month before the shock (equalling 112 USD on July 29, 2024), as their baskets might not capture the overall consumption accurately. This procedure generates a final data set including 757,000 households and 40 million weekly consumption baskets.⁷

Table 1 shows summary statistics for the households and displays for how many of them I observe a given variable. The average matched household has an income of 60,000 Swiss francs (adjusted for the square root of household size), and the mean cardholder is 56.6 years old, while 44.4% have a tertiary education, and 80% live in multi-person households. Comparing these statistics to the entire administrative data shows that the matched sample represents the population well. Further, Table 2 shows summary statistics for the transactions. The average household makes 6.1 transactions and spends 92 Swiss francs (104 USD on July 29, 2024) per week or 391 Swiss francs per month (445 USD on December 10, 2024). This corresponds to roughly 63% of the average household's grocery expenditures based on administrative consumption 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. To this end, 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 and a total of 1,787

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.

 $^{^{5}}$ This representative cross-sectional survey selects 200,000 people above age 15 every year. Customers can be selected repeatedly, and participation is mandatory. To measure education, I use the highest-reported education between 2010 and 2021 and exclude customers younger than 30 to capture students. For commuting, I only use the surveys since 2018 as workplaces are less stable than education.

⁶Primary (or compulsory) education ends at the latest after around eleven mandatory years of school (including kindergarten). Customers who completed high school or an upper-secondary specialized school have a secondary education. Completing any degree at a university, university of applied sciences, or university of teacher education results in a tertiary degree.

⁷See Kluser and Pons (2024) and Kluser, Seidel and von Ehrlich (2024) for additional information on the two data sources, the matching procedure, and the representativeness of the matched households for the general population.

	Final	Sample	Pop	ulation
Panel a)	Mean	SD	Mean	SD
Age	56.63	15.91	50.43	18.17
Income $(1,000 \text{ CHF})$	100.66	129.99	106.01	132.48
Income Adjusted (1,000 CHF)	60.09	80.29	64.90	78.96
Time Home to Work (min.)	28.21	23.02	29.12	23.70
Time Home to Border (min.)	57.69	24.27	56.13	25.28
Time Work to Border (min.)	58.28	31.75	56.08	23.81
Panel b)	Pct.	Ν	Pct.	Ν
Education		$505,\!309$		$4,\!413,\!173$
Primary	9.8	49,747	11.3	498,292
Secondary	45.8	$231,\!237$	44.3	$1,\!954,\!810$
Tertiary	44.4	$224,\!325$	44.4	$1,\!960,\!071$
Household Size		$757,\!629$		7,043,734
1	19.3	$146{,}593$	20.9	$1,\!471,\!897$
2	36.0	$272,\!663$	36.1	$2,\!544,\!442$
3-4	36.1	$273,\!742$	33.8	$2,\!381,\!660$
5+	8.5	$64,\!631$	9.2	645,735
Language		$756,\!936$		$7,\!036,\!484$
German	76.2	576,786	71.2	5,010,326
French	20.2	$153,\!279$	24.1	$1,\!697,\!654$
Italian	3.5	26,871	4.7	$328,\!504$
Population Density		$756,\!936$		$7,\!036,\!484$
Urban	24.4	$184,\!556$	30.2	$2,\!122,\!190$
Suburban	57.6	$436,\!372$	51.9	$3,\!649,\!595$
Rural	18.0	136,008	18.0	$1,\!264,\!699$
Nationality		$757,\!568$		7,042,341
Swiss	85.6	$648,\!380$	74.0	$5,\!210,\!215$
European	12.5	$94,\!605$	22.0	$1,\!551,\!076$
African	0.5	3,507	1.1	77,266
Asian	1.0	$7,\!255$	1.9	$131,\!883$
N.American	0.1	1,025	0.3	$21,\!530$
S.American	0.4	2,796	0.7	$50,\!371$
Commuting Mode		$103,\!295$		$923,\!718$
Car	59.0	60,973	55.4	511,779
Public Transport	24.8	$25,\!595$	27.8	$256,\!869$
Other	16.2	16,727	16.8	$155,\!070$
Observations		757,629		7,043,734

Table 1: Household Summary Statistics

Notes: The table shows summary statistics for the customers uniquely matched to the administrative data and compares them to the entire Swiss population above legal age. *Income* equals the total annual labor market income of a household in 1,000 Swiss Francs, and *Income Adjusted* adjusts for the square root of household size. All *Time* variables measure the uncongested car travel time in minutes to the work location or the closest cross-border location. The variables *Commuting Mode* and *Education* are only available for the sub-sample participating in the *Structural Surveys*.

Group	Mean	SD	p50	p1	p99
Weekly Grocery Purchases					
Expenditures in Matched Sample	92.5	64.1	75.5	12.9	300.7
Expenditures in Full Sample	88.7	62.3	72.0	12.2	293.1
Shop Visits in Matched Sample	6.1	3.5	5.5	0.8	17.5
Shop Visits in Full Sample	6.1	3.5	5.5	0.8	17.4
Expenditures by Age Group					
20 - 34	82.2	53.9	68.7	11.8	251.1
35 - 44	107.9	70.6	91.6	13.8	317.6
45 - 54	110.2	74.5	92.1	14.2	336.7
55 - 64	94.6	63.7	79.1	13.6	301.7
65 - 74	79.4	51.3	67.1	12.7	247.4
75+	68.3	44.4	57.4	11.2	217.4
Expenditures by Income Quintile					
25,000-73,000	79.3	53.1	65.7	12.7	255.5
73,001–106,000	90.7	59.7	75.5	13.4	280.5
106,001 - 137,000	104.0	66.6	89.6	14.2	302.4
$137,\!001181,\!000$	111.9	71.0	97.6	14.3	321.4
181,001+	119.3	79.4	102.5	13.6	357.8
Expenditures by Education					
Primary	69.8	47.7	57.3	11.4	232.8
Secondary	90.5	60.2	75.6	13.3	284.2
Tertiary	107.9	71.9	91.3	13.7	328.8
Expenditures by Household Size					
1	60.0	37.3	51.8	11.2	191.0
2	83.2	51.5	72.5	12.6	244.0
3-4	111.5	71.0	97.1	14.5	319.9
5+	125.0	84.8	105.9	14.4	373.6
Transactions in Matched Sampled	d Sampled 40,179,519				
Transactions in Full Sampled	95,192,993				

Table 2: Transactions Summary Statistics

Notes: The table shows summary statistics for the weekly expenditures and trip frequency of customers that I can match to residents in the administrative data. I compare these statistics to the full transaction data set, including the unmatched customers, and report statistics on sub-samples for the matched data. The statistics for the *Full Sample* apply the same sample selection criteria used for the matched sample to the 120 million weekly baskets (600 million shop visits) in the transaction data set.

stores, of which 691 have at least 100 Google ratings. Table A1 lists the largest identified crossborder locations, showing the number of stores with at least 100 and 500 Google ratings. A municipality with a large number of stores typically also has many larger stores with numerous Google reviews, and 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. As cross-border shoppers likely focus on larger stores, I define a cross-border location as a foreign municipality with at least three stores that have more than 100 Google ratings.⁸ Next, I scrape

⁸My results are robust if I define cross-border locations alternatively as (i) locations with at least one store



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.

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 reach 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 closest cross-border location (57 minutes) and the work location (28 minutes). 59% commute to work by car, while 24.8% use public transportation.

3 Empirical Strategy

I study the impact of the border closure on household expenditures by comparing households living within a half-hour 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 define the control group as households living more than 80 car minutes away (the fifth quintile) and drop all individuals residing within the doughnut area to ensure a clean control group. This results in a sample of roughly 150,000 treated and control households.⁹ Figure 1 shows these travel distance bins to

with 500 Google reviews or as (ii) locations with at least three stores with 500 Google reviews.

⁹If a fraction of control units still reacted to the border closure because the distance to the border is not large enough, my estimates should be regarded as a lower bound. I will address this further in Section 4.3, showing

Table	3:	Balance	Checks
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	ſ	Treatmen	nt Group			Control	l Group			
	201	9	202	1	201	9	202	1	Δ in	ı p.p.
	Count	%	Count	%	Count	%	Count	%	Coeff	SE
Labor Market Status										
Working	22,836	43.61	25,798	43.88	14,907	38.62	14,703	39.07	-0.2	(0.473)
Not Working	29,529	56.39	$32,\!997$	56.12	$23,\!696$	61.38	22,927	60.93	0.2	(0.473)
Commuting										
No Commuting	5,043	17.52	6,786	21.05	4,192	17.98	$4,\!657$	20.58	0.9	(0.481)
Within Mun.	6,943	24.12	7,317	22.70	5,537	23.75	5,245	23.18	-0.9	(0.531)
Within Canton	12,092	42.00	12,852	39.87	10,313	44.23	9,711	42.91	-0.8	(0.587)
Within CH	4,711	16.36	$5,\!281$	16.38	3,273	14.04	$3,\!019$	13.34	0.7	(0.443)
Commuting Means										
Walking / Bicycle	4,612	18.84	5,231	19.96	3,365	17.25	$3,\!370$	18.45	-0.1	(0.515)
Individual	11,810	48.23	13,562	51.74	$11,\!431$	58.61	11,031	60.38	1.7^{**}	(0.657)
Public	7,984	32.61	$7,\!274$	27.75	$4,\!648$	23.83	3,794	20.77	-1.8^{**}	(0.610)
Weekly Two-Way Trips to Work										
5+ trips	17,498	73.72	17,365	68.30	12,467	66.05	$11,\!124$	62.91	-2.3^{***}	(0.631)
Less than 5 trips	6,239	26.28	8,061	31.70	6,407	33.95	$6,\!557$	37.09	2.3^{***}	(0.631)
Jobs										
Managers	3,156	10.92	3,835	11.88	2,178	9.41	2,438	10.86	-0.5	(0.359)
Professionals	7,296	25.24	8,478	26.26	5,079	21.95	5,024	22.39	0.6	(0.515)
Technicians	5,317	18.40	5,837	18.08	4,061	17.55	3,970	17.69	-0.5	(0.479)
Clerical Support	3,833	13.26	3,934	12.18	2,734	11.82	2,626	11.70	-1.0^{*}	(0.398)
Service / Sales	3,726	12.89	4,182	12.95	3,605	15.58	3,290	14.66	1.0^{*}	(0.423)
Agriculture / Forestery	357	1.24	433	1.34	730	3.16	671	2.99	0.3	(0.186)
Craft / Trade Workers	2,474	8.56	2,668	8.26	2,511	10.85	2,245	10.00	0.5	(0.374)
Machine Operators	1,024	3.54	1,103	3.42	980	4.24	974	4.34	-0.2	(0.247)
Elementary Occupation	1,720	5.95	1,819	5.63	1,258	5.44	1,205	5.37	-0.2	(0.286)
Income										
Q1	$520,\!210$	27.64	$518,\!353$	27.27	$384,\!961$	25.00	$396,\!237$	25.41	-0.8***	(0.069)
Q2	$465,\!295$	24.73	$474,\!201$	24.94	$394,\!016$	25.59	$394,\!251$	25.29	0.5^{***}	(0.066)
Q3	$416,\!584$	22.14	$426,\!491$	22.43	$408,\!538$	26.54	$412,\!171$	26.44	0.4^{***}	(0.065)
Q4	479,777	25.49	482,052	25.36	352,027	22.87	$356,\!517$	22.87	-0.1*	(0.065)

Notes: This table provides balance checks between the control and treatment groups for the year before (2019) and after (2021) the border-closure shock. The table uses the complete individual-level data available in the Structural Surveys for the years 2019 and 2021 for all variables except income, which is based on data from the Old-Age and Survivor's Insurance. The column Δ in p.p. reports the percentage point change in the difference between the percentage shares between the control and treatment groups. Standard errors are from 1,000 bootstrap replications.

the closest foreign location across Switzerland. 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 morphology of the landscape.

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. Yet, the onset of COVID-19 potentially introduced significant behavioral changes that are not captured by time-constant fixed effects. Thus, if the COVID-19 pandemic affected

that my results are robust if I use alternative comparison distances of 90 or 100 minutes.

treated and control units differently – beyond the border closure I exploit – this could bias my estimates if not carefully addressed. While time-varying covariates could control for these confounders, they introduce unintended identifying variation, even in the case of a differencein-differences setting with common treatment timing, and the resulting estimates are not ATTs (see Goodman-Bacon, 2021 and Słoczyński, 2022).

To address this challenge, I forgo the inclusion of any control variables and provide instead a balance-check table that demonstrates the comparability of the treatment and control groups across key variables in Table 3, showing that the two groups did not diverge over time in any meaningful way. In addition to these balance checks, I also display in the Appendix (i) the distribution of travel times from home to work for both groups in 2019 and 2021 (Figure A1) and (ii) the number of COVID-19 cases as well as the mitigation policies' stringency for the treatment and control groups throughout 2020 (Figure A2). Both plots confirm that any disparities in commuting trip duration, as well as the COVID-19 incidence and governmental mitigation measures between these groups, are minimal. Together, these analyses (and additional robustness checks following) strengthen my key identification assumption, arguing that any observed differences in outcomes are attributable to the border closure itself rather than other changes during the pandemic.

In order to estimate the average treatment effect, I follow the suggestions in Chen and Roth (2024) and Wooldridge (2023) and estimate a QMLE-Poisson model, as some households record zero expenditures in a given week:¹⁰

$$Y_{it} = \exp\left(\alpha_i + \gamma_t + \sum_{j=1}^{52} \beta_j (D_i \times T_j)\right) \epsilon_{it},\tag{1}$$

where Y_{it} are the grocery expenditures of household *i* in week $t \in 1, ..., 52$. 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, the dummy variables T_j indicate the weeks of the year 2020, and β_j are the associated pre- and post-treatment coefficients for each period *j*.

Treatment starts in week twelve, and I normalize coefficients to the average in the pre-treatment period. I cluster standard errors in the QMLE Poisson regressions on the zip-code level and report in all tables and figures the transformed coefficients $\hat{\beta}_{ATT\%} = exp(\hat{\beta}-1)$, which gives the average proportional treatment effects and allows me to interpret the coefficients as percentage changes. I calculate the corresponding standard errors using the delta method.¹¹

To analyze heterogeneities in the treatment effect, I use a static version of the model and interact

¹⁰Chen and Roth (2024) show that using a linear model with log(Y + 1) as a dependent variable does not allow interpreting the coefficients as percentage changes. Instead, estimating a QMLE-Poisson model and reporting the transformed coefficients $\hat{\beta}_{ATT\%} = exp(\hat{\beta} - 1)$ leads to the desired result.

¹¹Alternatively, I calculate standard errors from 1,000 clustered bootstrap replications for the main results. The bootstrapped standard errors give very similar results.

the treatment indicator with a categorical variable x_i :

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

where $Post_t = 1$ if $t \ge 12$, $k \in \mathcal{K}$ indexes the individual categories of x_i , $x_{ik} = \mathbb{1}(x_i = k)$, and β_k is the average treatment effect for each group k. In this specification, the time dimension of the treatment effect 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.

4 Results and Discussion

This section presents three sets of results. First, I analyze the average treatment effect of the border-closing policy on grocery expenditures over time. Second, I study the unequal response to the policy for different household backgrounds and commuting behaviors, documenting which characteristics particularly benefit from cross-border shopping. Third, I examine the role of distance, assessing how actively customers shop abroad as travel costs increase. This furthermore allows for a discussion on potential spillovers to the control group. Finally, I connect all of these insights to calculate a measure for the annual reduction in domestic grocery sales due to cross-border shopping activity.

4.1 Response to the COVID-19 Border Closure

Figure 2 shows the results for the dynamic difference-in-differences outlined in Equation (1). The borders close in week 12 and reopen in week 25, and vertical dashed lines indicate both events. Grouping all months during the border closure together, I find that the border closure temporarily increases domestic grocery expenditures significantly by 10.9% (s.e.: 0.006) at the border in comparison to households residing further inland, with week-specific effects ranging from 8% to 14%. These findings are in line with Burstein, Lein and Vogel (2024), who estimate that Swiss households close to the border spend roughly 8% of their expenditures abroad. Further, this expenditure 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 border closure and completely switched back to their old demeanor as soon as possible. This result suggests that cross-border shopping follows deeply rooted routines that withstand major temporary shocks.

One concern might be that consumers adapted their shopping behavior before the actual introduction of pandemic restrictions, especially in strongly affected areas (for example, in the form of stockpiling or by avoiding larger crowds). Yet, the insignificant pre-treatment coefficients in Figure 2 do not indicate any anticipation effects nor a potential violation of the parallel trend





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 Equation (1) and uses 12 million observations. Coefficients are normalized to the pre-treatment periods' average, and standard errors are clustered at the zip code level. Coefficients are exponentiated such that they equal proportional effects.

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.

Furthermore, the estimation results in Figure 2 remain unchanged under various robustness checks. For example, I (i) restrict the analysis to households who did not move during 2020, (ii) exploit the full sample of available transactions in the grocery data rather than focusing on the sub-sample of customers matched to residents in the administrative data, and (iii) use another definition of cross-border locations where I only consider very large foreign stores that may be more attractive to travel to, (see the corresponding event study plots in the Appendix, Figure A4, Figure A5, and Figure A6).

4.2 The Unequal Benefits of Cross-Border Shopping

In the following, I expand on these average treatment effects to study the potentially unequal benefits of cross-border shopping, studying heterogeneities across socioeconomic backgrounds, the closest neighboring country, and differences in commuting behavior.

The Role of Socioeconomic Backgrounds

Consumers' preferences for cross-border shopping might vary based on their socioeconomic background, resulting in unequal benefits of cross-border shopping. Hence, I analyze treatment effect heterogeneities for different household characteristics in the rich administrative register data and Table 4 reports the estimation results of Equation (2) for the variables household size, age, income, education, and nationality in the panels a) to e). The table also reports p-values, testing the treatment effects' equality over the different groups (meaning, the null hypothesis is $\beta_k = \beta \forall k$).

First, I find that the effect rises in household size. While a treated one-person household increases their expenditures by only 6.8% in response to the border closure, I document an increase by 10.3% for two-person households, and by 14% for households with at least three members. Hence, larger households engage in more cross-border shopping. Traveling abroad to shop at lower prices is particularly tempting if one buys regularly large quantities, as it increases the trip's savings while the trip's traveling costs are fixed. 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 heterogeneous effects over age in the response to the border closure. The estimated effect lies around 14% for young households between age 20 and 44 and decreases gradually 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). This result might be driven by the sharp decline in their income after retirement, which induces them to still shop abroad at lower prices. Furthermore, they presumably also face lower opportunity costs. Note that this heterogeneity 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. 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. For instance, high-income households in my data (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, less affluent households might be less mobile, for example, because of lower car ownership rates. While 90% of high-income households in Switzerland (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. Similarly, lower-income households travel, on average, shorter distances on a given day (30.2 kilometers vs. 40.8 kilometers).

The results in panel c) show that the first line of arguments dominates the narrative: the treatment effect decreases from 15.0% for the lowest-earning quintile to 9.9% for the highest-earning households. Hence, although traveling costs are relatively high for many of them, lower-income households still engage in more cross-border shopping activity.

Dep. Variable: Household Expenditures								
a) House	hold Size	b) A	ge	c) I	ncome			
Group	Coeff	Group	Coeff	Group	Coeff			
1	0.068^{***} (0.006)	20-34	0.138^{***} (0.010)	Q1	0.150^{***} (0.008)			
2	0.103^{***} (0.007)	35-44	0.142^{***} (0.009)	Q2	0.144^{***} (0.008)			
3-4	0.136^{***} (0.008)	45-54	0.134^{***} (0.008)	Q3	0.128^{***} (0.008)			
≥ 5	0.145^{***} (0.009)	55-64	0.122^{***} (0.008)	$\mathbf{Q4}$	0.117^{***} (0.007)			
		65-74	(0.130^{***}) (0.009)	Q5	(0.099^{***}) (0.009)			
		75+	$\begin{array}{c} 0.114^{***} \\ (0.010) \end{array}$					
p-value n	$0.000 \\ 6,434,950$	p-value n	$0.000 \\ 5,700,245$	p-value n	$0.003 \\ 5,700,245$			
d) Edu	lcation	e) Natio	nality	f) Country				
Group	Coeff	Group	Coeff	Group	Coeff			
Primary	0.137^{***} (0.010)	African	0.197^{***} (0.038)	AT	0.074^{***} (0.013)			
Secondary	0.108^{***} (0.006)	Asian	0.163^{***} (0.025)	GER	0.110^{***} (0.008)			
Tertiary	0.108*** (0.007)	European	0.155^{***} (0.012)	\mathbf{FR}	0.120^{***} (0.009)			
	()	N.American	0.166^{**} (0.062)	IT	0.350^{***} (0.040)			
		S.American	(0.120^{**}) (0.041)		(~)			
		Swiss	$\begin{array}{c} (0.011) \\ 0.105^{***} \\ (0.006) \end{array}$					
p-value n	$0.000 \\ 6,434,950$	p-value n	$0.000 \\ 6,434,398$	p-value n	$0.000 \\ 6,235,192$			

 Table 4: Treatment Effects by Socioeconomic Subgroups

Notes: The table shows the border closure's average treatment effect on household expenditures within a 30minute 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, the highest *education* in the household, the cardholders' *nationality*, and the *country* of their closest cross-border shopping location. The regression estimates Equation (2), standard errors are clustered at the zip code level, and the reported p-values test the equality of all coefficients. Coefficients are exponentiated such that they equal proportional effects.

Fourth, higher-educated customers may have broader knowledge and access to more information to strategically optimize their consumption behavior while being less budget-constrained. Yet, households with at least one member holding a tertiary education react less to the border closure than comparable households further inland. While high-educated households increase their expenditures by 10.8%, I estimate a higher effect of 13.7% for low-educated households.

Overall, these socioeconomic heterogeneities suggest that many households engage in crossborder shopping either (i) 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.

The Role of Cross-Border Locations

As a final heterogeneity, I look at the role of neighboring countries and their grocery prices. Panel f) 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.¹² The results show a large estimate for households living closest to Italy (35%), with smaller values for households living close to Germany, France, and Austria (12%, 11%, and 7.4%, respectively). To assess the role of prices behind these findings, I show in Table A2 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, a 1% increase in the price index of a neighboring country is associated with a 0.61% 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 charges the same prices throughout the country. Yet, not all foreign retailers charge the same prices across the entire country, and foreign prices may be higher close to the Swiss border. 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.

Commuting Behavior and Trip Chaining

Furthermore, I analyze the interaction of cross-border shopping behavior and specific work trips, as a key determinant of a household's shopping behavior may be her daily commute to work (see, for example, Miyauchi, Nakajima and Redding, 2022). Cross-border shopping and commuting might interact in two ways. First, households can combine commuting and shopping through trip

¹²For this spatial heterogeneity, I use week fixed effects compared to the week-group fixed effects in the case of socioeconomic variables.

	Dep. Var: Household Expenditures				
Δ Border Access	Commute Towards Border	Commute Away f. Border	p-value		
Treat \times 5-15 min.	0.145**	0.088***	0.439		
	(0.017)	(0.017)			
Treat \times 15-25 min.	0.148^{***}	0.107^{***}	0.008		
	(0.051)	(0.024)			
n	357	,492			

Table 5: Treatment Effect for Different Commuting Behaviors

Notes: The table shows the border closure's average treatment effect on household expenditures within a 30minute 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 and 15-25 minutes, 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 Equation (2) and standard errors are clustered at the zip code level. Coefficients are exponentiated such that they equal proportional effects.

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 distance and traveling costs and influence her likelihood of traveling abroad, even if her workplace lies far away from the border. Hence, I use Equation (2) 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 5 shows the estimation results. On the one hand, households with a commute taking them 5 to 15 minutes closer to the border increase their cross-border shopping by 14.5% in response to the border closure. For households whose workplace is 15-25 minutes closer to a cross-border location, I estimate an effect of 14.8%. On the other hand, I observe for households commuting away from the border lower effects of 8.8% and 10.7%, respectively. Therefore, these two observations provide conclusive evidence that households combine work commutes with cross-border shopping trips in the form of trip chaining. This adds additional evidence to the discussion on strategic trip chaining in Miyauchi et al. (2022), Oh and Seo (2023), and Relihan (2024) in the context of cross-border shopping activity.

4.3 The Role of Distance

Throughout the previous sections, I choose a doughnut-specification with control households living at least an 80-minute car drive from the closest cross-border shopping location. Yet, choosing the radius of the inner doughnut defines the households left out in my analysis and features a trade-off between (i) ensuring that the treatment does not contaminate the control units and (ii) having a large and representative enough control group. If households living 80 minutes from a cross-border location are still affected, my results should be regarded as lower bounds. To investigate this, I now consider larger doughnut areas. Figure 3 compares the distance decay function for my preferred specification to two alternative approaches based on control households with at least a 90-minute and 100-minute trip to the closest cross-border location.

Focusing on the preferred specification of 80 minutes in Figure 3, I find that households living within a short distance of 15 minutes from the closest cross-border destination increase their expenditures by 16% during the border closure. This effect first declines linearly up to a distance of 50 minutes before flattening out, although remaining significant for at least 80 minutes. 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 rather than at the closest location.

The comparison to the alternative specifications indicates that some control units in my baseline results are likely still affected by the border closure, as the coefficient for the last distance bin is significant. As the alternative approaches consistently report higher point estimates, I likely underestimate the true effect. On the other hand, the size of the control group shrinks significantly from 150,000 to 68,000 and 28,000 households for the stricter definitions of control units. To balance this trade-off, I select the most conservative approach and present in the paper all estimates with a control group consisting of households living 80 minutes from the border. In the Appendix, Figure A7 displays the event study results for a 90-minute and 100-minute control group, while Table A3 to Table A7 replicate all previous results for a control distance of 100 minutes and show that all my conclusions and arguments remain qualitatively the same.

4.4 Quantify the Total Effect of Cross-Border Shopping on Domestic Sales

To quantify the overall domestic sales lost due to cross-border shopping, I estimate the following equation:

$$Y_{it} = \exp\left(\alpha_i + \gamma_t + \beta(D_i \times Post_t \times \mathbf{X}_i)\right)\epsilon_{it},\tag{3}$$

where the interacted controls \mathbf{X}_i include all variables considered in the heterogeneity analysis (income bins, education levels, age bins, household size, and neighboring country dummies). This allows me to calculate an estimate for the sales lost as follows. First, I take for the treated households the difference between the fitted values of expenditures \hat{Y}_{it} and the predicted values for the counterfactual without a border closure policy (meaning, $D_i = 0$). Second, I aggregate these differences to an annual total value, weighting them with the inverse of the number of customers in my sample relative to the number of residents in the customers' municipality. This rescales my estimates of the entire market under the assumption that the unobserved customers are comparable to the observed ones. Based on the previous discussion of my data's representativeness, this assumption appears plausible. Finally, I take into account that we observe a subsample of the household's total expenditures. Kluser and Pons (2024) show that my data captures a representative 65% of the average household's total expenditures, and I rescale my result accordingly. This results in an estimated total loss of grocery food sales caused by outgoing cross-border shoppers of 1.5 billion Swiss frances, corresponding to 3.8% of the total





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, 90, and 100 minutes from the closest cross-border location, respectively. Standard errors are clustered at the zip code level. The regressions estimate Equation (2) and use 17.4 million observations in all three cases. Coefficients are exponentiated such that they equal proportional effects.

Swiss market volume. This estimate based on the temporarily imposed autarky is considerably lower than the survey-based 3.3 billion calculated for Swiss food expenditures abroad by Rudolph et al. (2022).

5 Conclusion

This paper exploits the Swiss COVID-19-related border closure as a natural experiment to study the heterogeneous benefits of cross-border shopping. I find that cross-border shopping is a widespread and persistent phenomenon in Switzerland and that domestic sales would be 10.9% higher in border regions without it. I then investigate heterogeneities, indicating 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. Namely, commuting trips taking a household closer to the border correspond to an expenditure increase, while commuting to a workplace further inland has no effect.

These results have important implications. First, the uncovered unequal benefits from crossborder shopping may enhance normative analyses of the optimal spatial supermarket allocation, giving additional weight to households with a lower willingness to travel. Second, my findings might improve policies targeting the negative externalities of cross-border shopping on employment, consumption, sales, and tax collection (see again Leal, López-Laborda and Rodrigo, 2010, Knight and Schiff, 2012, or Baggs, Fung and Lapham, 2018). Ultimately, 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 still needs to be studied more thoroughly. One notable exception is Miyauchi, Nakajima and Redding (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 bridge this gap, incorporating the empirical findings on shopping in this and other papers into theoretical models. This would result in a more encompassing picture of the spatial equilibrium and allow for more credible counterfactual analyses.

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A Appendix

	Location	Country	Population	Number of Stores		Rank			
				Goog	le Revi	ews	Go	ogle Rea	views
				-	100	500	-	100	500
1	Annecy	\mathbf{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	\mathbf{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	\mathbf{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	\mathbf{FR}	$25,\!806$	25	10	3	23	22	34
Over	rall								
117			1,980,614	1,787	691	304			

 Table A1: Cross-Border Locations

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 A1: Time to Work

Notes: The figure shows the density of car travel times to workplaces in minutes for the treatment group (Figure A1a) and the control group (Figure A1b) before (2019) and after (2021) the treatment.



Figure A2: COVID-19 and Mitigation Measures

Notes: Figure A2a shows the evolution of the cantonal COVID-19 cases per 1,000 inhabitants for the treatment and control group over time. Figure A2b shows the KOF Stringency Index for the mitigation measures' stringency in Switzerland, again separated by the two groups.



Figure A3: Distribution of Travel Times

Car travel time [min]

100

150

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.

50

0

	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%

Table A2: Prices in Neighboring Countries, 2015–2020

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.





Notes: The figure shows the border closure's effect on household expenditures within a 30-minute car ride from a crossborder location compared to households living further away than 80 minutes. I indicate the period of border closure by vertical dashed lines. The regression estimates Equation (1) and uses all the 10.8 million observations in the full grocery transaction data. Coefficients are normalized to the pre-treatment periods' average, and standard errors are clustered at the zip code level. Coefficients are exponentiated such that they equal proportional effects.

Figure A5: 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 crossborder location compared to households living further away than 80 minutes. I indicate the period of border closure by vertical dashed lines. The regression estimates Equation (1) and uses all the 28.1 million observations in the full grocery transaction data. Coefficients are normalized to the pre-treatment periods' average, and standard errors are clustered at the zip code level. Coefficients are exponentiated such that they equal proportional effects.





(a) At Least One Store With More Than 500 Google Reviews

Notes: Figure A6a shows the border closure's effect on household expenditures within a 30-minute car ride from a crossborder location compared to households living further away than 80 minutes. I consider all cross-border locations with at least one store with more than 500 Google reviews. In comparison, Figure A6b shows the same results but considers locations with at least three stores with more than 500 Google reviews. Both regressions estimate Equation (1) and use 12 million observations. Standard errors are clustered at the zip code level. Coefficients are exponentiated such that they equal proportional effects.



Figure A7: Robustness of the Dynamic Treatment Effects: Different Control Distance (a) Control Group: More than 90 min. Distance

(b) Control Group: More than 100 min. Distance



Notes: Figure A7a shows the border closure's effect on household expenditures within a 30-minute car ride from a crossborder location compared to households living further away than 90 minutes. I indicate the period of border closure by vertical dashed lines. The regression estimates Equation (1) and uses 8.8 million observations. Figure A7b also estimates Equation (1) for a distance of 100 minutes using 7.1 million observations. Coefficients are normalized to the pre-treatment periods' average, and standard errors are clustered at the zip code level. Coefficients are exponentiated such that they equal proportional effects.

Dep. Var.: Household Expenditures							
Treat \times Border Closed	0.126^{***}						
	(0.008)						
Treat \times Border Open	-0.008						
	(0.005)						
n	$7,\!051,\!422$						

Table A3: Average Treatment Effects (With a 100 min. Control Group)

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 100 minutes. The regression follows Equation (1) but groups the periods during and after the border closure together (*border closed* and *border open*, respectively). Standard errors are clustered at the zip code level. Coefficients are exponentiated such that they equal proportional effects.

		Dep.	Variable: Ho	ousehold F	Expenditures	3	
a) Hous	sehold Size	b)	Age	b) I	ncome	b) Edu	lcation
Group	Coeff	Group	Coeff	Group	Coeff	Group	Coeff
1	0.095^{***} (0.011)	20-34	0.152^{***} (0.016)	Q1	0.155^{***} (0.010)	Primary	0.134^{***} (0.016)
2	(0.0012) (0.117^{***}) (0.008)	35-44	(0.012) (0.012)	Q2	(0.013) (0.145^{***}) (0.011)	Secondary	(0.000) (0.111^{***}) (0.009)
3-4	0.152^{***} (0.010)	45-54	0.153^{***} (0.011)	Q3	0.133^{***} (0.011)	Tertiary	0.130^{***} (0.011)
≥ 5	0.162^{***} (0.014)	55-64	0.140 ^{***} (0.011)	$\mathbf{Q4}$	0.132^{***} (0.011)		× ,
		65–74	0.147^{***} (0.011)	Q5	0.132^{***} (0.014)		
		75 +	0.131^{***} (0.013)				
p-value n	0.000 3,771,701	p-value n	0.220 3,770,827	p-value n	0.199 2,979,910	p-value n	$0.062 \\ 2,509,512$

Table A4: Treatment Effects by Socioeconomic Subgroups (With a 100 min. Control Group)

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 100 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 Equation (2), standard errors are clustered at the zip code level, and the reported p-values test the equality of all coefficients. Coefficients are exponentiated such that they equal proportional effects.

Dep. Variable: Household Expenditures							
a) Natio	onality	b) C	ountry				
Group	Coeff	Group	Coeff				
African	0.169^{**} (0.059)	AT	0.097^{**} (0.034)				
Asian	(0.044) (0.044)	GER	(0.129^{***}) (0.010)				
European	0.168^{***} (0.017)	\mathbf{FR}	0.131^{***} (0.015)				
N.American	0.159^{*} (0.083)	IT	0.412^{***} (0.042)				
S.American	0.132^{*} (0.065)		· · ·				
Swiss	0.124^{***} (0.008)						
p-value n	0.071 3,771,425	p-value n	0.000 3,573,599				

Table A5: Treatment Effects by Cultural and Spatial Subgroups (With a 100 min. Control Group)

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 100 minutes, separately for different household characteristics. These characteristics include the cardholders' *nationality* and the *country* of their closest crossborder shopping location. The regression estimates Equation (2), standard errors are clustered at the zip code level, and the reported p-values test the equality of all coefficients. Coefficients are exponentiated such that they equal proportional effects.

	Dep. Var: HH Expenditures					
Dist. to ntl. Border	German	French	p-value			
Treat \times 30-45 min.	0.111^{***} (0.015)	0.014 (0.017)	0.000			
Treat \times 45-55 min.	0.064^{***} (0.018)	0.034 (0.019)	0.184			
Treat \times 55-65 min.	0.049^{***} (0.014)	0.053^{***} (0.014)	0.812			
n	695	,593				

Table A6: Cultural Differences: Effect at Language Border (With a 100 min. Control Group)

Notes: The table 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 100 minutes from the closest cross-border location. The regression estimates Equation (2) and standard errors are clustered at the zip code level. Coefficients are exponentiated such that they equal proportional effects.

	Dep. Var: Household Expenditures		
Δ Border Access	Commute Towards Border	Commute Away f. Border	p-value
Treat \times 5-15 min.	0.157^{**}	0.099***	0.459
	(0.020)	(0.020)	
Treat \times 15-25 min.	0.158^{***}	0.118^{***}	0.008
	(0.052)	(0.027)	
n	174,180		

Table A7: Treatment Effect for Different Commuting Behaviors (With a 100 min. Control Group)

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 100 minutes for different household commuting trips. These trips include commutes by car for 5-15 minutes and 15-25 minutes, 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 Equation (2) and standard errors are clustered at the zip code level. Coefficients are exponentiated such that they equal proportional effects.