Who Shops Online? The Role of Policy, Household Characteristics, and Family Networks *

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Abstract

This paper examines the unintended effects of public policy measures and social dynamics on e-commerce adoption, using a comprehensive dataset of household-level transactions at Switzerland's largest retailer matched to administrative registers. First, we study how the COVID-19 pandemic and temporary policy measures impacted the adoption of online grocery shopping in Switzerland and we document a substantial increase in online expenditures. This shift is heterogeneous: younger, larger, and richer households, as well as those with limited local store access, are particularly responsive. Moreover, we find that stricter mitigation policies intensify online usage. Second, we analyze the role of social networks in accelerating e-commerce diffusion. We highlight strong peer effects: within multi-generational families and among neighbors, the adoption of online shopping by one household significantly raises the likelihood of adoption by others. These findings underscore the impact of policy measures and the importance of social networks in shaping digital consumption behavior.

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1 Introduction

The ongoing rise of online shopping has reshaped consumption behaviors, reducing traditional search costs, expanding product varieties, and altering local retail landscapes. Thereby, e-commerce has the potential to generate substantial welfare gains, making it crucial to understand how adoption can be facilitated and how these gains are distributed across different groups.[1] Dolfen et al. (2023) quantify welfare gains from e-commerce, showing that variety and convenience effects are equivalent to a permanent income increase of about USD 1,000 per capita. Yet, although much research has focused on such market-side determinants of e-commerce expansion, the role of policy interventions in shaping adoption patterns remains largely unexplored. Similarly, while digital diffusion is often assumed to be driven by individual preferences and technological access, the role of social interactions – particularly within families – has received little attention. This paper fills these gaps by examining how government policies and peer effects within families and neighborhoods influence the adoption and diffusion of online shopping.

While these long-term trends were already reshaping retail, the COVID-19 pandemic dramatically accelerated this shift. In Switzerland, the adoption of online grocery shopping surged following the introduction of lockdown measures in March 2020. Understanding the dynamics of this shift is critical for retailers, policymakers, and researchers interested in consumer behavior and its determinants. However, few studies explore the interaction between such measures and household-specific characteristics, leaving a gap in understanding how policy and personal circumstances jointly drive behavior.

In this paper, we exploit the universe of customer-linked transactions completed online and in-store at the largest Swiss retailer between 2019 and 2020, matched with administrative register data on the entire Swiss population, to contribute in two directions to the emerging literature on e-commerce.

First, we study the heterogeneous household responses to the COVID-19 pandemic and the related governmental mobility restrictions. Note that our work also extends to other policies affecting the relative prices of online and offline shopping, such as changes in physical access to or opening hours of brick-and-mortar stores. While the COVID-19 period led to a substantial increase in e-commerce on average, we find considerable heterogeneities in the first dimension of our analysis. For instance, younger, larger, and richer households, as well as those with worse access to physical retailers, are more active e-commerce users.

We show that more stringent national mitigation policies – which raised the relative costs of visiting brick-and-mortar stores – led to increased online shopping activity. These effects translated into a persistent rise in e-commerce use of about 14 percent of the baseline probability,

[1] For instance, Brynjolfsson and Smith (2000) document lower prices and narrower dispersion online, while Bakos (2001) describes online shopping's welfare gains through reduced search costs and better fits for buyers and sellers. Such digital features remove long-standing barriers of geography – for example, Lendle, Olarreaga, Schropp and Vézina (2016) show how distance-based frictions diminish on platforms like eBay – and facilitate cross-border shopping that was once prohibitively costly.

driven largely by adoption at the extensive margin. At the same time, the underlying dynamics remained stable and continued after COVID-19 along the same pre-pandemic trend.

Second, we analyze the role of peer effects in a unique setting where one household in a multi-generational family structure adopts online shopping for the first time (meaning, parents or children act as adopters with the other generation taking the role of a potential follower). We find that parents as first adopters of e-commerce strongly increase the probability that their children adopt in the following month and *vice versa*. The effect's magnitude across our different specifications is an increase of 100–200% in both cases. We also find a sizable peer effect between neighbors.

Relating to the existing literature, prior work has largely focused on how e-commerce reshapes market structures, particularly the competition between online and offline retailers. For instance, Goldmanis, Hortacsu, Syverson and Emre (2010) and Hortacsu and Syverson (2015) find that digital commerce disrupts existing retail hierarchies, empowering certain firms while displacing others with consumers combining digital and brick-and-mortar experiences. These shifts in shopping patterns have notable implications for consumer outcomes. For instance, Cavallo (2017) documents that online and offline prices in large multi-channel retailers are identical 72% of the time, while Jo, Matsumura and Weinstein (2024) find that more efficient online markets enhance consumer welfare and exert downward pressure on markups. Similarly, Pozzi (2012) shows how reduced search costs spur greater brand exploration in online grocery shopping, while Goolsbee (2000) and Einav, Knoepfle, Levin and Sundaresan (2014) study the link between digital efficiency and tax policies. The shift toward digital platforms also intersects with consumer health, as Harris-Lagoudakis (2022) reports that online shopping patterns can influence the nutritional quality of households' grocery baskets. In comparison, we emphasize heterogeneities on the consumer side, showing that adoption patterns differ across demographic and spatial dimensions. By analyzing these differences, we shed light on the structural drivers of digital market expansion.

Furthermore, online shopping interacts with the spatial economy. Chen, Liu, Song and Zhang (2024) demonstrate that government-led e-commerce expansions can boost rural incomes, bridging economic divides previously reinforced by distance. Relihan (2024) and Farrell, Wheat, Ward and Relihan (2024) explore the complementarity and interplay between digital retail channels and localized services, especially salient during the COVID-19 period, which forced firms and consumers to adapt. Meanwhile, Einav, Farronato and Levin (2016) study how peer-to-peer platforms reconfigure traditional notions of ownership and usage, extending the logic of online retail to services and secondhand markets. Our findings align with these papers on the importance of physical access for e-commerce adoption. Beyond these geographic factors, we are the first paper to document significant peer effects, illustrating how adoption spreads within family networks and neighborhoods, reinforcing the role of social and spatial proximity in digital transitions. Previous work has documented peer effects in a range of consumption choices, such as home computer adoption (Goolsbee and Klenow, 2002) or cell phone acquisitions (Bailey et al., 2022), and in financial decisions like retirement savings behavior (Duflo and Saez, 2002).

This paper is structured as follows. Section 2 introduces the data sources and presents stylized facts. Section 3 discusses our empirical analysis and findings. Section 4 concludes.

2 Data

Data Sources and Matching

We match the universe of customer-level online and offline transaction data from the largest Swiss retailer's loyalty program 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* between 2019 and 2020, collected through their loyalty program. We observe online grocery sales as well as in-store expenditures. 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. Stores of similar size also generally offer similar goods, except for local products. The data set contains the universe of 1.3 billion customer-linked in-store purchases as well as 2 million online purchases 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.

We enrich the purchase data with individual-level administrative records for the entire Swiss population (8.7 million inhabitants in 2020), including information on gender, age, household members, labor market income, family linkages, and residence location on the same 100×100 meter grid. 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. We 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, we can match 54% of the 2.4 million regular customers, corresponding to 20% of all adult Swiss residents. We aggregate the individual online and offline shopping trips into monthly baskets and exclude customers spending less than 50 Swiss francs per capita a month, as their baskets might not capture the overall consumption accurately. Our variable of interest will, in most cases, be the share of online grocery expenditures relative to total expenditures at the retailer. This procedure generates a final data set including 1,064,155 households and 22 million monthly consumption baskets.[2]

[2] See Kluser and Pons (2024) and Kluser (2025) for additional information on the two data sources, the matching procedure, and the representativeness of the matched households for the general population.

Table 1: Final Data Summary Statistics

	Final Sample		Population	
Panel a)	Mean	SD	Mean	SD
Expenditures in-store	286.58	220.01		
Expenditures online	4.32	40.70		
Share E-Commerce	0.65%	4.89%		
Age	55.10	16.61	54.88	17.50
Panel b)	Pct.	N	Pct.	N
Household size				
1 member	21.4	227,560	37.1	1,471,897
2 members	36.2	384,950	32.9	1,306,437
3-4 members	35.0	372,375	25.0	991,644
5+ members	7.4	79,270	5.0	200,092
Observations		1,064,155		3,987,616

Summary Statistics

Table 1 provides further insights into the households included in the final dataset. On average, households spent 286 Swiss francs in physical stores (SD: 220) and 4.32 Swiss francs online (SD: 40.70), suggesting that while online grocery shopping remained a relatively small share of total expenditures during 2019 and 2020, its variability across households was substantial. The mean share of online grocery expenditures in our sample is 0.65 percent, but exhibited again a high standard deviation of 4.89 percent, indicative of considerable heterogeneity in the adoption of online grocery shopping.

The dataset captures a diverse range of household sizes. A significant share of households consisted of two members (36.2 percent), followed closely by three- to four-member households (35.0 percent). Furthermore, 57,000 households in the dataset (meaning, 5.4 percent) engaged in any online grocery shopping during the observed period. Of these, 40,000 households shopped online repeatedly, underscoring that many adopters integrated online shopping into their regular routines.

The data also reveal interesting patterns in shopping frequency and expenditure levels. The median household engaged in online shopping three times during the period, while the mean number of transactions was eight, indicating a skewed distribution in shopping frequency. For individual transactions, the median expenditure was 204 Swiss francs, while the mean was 228 Swiss francs, reflecting relatively high-value purchases. These patterns suggest that households relied on online grocery shopping for bulk purchases or infrequent, larger shopping trips, potentially to minimize delivery fees or reduce the need for repeated online interactions.

Stylized Facts

We start with descriptive insights into the adoption of online grocery shopping during the COVID-19 pandemic, highlighting key patterns in the data and setting the stage for the empirical analysis. COVID-19 cases began to rise sharply in Switzerland in early March 2020, prompting the government to implement stringent mitigation measures. These measures varied significantly over time and across regions due to the country's strong federalist structure. The index developed by Pleninger, Streicher and Sturm (2022) quantifies their stringency.[3] The measures notably restricted mobility and access to physical retail and might have pushed households toward digital alternatives, particularly for essential services such as grocery shopping.[4]

Supporting this hypothesis, Figure 1 documents indeed a rise in online grocery shopping during this period, which is parallel to the overall development of mitigation policies. The left panel shows the cumulative increase in the number of households adopting online grocery shopping, with a clear acceleration associated with the introduction of lockdown measures. The right panel highlights the growth in the share of total expenditures allocated to online grocery shopping, indicating a structural shift in consumption patterns. Together, these figures provide some first evidence of the pandemic's transformative impact on consumer behavior.

Overall, the descriptive evidence highlights the pandemic's role as a catalyst for the adoption of online grocery shopping, with patterns reflecting both the constraints imposed by COVID-19 mitigation measures and the heterogeneity in household characteristics. To place our findings in a broader context, Figure 1c contrasts our evidence with longer-term trends from payment transaction data provided by *Monitoring Consumption Switzerland*, a database covering detailed and representative credit card payment data for Switzerland introduced by Brown et al. (2023). The comparison confirms the representativeness of our data, as the two series are closely correlated during periods of overlap.[5] Both sources show similar pre-COVID-19 trends and a sharp increase at the pandemic's onset. We further document that these effects indicate a sustained shift toward e-commerce, even though expenditures later converged back to their pre-COVID-19 trajectory. These stylized facts form the basis for our empirical analysis, in which we quantify the role of policy measures restricting mobility during the pandemic and examine which types of households responded most strongly to the COVID-19 shock.

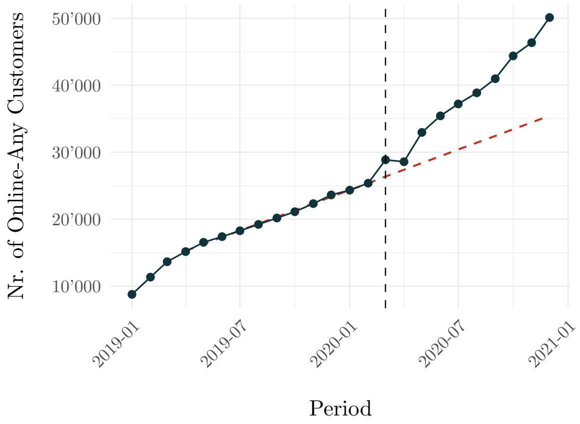
[3]The KOF stringency index ranges from 0 (= no measures) to 100 (= full lockdown). The index considers restrictions in areas such as school closing, workplace closing, cancellation of public events, restrictions on gatherings, closure of public transport, stay-at-home requirements, restrictions on internal movement, international travel controls, public info campaigns, and facial coverings. The daily index varies over time and the 26 Swiss cantons and we take the maximum cantonal value for each month.

[4]See https://kof.ethz.ch/prognosen-indikatoren/indikatoren/kof-stringency-index.html for a timeline of COVID-19 cases and stringency of COVID-19 Mitigation policies in Switzerland.

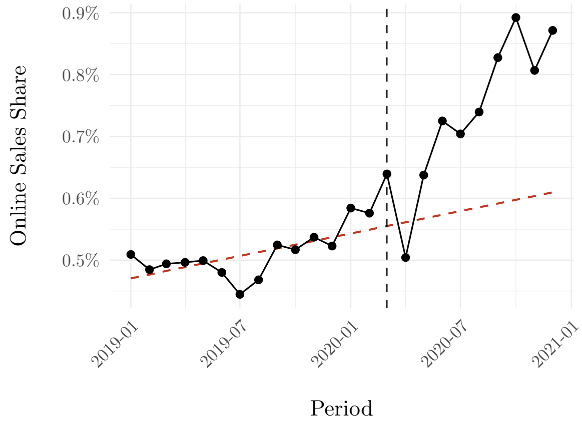
[5]We compute the online expenditure share of total grocery expenditures from the credit card payments data. We observe a divergence between the two sources in the first month of the COVID-19 pandemic, likely reflecting capacity constraints in scaling up *Migros*' online grocery services.

Figure 1: Recent Evolution of E-Commerce in Switzerland

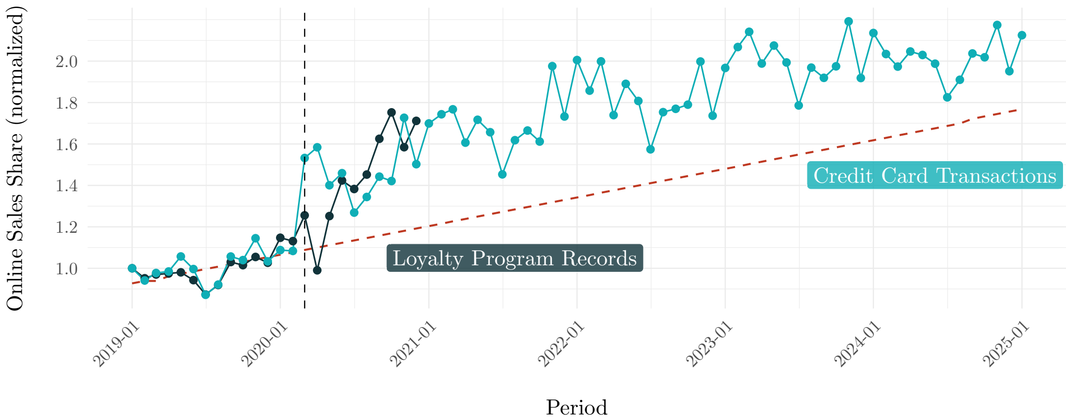
(a) Number of E-Commerce Adopters



(b) Avg. Share of Online Expenditure



(c) Online Expenditures from Grocery vs. Credit Card Payment Data



Notes: Figure 1a shows the number of e-commerce adopters over time; i.e. the cumulative number of households that use e-commerce in our loyalty program records for grocery shopping. The blue line shows a linear continuation of the pre-pandemic evolution (with the first periods omitted as a "burn-in" period). Figure 1b shows the average share of online household expenditures in the loyalty program records relative to total online and in-store expenditures in our estimation sample. Figure 1c compares our loyalty program records to credit card transactions on online expenditures for groceries from *Consumption Monitoring Switzerland* (see Brown et al., 2023). We normalized both time series to one at the start of the series. The dashed line indicates the extrapolated pre-pandemic household trend.

3 Empirical Analysis

This section presents our empirical approach and findings. The first part discusses emerging patterns in e-commerce that we observe in our data and studies how the COVID-19 pandemic and related mitigation policies correlate with the observed online shopping behavior. The second part studies how digital e-commerce technologies spread within multi-generational families and neighborhoods.

3.1 COVID-19 Restrictions and Online Shopping

Estimation

We estimate the evolution of e-commerce in Switzerland over time with the following estimation equations:

$$Y_{it} = \delta_i + \alpha t + \gamma D_t + \beta(D_t \times X_i) + \epsilon_{it}, \tag{1}$$

$$Y_{it} = \delta_i + \alpha_t + \beta(D_t \times X_i) + \epsilon_{it}, \tag{2}$$

where Y_{it} is the percentage share of household i's online grocery expenditures relative to the total expenditures (meaning, online and in-store) in month t. The binary treatment indicator D_t turns one as soon as Switzerland imposes the first rigorous measures to mitigate the spread of the COVID-19 pandemic in March 2020. Hence, D_t does not vary between individual households. δ_i are time-constant household-level fixed effects, and X_{it} includes time-constant household- and location-level covariates interacted with the treatment. Finally, αt allows for a linear trend in the outcome variable in some specifications that we discuss, while Equation (2) estimates more flexible time fixed effects for every week. Note that in the latter case, it is not possible to estimate γ, as α_t and D_t are perfectly multicollinear. Furthermore, we always cluster on the household level.

We extend our analysis by incorporating a continuous measure of mitigation policies. Specifically, we replace the binary treatment indicator D_t with the continuous stringency index S_{ct}, as introduced by Pleninger et al. (2022):

$$Y_{ict} = \delta_i + \alpha t + \theta S_{ct} + \beta(S_{ct} \times X_i) + \epsilon_{ict}, \tag{3}$$

$$Y_{ict} = \delta_i + \alpha_t + \theta S_{ct} + \beta(S_{ct} \times X_i) + \epsilon_{ict}. \tag{4}$$

In these specifications, S_{ct} captures the time- and region-specific stringency of policy measures implemented in canton c at time t, while all other variables remain unchanged. Specification (4), in particular, exploits regional variation in policy stringency and the associated increased mobility costs to estimate its impact on online shopping behavior.

This framework can be interpreted as a difference-in-differences design with continuous treatment intensity (see, for example, Finkelstein, 2007 or Ahlfeldt et al., 2018). Identification relies on a generalized parallel trends assumption, which imposes that in the absence of changes in policy stringency, differences in online expenditure shares across cantons would have followed similar trends. In addition, the causal identification rests on the assumption that changes in stringency are exogenous to canton-specific shocks in shopping behavior.

Determinants of Online Shopping

We start discussing our findings with the first specification, later elaborating on the relevant changes if we incorporate the stringency of policy measures. Table 2 presents the baseline correlations between the COVID-19 pandemic and online grocery shopping, as measured by the share of household grocery expenditures spent online. Model (1) starts with the COVID-19 dummy and a linear trend as independent variables. Model (2) adds income, age, and the distance to the closest store of our retailer to the estimation. In model (3), we replace the simple distance to the closest Migros supermarket with a more global measure for supermarket accessibility in a given location as estimated in Kluser, Seidel and von Ehrlich (2024).[6] Model (4) adds the number of household members as a categorical variable (with two-person households as the baseline), while model (5) replaces the linear trend with the time fixed effects in Equation (2).

Overall, our results underscore a significant shift in consumer behavior during the pandemic. The binary COVID-19 indicator captures the initial effect of the pandemic's onset, revealing a robust and significant increase in online shopping. Specifically, the pandemic is associated with a baseline increase in online expenditures of approximately 0.07 percentage points, a substantial relative increase of 14% relative to the pre-treatment average e-commerce share of 0.51%. This result highlights the immediate behavioral response to the first lockdown measures introduced in Switzerland in March 2020. Moreover, the positive and highly significant linear trend in all specifications suggests that this shift in behavior was not merely transitory but part of a broader structural transformation in consumer habits.

Household-level heterogeneities provide further insights. Older households exhibited smaller increases in online expenditures, as reflected by the negative coefficient on the interaction term between COVID-19 and age. The coefficients are estimated using demeaned variables, meaning the effect of COVID-19 policies on online expenditures approaches zero at approximately 22 years above the mean age of 55. Similarly, households located further from physical stores showed larger increases in online expenditures, underscoring the importance of geographical accessibility in shaping the relative attractiveness of online shopping. Again, the effects are quantitatively relevant; a ten percent increase in the distance to the next store (relative to the mean distance) increases the impact of the COVID-19 pandemic by about 0.22 percentage points. Larger and richer households also responded more strongly. The increase is the most pronounced for those with three to four members. These households likely faced heightened logistical challenges during the pandemic, making the convenience of online shopping particularly appealing. In fact, the effect almost doubles for three-to-four-person households compared to the average two-person household. In contrast, households with five or more members exhibited no significant differential response, potentially reflecting alternative coping mechanisms or a higher reliance on in-store shopping for bulk purchases. Finally, a higher household income significantly increases

[6] The paper uses supermarket openings to estimate causal equivalents to standard gravity equation estimates, suffering from the endogeneity of residential and store location choice. The authors use their empirical estimates combined with a simple theoretical model of spatial shopping to provide utility-based measures for shopping access in Switzerland with a high spatial resolution of 100×100-meter cells.

Table 2: Determinants of Online Shopping Behavior

Dependent Variable:	Share of Online Grocery Expenditures × 100 *Pre-treatment mean: 0.51%*				
Model:	(1)	(2)	(3)	(4)	(5)
COVID-19	0.0708***	0.0704***	0.0702***	0.0499***	
	(0.0051)	(0.0051)	(0.0051)	(0.0074)	
Linear Trend	0.0168***	0.0169***	0.0169***	0.0168***	
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	
COVID-19 × Log income		0.0285***	0.0304***	0.0240***	0.0245***
		(0.0047)	(0.0047)	(0.0047)	(0.0047)
COVID-19 × Age		-0.0218***	-0.0216***	-0.0221***	-0.0217***
		(0.0019)	(0.0019)	(0.0019)	(0.0019)
COVID-19 × Age^2		0.0002***	0.0002***	0.0002***	0.0002***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
COVID-19 × Log dist. next store		0.0218***		0.0202***	0.0198***
		(0.0037)		(0.0037)	(0.0037)
COVID-19 × Access			-0.0103**		
			(0.0044)		
Household Members (Base: 2 members)					
COVID-19 × 1 member				-0.0381***	-0.0381***
				(0.0107)	(0.0107)
COVID-19 × 3-4 members				0.0698***	0.0701***
				(0.0099)	(0.0099)
COVID-19 × 5+ members				-0.0401**	-0.0396**
				(0.0182)	(0.0182)
Household Fixed Effects	Yes	Yes	Yes	Yes	Yes
Period Fixed Effects					Yes
Observations	18,563,332	18,563,332	18,563,332	18,563,332	18,563,332
R^2	0.54224	0.54227	0.54227	0.54228	0.54240

Notes: This table presents estimates from Equation (1) and Equation (2), examining how the COVID-19 pandemic and household characteristics correlate with the share of grocery expenditures conducted online. The dependent variable is the percentage of total expenditures made online. The binary COVID-19 indicator captures the immediate shift after the onset of the pandemic in March 2020. Interactions with age, income, store accessibility, and household size identify heterogeneous responses. Models differ by whether they include a linear time trend or time fixed effects. The logarithms of *income* and the *distance* to the next store, *Age*, and Age^2 are demeaned, while *Access* is standardized. Columns (4) and (5) use two-person households as the reference group. Standard errors are clustered at the household level. The baseline mean of online expenditure share before the pandemic is about 0.51%.

the effect of policy measures on online expenditures. A ten percent increase in income yields a 0.29 percentage point increase (4%) in the policy response relative to the average. This pattern is consistent with richer households reducing mobility during the crisis by working from home and substituting more strongly toward e-commerce. By contrast, households whose members continued commuting to workplaces or service jobs still incurred the costs of city-center mobility and interpersonal contact, making brick-and-mortar shopping relatively less substitutable (see Dingel and Neiman, 2020).

Table 3: Determinants of Online Shopping Behavior (including Stringency)

Dependent Variable:	Share of Online Grocery Expenditures × 100 *Pre-treatment mean: 0.51%*				
Model:	(1)	(2)	(3)	(4)	(5)
Stringency	0.3338***	0.0022**	0.0022**	-0.0012	0.3308***
	(0.0276)	(0.0011)	(0.0011)	(0.0017)	(0.0276)
Linear Trend		0.0206***	0.0206***	0.0206***	
		(0.0004)	(0.0004)	(0.0004)	
Stringency × Log income		0.0064***	0.0068***	0.0053***	0.0056***
		(0.0011)	(0.0011)	(0.0011)	(0.0011)
Stringency × Age		-0.0042***	-0.0042***	-0.0042***	-0.0041***
		(0.0004)	(0.0004)	(0.0004)	(0.0004)
Stringency × Age^2		0.0001***	0.0001***	0.0001***	0.0001***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
Stringency × Log dist. next store		0.0038***		0.0035***	0.0033***
		(0.0009)		(0.0009)	(0.0009)
Stringency × Access			-0.0026***		
			(0.0010)		
Household Members (Base: 2 members)					
Stringency × 1 member				-0.0111***	-0.0112***
				(0.0025)	(0.0025)
Stringency × 3-4 members				0.0148***	0.0146***
				(0.0023)	(0.0023)
Stringency × 5+ members				-0.0132***	-0.0131***
				(0.0043)	(0.0043)
Household Fixed Effects	Yes	Yes	Yes	Yes	Yes
Period Fixed Effects	Yes				Yes
Observations	18,563,332	18,563,332	18,563,332	18,563,332	18,563,332
R^2	0.54237	0.54224	0.54224	0.54225	0.54239
Post-Treat Mean of Stringency	57.97	57.97	57.97	57.97	57.97

Notes: This table extends the results from Table 2 by including a continuous, regionally varying stringency index from Pleninger, Streicher and Sturm (2022) and estimating Equation (3) and Equation (4). Note that this indicator has been standardized. Again, *income*, the *distance* to the next store, *Age*, and Age^2 are demeaned, while *Access* and *Stringency* are standardized. Standard errors are clustered at the household level.

Role of Mitigation Policies' Stringency

Table 3 refines our analysis by replacing the binary COVID-19 indicator with a continuous, regionally varying stringency index. This allows us to capture more granular associations between mitigation policies and online grocery consumption. It also brings us closer to a causal interpretation, as stringency measures are arguably exogenous to online shopping behavior. Our estimates reveal a positive and highly significant effect: stricter mitigation measures were associated with a substantial increase in the share of online grocery expenditures. This result highlights that beyond the pandemic's direct shock, the intensity of restrictions played a crucial role in driving adoption, with regions and periods facing tighter measures experiencing stronger shifts toward online shopping. When we include period-specific fixed effects in column (5), exploiting only spatial variation in stringency, we find that a one-standard-deviation increase in stringency raises the probability of online shopping by 0.33 percentage points, corresponding to about 60 percent of the baseline probability. **@Max: do you have to codes open to finish this XX number?** – Comparing the canton with the highest stringency to the canton with the lowest, we estimate that the former experienced a [XX%] stronger growth in e-commerce activity.

Demographic and spatial heterogeneities in Table 3 closely mirror those observed in Table 2. Older households continued to show more modest initial increases, while distance to the nearest physical store and income remained strong determinants of online adoption, reinforcing the idea that geographical barriers heightened the utility of online shopping. Differential responses by household size also persisted, with three- to four-member households exhibiting the strongest uptake. Taken together, Table 2 and Table 3 demonstrate not only the widespread behavioral shifts induced by the pandemic but also the critical role of policy and household characteristics in shaping these changes.

Extensive Margin

Table 4 reports the determinants of online shopping behavior at the extensive margin, where the dependent variable is an indicator for whether a household shops online. Before the pandemic, the mean probability of online shopping was just 0.94%, highlighting the limited use of online grocery services.

Columns (1)–(3) present the COVID-19 specifications, where treatment is a binary indicator equal to one after the onset of the pandemic in March 2020. Across these specifications, the COVID-19 shock increased the likelihood of shopping online by about 0.14 percentage points relative to the baseline, a large effect given the low pre-treatment mean of 0.94%. Heterogeneity analysis shows that higher-income households and those living farther from grocery stores were significantly more likely to adopt online shopping at the beginning of the pandemic. Household size also plays an important role: single-member households were less likely to switch online, whereas households with three to four members showed substantially higher adoption rates.

Columns (4)–(6) report the stringency specifications, where treatment intensity is measured using the continuous, regionally varying index from Pleninger et al. (2022). We see that greater policy stringency is strongly associated with higher online shopping participation. The main effects are large and statistically significant across specifications, confirming that mobility restrictions were a powerful driver of adoption. Heterogeneity patterns largely mirror those from the COVID-19 specifications: income and distance to the nearest store amplified the effect of stringency, while older age reduced it moderately. Single households remained less responsive, whereas medium-sized households of three to four members showed the largest increases.

From an identification perspective, column (6) provides the most credible estimates, as it includes both household and period fixed effects. The coefficient implies that exposure to one standard deviation higher stringency raised the probability of starting online shopping by about 0.55 percentage points (roughly half the baseline probability), indicating a quantitatively meaningful

Table 4: Determinants of Online Shopping Behavior – Extensive Margin

Dependent Variable:	Probability of online shopping (%) *Pre-treatment mean: 0.94%*					
	Treat = COVID-19			Treat = Stringency		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Treat	0.1373***	0.1365***		0.5625***	0.0171***	0.5549***
	(0.0088)	(0.0088)		(0.0456)	(0.0018)	(0.0457)
Linear Trend	0.0312***	0.0314***			0.0358***	
	(0.0006)	(0.0006)			(0.0006)	
Treat × Log income		0.0628***	0.0542***		0.0151***	0.0133***
		(0.0076)	(0.0077)		(0.0018)	(0.0018)
Treat × Log dist. next store		0.0250***	0.0201***		0.0041***	0.0028**
		(0.0061)	(0.0061)		(0.0014)	(0.0014)
Treat × Age		-0.0358***	-0.0359***		-0.0067***	-0.0067***
		(0.0032)	(0.0032)		(0.0007)	(0.0007)
Treat × Age^2		0.0003***	0.0003***		0.0001***	0.0001***
		(0.0000)	(0.0000)		(0.0000)	(0.0000)
Household Members (Base: 2 members)						
Treat × 1 member			-0.0939***			-0.0263***
			(0.0168)			(0.0039)
Treat × 3-4 members			0.1492***			0.0331***
			(0.0162)			(0.0038)
Treat × 5+ members			-0.0235			-0.0095
			(0.0302)			(0.0071)
Household Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Period Fixed Effects			Yes	Yes		Yes
Observations	18,563,332	18,563,332	18,563,332	18,563,332	18,563,332	18,563,332
R^2	0.49769	0.49773	0.49789	0.49785	0.49770	0.49788

Notes: This table presents the extensive margin estimates for the COVID-19 and the stringency models. The dependent variable is an indicator of whether a household shops online or not. The first three columns refer to the COVID-19 specifications with a binary COVID-19 indicator capturing the immediate shift after the onset of the pandemic in March 2020. The second three columns refer to the stringency specifications using a continuous, regionally varying stringency index from Pleninger, Streicher and Sturm (2022) as treatment. Note that the latter index has been standardized. In each specification, we allow for interactions with age, income, store accessibility, and household size to identify heterogeneous responses. Models differ by whether they include a linear time trend or time fixed effects. The logarithms of *income* and the *distance* to the next store, *Age*, and Age^2 are demeaned. Standard errors are clustered at the household level. The baseline probability of shopping online before the pandemic is about 0.94%.

and plausibly causal effect of policy restrictions.

Taken together, the results on expenditure shares and online shopping probabilities indicate that both the pandemic shock and variation in policy stringency substantially altered household consumption behavior. The similarity between the binary and continuous treatment results reinforces the interpretation that mobility restrictions played a central role in driving online adoption at the extensive margin. Overall, the pandemic's impact appears to have operated primarily through the extensive rather than the intensive margin of e-commerce usage. Heterogeneous responses further highlight that adoption drivers were not uniform: households with higher opportunity costs of in-store shopping, like higher-income families, larger households, and those living farther from stores, were particularly likely to switch online.

Table 5: Peer Effects in Online Shopping Adoption

Dependent Variables:	Any Online Expenditure Follower								
	Child→ Parents			Parents→ Child			Neighbors		
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	0.0084***			0.0489***			0.0352***		
	(0.000)			(0.0001)			(0.0002)		
Adopter, t-1	0.0198***	0.0131***	0.0097***	0.0963***	0.0662***	0.0492***	0.0134***	0.0166***	0.0028***
	(0.0002)	(0.0007)	(0.0007)	(0.0010)	(0.0034)	(0.0034)	(0.0005)	(0.0003)	(0.0003)
Follower F. E.		Yes	Yes		Yes	Yes		Yes	Yes
Period F. E.			Yes			Yes			Yes
Observations	4,622,340	4,622,340	4,622,340	4,622,340	4,622,340	4,622,340	11,442,875	11,442,875	11,442,875
R^2	0.00199	0.68155	0.68460	0.00183	0.77211	0.77962	0.0009	0.8725	0.8742
Avg. Follower F.E.	-	0.0094	0.0094	-	0.0497	0.0497	-	0.0239	0.0239

Notes: This table reports estimation results for peer effects in online shopping adoption from Equation (5). Columns (1)–(3) show how parental online adoption responds to a child's first-time online shopping in the previous period, while Columns (4)–(6) show how children's adoption responds to parents' prior adoption. Household and time fixed effects are included in some specifications to control for unobservable, time-invariant household traits and common temporal shocks. Standard errors are clustered at the household level.

3.2 Peer Effects in Online Shopping Adoption

The second part of our analysis investigates peer effects in online consumption within families and neighborhoods. Following Kluser and Pons (2024), who exploit family linkages in administrative data to study intergenerational persistence in eating behaviors, we study how adopters of e-commerce trigger adoption among close social contacts. We extend the setting in two ways. First, we consider both directions of influence within the family (child → parent and parent → child). Second, we incorporate peer effects from neighbors.

Formally, we estimate the following regression specification:

$$Follower_{jt} = \beta Adopter^{H}_{i,t-k} + \delta_j + \alpha_t + \epsilon_{jt}, \tag{5}$$

where $Follower_{jt}$ indicates whether household j shops online in period t, and $Adopter^{H}_{i,t-k}$ captures adoption by a peer household i of type $H \in \{\text{parent, child, neighbor}\}$ in period t minus lag k. We define adopters as consumers engaging for the first time in online shopping at the observed retailer.[7] The specification includes household fixed effects δ_j and time fixed effects α_t, and standard errors are clustered at the household level. Furthermore, we define neighbors as households living in close proximity of less than 100 meters.[8]

A key challenge is that our sample window begins in January 2019, while adoption could have occurred earlier. Early adopters may therefore appear as if they adopted within our sample window. To address this, we use January–December 2020 as the main analysis window, treating 2019 as a "burn-in" period to correctly identify prior adopters.

[7] Robustness checks using online expenditures confirm the spillover results reported here.

[8] Spillovers persist for larger distances but decline with increasing distance.

Discussion

Table 5 presents the estimation results based on Equation (5), organized into three blocks. Columns (1)–(3) show the effect of children's adoption on their parents' subsequent online shopping behavior. Columns (4)–(6) reverse the direction, examining whether parents' adoption induces children to shop online. Columns (7)–(9) document neighborhood peer effects, where influence is undirected, reflecting exposure to nearby households rather than hierarchical family links.

Columns (1)–(3) indicate that children exert a strong influence on parental online adoption. In the simplest specification without fixed effects (Column 1), the baseline probability that parents shop online in a given period is roughly 0.8 percent. If a child adopted in the prior period, this probability rises by about 2 percentage points, more than tripling the baseline. Adding household and period fixed effects attenuates the effect but leaves it economically meaningful: the response remains near 1 percentage point in Column (3), still more than double the baseline. These findings suggest substantial upward intergenerational influence, with younger household members acting as early adopters of new technologies and prompting older generations to follow.

Columns (4)–(6) show that the reverse channel is also strong. Without parental adoption, the baseline probability that children shop online is around 4.9 percent. When parents adopt in the previous period, this probability increases by nearly 10 percentage points in the simplest specification (Column 4), raising adoption to over 14 percent or a threefold increase. With household and period fixed effects (Columns 5–6), the effect remains large at roughly 7 and 5 percentage points, respectively. Thus, children are about twice as likely to start shopping online when their parents have already adopted. Although point estimates suggest a slightly stronger spillover from parents to children, this difference is not statistically significant, highlighting bidirectional intergenerational dynamics.

The third block (Columns 7–9) documents neighborhood peer effects. Here, the baseline adoption probability is about 3.5 percent. Exposure to neighbors who adopted in the prior period increases this probability by 1.3 to 1.7 percentage points without fixed effects, a relative increase of roughly 40 to 50 percent. Including household and period fixed effects reduces the effect to 0.3 percentage points (Column 9), but it remains statistically significant. Compared to the strong intergenerational effects, neighborhood spillovers are more modest, yet they underscore the role of local social interactions in online shopping diffusion.

Overall, these results reveal robust and economically meaningful peer effects. Intergenerational influence within families doubles or triples adoption probabilities, emphasizing the importance of family links in shaping technology uptake. Neighborhood effects, although smaller, align with the broader literature on social interactions, showing that individuals are not only influenced by family members but also by peers in their local environment. The tight standard errors further reinforce the credibility of these findings.

4 Conclusion

The findings of this paper highlight the policy sensitivity of online shopping adoption and the crucial role of social dynamics, particularly within families and neighborhoods. Mobility restrictions during the COVID-19 pandemic had a transformative impact on online grocery shopping in Switzerland. Using detailed transaction-level data from Migros, the country's largest retailer, we document a substantial and persistent shift toward online shopping in 2020. Our analysis shows that both household characteristics and external factors, such as government restrictions, drove this behavioral change. While these policies were unique to the pandemic, similar shifts in the relative costs or convenience of online versus physical shopping could also arise from changes in regulations, such as store opening hours or access limitations.

The results reveal that the pandemic acted as a catalyst for online shopping adoption, with households located further from physical stores and certain demographic groups (younger, larger, and wealthier households) responding particularly strongly. Regional differences in the stringency of restrictions further shaped these effects: stricter measures initially slowed adoption but ultimately accelerated uptake as households adapted to prolonged limitations. Beyond these macro-level patterns, our analysis of intergenerational peer effects and neighborhood spillovers highlights the social dynamics of online shopping. The bidirectional influence between parents and children shows how digital adoption spreads within families, emphasizing the role of household interactions and information exchange in technology diffusion beyond the effect of physical closeness between neighbors. These findings have important implications. Policymakers should consider how digital infrastructure and support measures can ensure equitable access, while retailers can better serve households with limited physical access by offering attractive online alternatives.

While this paper provides valuable insights into the drivers and dynamics of online grocery shopping, future research could examine the long-term persistence of these behavioral shifts. Additionally, investigating the environmental and nutritional consequences of increased online shopping could also provide a more comprehensive view of its societal impact. In sum, the pandemic-induced surge in online grocery shopping represents not only a response to an extraordinary global event but also a potential structural transformation in consumer behavior, with lasting implications for the retail landscape.

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