Determinants of Online Shopping Behavior *

Frédéric Kluser †
University of Bern

Maximilian v. Ehrlich ‡
University of Bern

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Abstract

This paper investigates two areas of e-commerce adoption. First, we study how the COVID-19 pandemic and related policy measures shaped online grocery shopping adoption in Switzerland. Second, we analyze the role of close family ties in accelerating e-commerce diffusion. Using a comprehensive dataset of household-level transactions at the nation's largest retailer matched to administrative registers, we document a substantial increase in online expenditures. This shift is heterogeneous: younger and larger households, as well as those with limited local store access, are particularly responsive. Moreover, using a stringency index, we find that stricter mitigation policies intensify online usage. We also highlight strong intergenerational peer effects: within multi-generational families, when one generation adopts online shopping, the other is one to two times more likely to adopt as well. Our findings highlight both the policy sensitivity of digital market penetration and the social dynamics that accelerate technology diffusion in retail.

1 Introduction

The ongoing rise of online shopping has reshaped consumption behaviors, reducing traditional search costs, expanding product varieties, and altering local retail landscapes. For instance, Brynjolfsson and Smith (2000) document lower prices and narrower dispersion online, while Bakos (2001) describes the welfare gains through reduced search costs and better fits for buyers

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†University of Bern, Department of Economics, Schanzeneckstrasse 1, CH-3001 Bern, frederic.kluser@unibe.ch

‡University of Bern, Department of Economics and the Center for Regional Economic Development (CRED), Schanzeneckstrasse 1, CH-3001 Bern, maximilian.vonehrlich@unibe.ch

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. At the same time, Goolsbee (2000) and Einav, Knoepfle, Levin and Sundaresan (2014) underscore how tax policies continue to influence these new marketplaces, highlighting the link between digital efficiency and regulatory constraints.

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. 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). 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 and larger households and those with worse access to physical retailers are more active e-commerce users. We show that the stringency of national mitigation measures plays an important role. Using the KOF Stringency index from Pleninger, Streicher and Sturm (2022), we find that a more stringent mitigation policy – increasing the relative costs of visiting a brick-and-mortar store – is associated with an increase in online shopping activity. Our second contribution is on peer effects. 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 a 100–200% increase in both cases.

Relating to the existing literature, previous contributions refined our understanding of how e-commerce affects both market structure and welfare in general. 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. 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.

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.

Underpinning these transformations is the broader digital economy that rewires how information is produced, exchanged, and consumed. Goldfarb and Tucker (2019) synthesize a decade of digital economics, documenting how technology platforms shape market outcomes and consumer behaviors. Even the allocation of time interacts with these changes: Aguiar and Hurst (2007) illustrate how shifting leisure trends over decades create space for more online engagement, reinforcing the e-commerce ecosystem's growth and stability. In turn, Willis (2004) questions what these changes mean for the economy as a whole, discussing digitalization's impact on productivity, employment, and regional development.

This paper is structured as follows. Section 2 introduces the data, 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

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

members, 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.[1]

Summary Statistics

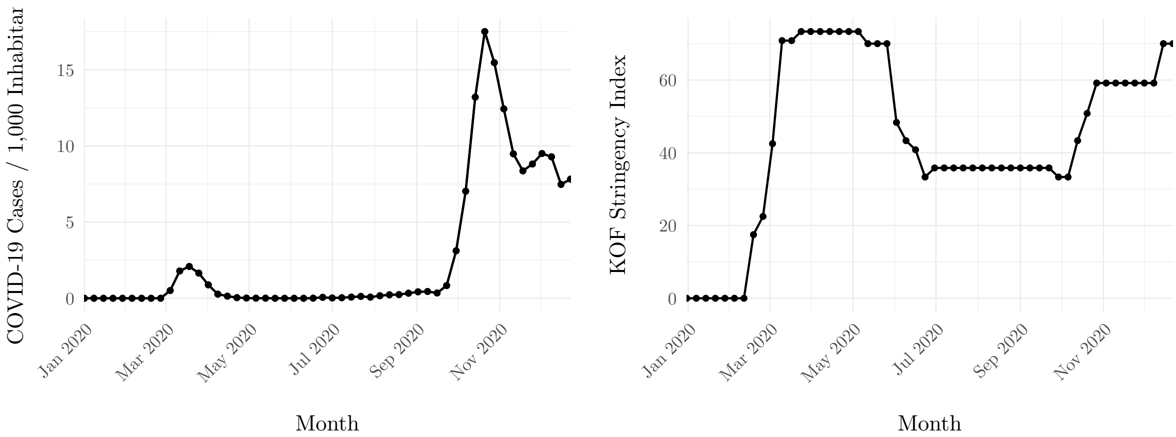
Table 1 provides further insights into the households included in the final dataset. On average, households spent 286 Swiss francs in physical stores (SD: 220) and 4.32 Swiss francs online (SD: 40.70), suggesting that while online grocery shopping remained a relatively small share of total expenditures 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

[1]See 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.

Figure 1: COVID-19 and Mitigation Measures

(a) Evolution of COVID-19 Cases

(b) Stringency of COVID-19 Mitigation



Notes: Figure 1a shows the evolution of the cantonal COVID-19 cases per 1,000 inhabitants. Figure 1b shows the KOF Stringency Index for the mitigation measures' stringency in Switzerland.

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). 57,000 households in the dataset (meaning, 5.4 percent) engaged in 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.

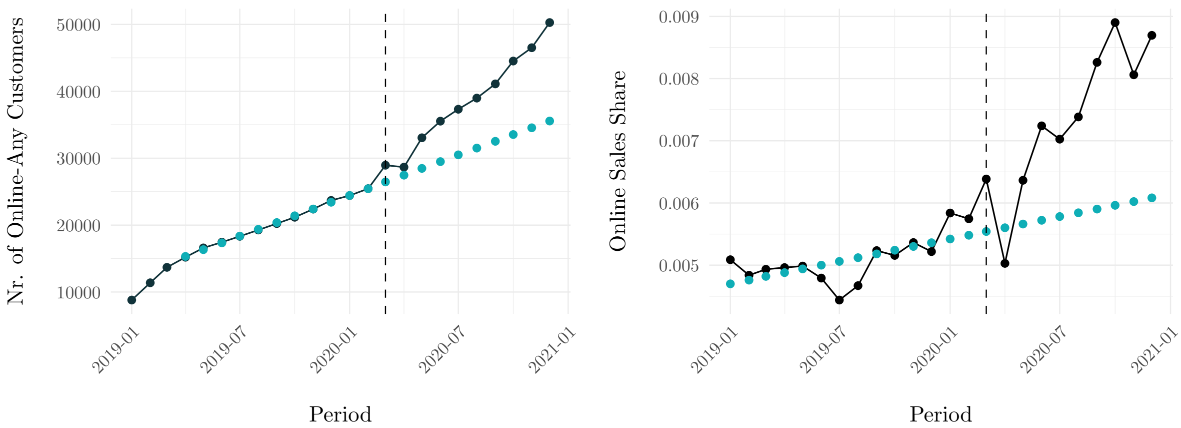
The data also reveal interesting patterns in shopping frequency and expenditure levels. The median household engaged in online shopping three times during the period, while the mean number of transactions was eight, indicating a skewed distribution in shopping frequency. For individual transactions, 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. Figure 1 illustrates the evolution of COVID-19 cases and the corresponding governmental response in Switzerland. The timeline is marked by a sharp rise in cases beginning in March 2020 and the corresponding introduction of stringent mitigation measures, as

Figure 2: Recent Evolution of E-Commerce in Switzerland

(a) Number of E-Commerce Adopters (b) Avg. Share of Online Expenditure



Notes: Figure 2a shows the number of e-commerce adopters over time. The blue line shows a linear continuation of the pre-pandemic evolution (with the first periods omitted as a "burn-in" period). Figure 2b shows the average share of online household expenditures relative to total online and in-store expenditures in our estimation sample.

captured by the KOF Stringency from Pleninger, Streicher and Sturm (2022).[2] These measures, which restricted mobility and access to physical retail, might have pushed households toward digital alternatives, particularly for essential services such as grocery shopping.

Supporting this hypothesis, Figure 2 documents indeed a parallel rise in online grocery shopping during this period. 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. These stylized facts provide a foundation for understanding the mechanisms driving the observed behavioral changes, which are further explored in the empirical analysis that follows.

[2]The KOF stringency index range from 0 (= no measures) to 100 (= full lockdown), measuring the stringency of mitigation policies. 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, facial coverings. The daily index varies over time and the 26 Swiss cantons and we take the maximum cantonal value for each month.

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 the adaption of digital e-commerce technologies spread within multi-generational families.

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:

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

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

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 multi-collinear. Furthermore, we always cluster on the household level.

We extend these analyses with further evidence on the role of mitigation policies by incorporating the continuous, regionally varying KOF stringency index:

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

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

where S_{ct} is the policy measures' stringency in canton c at time t and everything else remains unchanged.

Determinants of Online Shopping

We start discussing our findings with the first specification, later elaborating on the relevant changes if we add stringency to the model. Table 2 presents the baseline correlations between the COVID-19 pandemic and online grocery shopping, as measured by the share of household grocery expenditures conducted online. Model (1) starts with the COVID-19 dummy and a linear trend as independent variables. Model (2) adds 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).[3] Model (4) adds the number of household measures as a categorical variable, 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 0.08 percentage points, a substantial relative increase given the pre-treatment mean 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. Similarly, households located further from physical stores showed larger increases in online expenditures, underscoring the role of geographical accessibility in shaping the relative attractiveness of online shopping. Larger households also responded more strongly, with the increase 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 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.

Role of Mitigation Policies' Stringency

Table 3 extends the analysis by incorporating a continuous, regionally varying measure of government-imposed stringency during the pandemic. This allows for a more nuanced examina-

[3] 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 on spatial shopping to provide utility-based measures for shopping access in Switzerland with 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	0.0876***	0.0762***	0.0778***	0.0099	
	(0.0043)	(0.0051)	(0.0051)	(0.0078)	
Linear Trend	0.0139***	0.0140***	0.0140***	0.0140***	
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	
COVID-19 × Age		-0.0045***	-0.0045***	-0.0037***	-0.0038***
		(0.0002)	(0.0002)	(0.0002)	(0.0002)
COVID-19 × Age^2		3.79×10^{-5}***	3.15×10^{-5}***	5.26×10^{-5}***	4.86×10^{-5}***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
COVID-19 × Dist. next store		0.0228***		0.0205***	0.0201***
		(0.0031)		(0.0031)	(0.0031)
COVID-19 × Access			-0.0076**		
			(0.0037)		
Household Members					
COVID-19 × 2				0.0615***	0.0617***
				(0.0077)	(0.0077)
COVID-19 × 3-4				0.1129***	0.1136***
				(0.0101)	(0.0101)
COVID-19 × 5+				0.0016	0.0023
				(0.0182)	(0.0182)
Household Fixed Effects	Yes	Yes	Yes	Yes	Yes
Period Fixed Effects					Yes
Observations	22,884,356	22,884,356	22,884,356	22,884,356	22,884,356
R^2	0.54072	0.54076	0.54076	0.54077	0.54086
Within R^2	0.00099	0.00108	0.00107	0.00110	0.00011

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, store accessibility, and household size identify heterogeneous responses. Models differ by whether they include a linear time trend or time fixed effects. 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. The baseline mean of online expenditure share before the pandemic is about 0.51%.

tion of how policy measures shaped online grocery shopping behavior. The binary COVID-19 variable retains its positive and significant effect, confirming that the COVID-19 pandemic itself was a major catalyst for online adoption. However, the inclusion of the stringency measure refines this understanding. The negative and significant coefficient on the stringency variable indicates that regions with stricter baseline restrictions initially saw lower online grocery expenditures. This finding could reflect disparities in digital readiness or initial consumer resistance in heavily restricted regions. Importantly, the interaction between the COVID-19 variable and stringency is also negative and significant, suggesting that stricter restrictions initially tempered the overall increase in online expenditures. This counterintuitive finding may stem from the abrupt and widespread nature of the restrictions, which created logistical challenges for both consumers and retailers in the early stages of the pandemic.

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)
COVID-19	0.1955***	0.1442***	0.1461***	0.0779***	
	(0.0080)	(0.0065)	(0.0065)	(0.0088)	
Linear Trend	0.0131***	0.0132***	0.0132***	0.0132***	
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	
Stringency	-0.0515***				
	(0.0034)				
COVID-19 × Stringency		-0.0523***	-0.0525***	-0.0524***	0.5632***
		(0.0034)	(0.0034)	(0.0034)	(0.0457)
COVID-19 × Age		-0.0045***	-0.0046***	-0.0037***	-0.0038***
		(0.0002)	(0.0002)	(0.0002)	(0.0002)
COVID-19 × Age^2		3.72×10^{-5}***	3.09×10^{-5}***	5.19×10^{-5}***	4.84×10^{-5}***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
COVID-19 × Log dist. next store		0.0227***		0.0204***	0.0203***
		(0.0031)		(0.0031)	(0.0031)
COVID-19 × Access			-0.0079**		
			(0.0037)		
Household Members					
COVID-19 × 2				0.0615***	0.0624***
				(0.0077)	(0.0077)
COVID-19 × 3-4				0.1130***	0.1133***
				(0.0101)	(0.0101)
COVID-19 × 5+				0.0016	0.0026
				(0.0182)	(0.0182)
Household Fixed Effects	Yes	Yes	Yes	Yes	Yes
Period Fixed Effects					Yes
Observations	22,884,356	22,884,356	22,884,356	22,884,356	22,884,356
R^2	0.54073	0.54077	0.54076	0.54078	0.54087
Within R^2	0.00101	0.00109	0.00109	0.00112	0.00013
Post-Treat Mean of Stringency	57.97	57.97	57.97	57.97	57.97

Notes: This table extends the baseline specifications from Equation (3) and Equation (4) in Table 2 by including the continuous, regionally varying KOF Stringency Index. 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.

Demographic and spatial heterogeneities in Table 3 closely mirror those observed in Table 2. Older households continued to show more modest initial increases. Distance to the nearest physical store remained a strong determinant of online adoption, reinforcing the argument that geographical barriers heightened the utility of online shopping. Additionally, the differential responses by household size persisted, with three- to four-member households exhibiting the strongest uptake.

Overall, Table 2 and Table 3 paint a comprehensive picture of how online grocery shopping evolved during the pandemic. They 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.

3.2 Peer Effects in Online Shopping Adoption

The second analysis we conduct is an investigation of peer effects within the multi-generation family, following Kluser and Pons (2024) who use the family linkages in the administrative register data sets to study the intergenerational persistence of eating behaviors. In contrast, we study how e-commerce adopters trigger their close social network to shop online.

Estimation

To this end, we define C_{it} as a dummy variable indicating that an adult "child" i's household ever engaged in online shopping in period $z \leq t$ and P_{jt} as the variable's equivalent for the parental generation j. Then, we study if one generation's adoption of online shopping (meaning, switching from previously 0 to 1) increases the likelihood that the other generation engages in online shopping in the following period:

$$P_{jt} = C_{i,t-1} + \delta_j + \alpha_t + \epsilon_{jt}, \tag{5}$$

$$C_{it} = P_{j,t-1} + \delta_i + \alpha_t + \epsilon_{it}, \tag{6}$$

where δ_i and δ_j are the household fixed effects and α_t the period fixed effects.

A key challenge in this context is that our sample window starts in January 2019, but adoption might have occurred earlier. Since we lack data on pre-2019 shopping behavior, individuals who actually adopted online shopping before our observation period appear as first-time adopters, potentially biasing our estimates of adoption dynamics. We address this issue by focusing on the window from January to December 2020 only. By excluding 2019, we effectively establish a "burn-in" period during which earlier adopters can emerge. As a result, households that had adopted online shopping before January 2020 are properly identified as existing users rather than first-time adopters, mitigating bias in our adoption estimates.

Discussion

Table 4 reports our estimates. Columns (1) to (3) show the response of parents if their children are first-time adopters in the previous period $t-1$ (Equation 5), while Columns (4) to (6) present the reaction of children if their parents adopt (Equation 6). We find significant estimates that are economically large, and the baseline probabilities are low, making these effects particularly striking. For parents, the constant term is (approximately) 0.8%, indicating that in the absence of prior adoption by their children, the baseline probability of parents making online expenditures in a given period is small. If a child acts as an online adopter, we estimate a parental response of 0.0198, nearly tripling the baseline probability of 0.0084. Even as controls become more stringent by introducing household and period fixed effects, the effect remains sizable at 0.0097.

Table 4: Peer Effects in Online Shopping Adoption

Dependent Variables:	Any Online Expenditures Parents			Any Online Expenditures Child		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.0084***			0.0489***		
	(0.000)			(0.0001)		
Adopter Child, t-1	0.0198***	0.0131***	0.0097***			
	(0.0002)	(0.0007)	(0.0007)			
Adopter Parents, t-1				0.0963***	0.0662***	0.0492***
				(0.0010)	(0.0034)	(0.0034)
Household Child Fixed Effect					Yes	Yes
Household Parents Fixed Effects		Yes	Yes			
Period Fixed Effects			Yes			Yes
Observations	4,622,340	4,622,340	4,622,340	4,622,340	4,622,340	4,622,340
R^2	0.00199	0.68155	0.68460	0.00183	0.77211	0.77962
Within R^2		0.00121	0.00066		0.00156	0.00088
Average Household Fixed Effect	-	0.0094	0.0094	-	0.0497	0.0497

Notes: This table reports estimation results for peer effects in online shopping adoption from Equation (5) and Equation (6). 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.

For children (Columns (4)-(6)), the baseline probability of making online expenditures is around 4.9%. The effect of parental adoption in the period before is 0.0963 in the simplest model (Column (4)), pushing the probability above 14% and representing roughly a threefold increase. Even with additional controls, the coefficients remain large: the estimates of about 0.0662 and 0.0492 in Columns (5) and (6) suggest that children's likelihood of engaging online increases by about 50%-100% compared to the baseline.

In sum, these coefficients translate into economically meaningful jumps from low base probabilities. They highlight a strong intergenerational peer effect: a child's prior adoption of online shopping can raise the parent's probability of doing so by roughly 100%-200%, and a parent's prior adoption can raise the child's probability by about 50%-200%. The tight standard errors (reported in parentheses and practically zero at three decimal places) indicate these estimates are highly statistically significant and precise.

4 Conclusion

The findings presented in this paper underscore the transformative impact of the COVID-19 pandemic on online grocery shopping behavior in Switzerland. Using detailed transaction-level data from the largest Swiss retailer *Migros*, we document a significant and persistent shift toward online shopping during 2020. Our analysis highlights the role of both individual household characteristics and external factors, such as governmental restrictions, in shaping this behavioral change.

The results reveal that the pandemic acted as a catalyst for online shopping adoption, with larger households, those located further from physical stores, and certain demographic groups exhibiting particularly strong responses. Regional variation in the stringency of restrictions further nuanced these effects, with stricter measures initially dampening adoption but ultimately leading to accelerated uptake as households adapted to prolonged limitations. Beyond these macro-level insights, our analysis of peer effects within multi-generational households highlights the social dynamics of online shopping behavior. The bidirectional influence between parents and children demonstrates how digital adoption spreads within families, suggesting that household interactions and information exchange with close peers play a critical role in the diffusion of new technologies. Altogether, these findings offer important implications for both policymakers and retailers. Policymakers should consider how digital infrastructure and support measures can facilitate equitable access to online platforms, particularly for vulnerable populations. Retailers, meanwhile, can enhance services for households with limited access to physical stores with attractive online alternatives.

While this paper provides valuable insights into the drivers and dynamics of online grocery shopping, future research could build on these findings by examining the long-term effects of these behavioral shifts. Additionally, investigating the environmental and nutritional implications of increased online shopping could provide a more comprehensive understanding of its broader 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 enduring implications for the retail landscape.

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