The Apple Does Not Fall Far From the Tree: Intergenerational Persistence of Dietary Habits *

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Abstract

Inadequate diets harm individual health, generate substantial healthcare costs, and reduce labor market income. Yet, the determinants of eating habits remain poorly understood. We provide novel evidence of the strong intergenerational transmission of healthy dietary choices from parents to children by exploiting unique grocery transaction records matched with administrative data. We estimate a rank-rank slope of 0.23 for fruit and vegetable spending and find that children with parents spending one percentage point more on fruits and vegetables also spend 0.23 percentage points more on these products. These results exceed comparable measures for income. Further, our findings suggest that only 12% of the intergenerational persistence of diet can be explained by transmission of income and education. Finally, we document heterogeneities between population subgroups and across labor markets and find that the intergenerational link in diet varies substantially across space and is more pronounced in rural areas and German-speaking regions.

Keywords: consumption inequality, intergenerational mobility, health behaviors
JEL-codes: D15, D83, I12, J12, L14.

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1 Introduction

Unhealthy eating habits not only impact our personal health and well-being but also put a substantial economic burden on our healthcare systems. A variety of health conditions, including obesity, cardiovascular diseases, and diabetes, has been linked to inadequate diet, accounting for 18% of all North American deaths (Afshin et al., 2019).[1] Additionally, these lifestyle-related diseases generate high medical costs. For example, according to the American diabetes association, every fourth healthcare dollar in the United States is spent on people with diabetes, and patients with diabetes generate more than twice as many medical costs as those without the disease. The detrimental consequences of poor dietary choices highlight the need to investigate the origins of unhealthy eating, opening the way for targeted interventions and policy recommendations. A growing literature has taken on the challenge of understanding determinants of dietary choices, and the general consensus is that eating patterns are highly persistent (see Hut 2020, Hut and Oster 2022, Atkin 2013, 2016) and withstand major personal shocks and interventions (see Oster 2018, Hut and Oster 2022, Allcott et al. 2019a).

In this paper, we study the role of the family in determining dietary patterns by analyzing how parents transmit their nutritional choices to their children. To this end, we exploit unique grocery transaction records matched with Swiss administrative data to analyze the intergenerational persistence of diet. Switzerland is an insightful case to study dietary patterns, as almost everyone has sufficient access to healthy food.[2] Our data contains customer-linked spending by product categories from 1.5 billion shop visits between 2019 and 2020 at the largest Swiss retailer. We enrich this consumption data with family linkages and individual socio-demographic information from the Federal Statistical Office, allowing us to observe the shopping behavior of 220'000 children (9% of the population of children) and their parents. The main variable of interest and our measure of the healthiness of a household's diet is the expenditure share of fresh fruits and vegetables relative to total food expenditures.

To analyze the transmission of diet across generations, we build on the intergenerational mobility literature and use established measures of persistence. Our findings show that family is a crucial determinant of dietary choices. We document an extensive intergenerational persistence in fruit and vegetable shares, indicating a strong transmission of eating choices from parents to children. We estimate a rank-rank slope of 0.23, and children whose parents spend one percentage point more on fruits and vegetables have a 0.23 percentage point higher spending themselves. Further, the children's probability of reaching the top quartile with parents at the bottom quartile is 12.2%. This is substantially smaller than the probability that children with parents at the top quintile remain at the top of the distribution (30.7%). A comparison of our

[1]The leading causes in 2017 were an excessive salt intake and an insufficient whole grain, fruit, and vegetable consumption. Globally, unhealthy diets were responsible for 11 million deaths in 2017 (Afshin et al., 2019).

[2]According to the World Bank, less than 0.1% do not have the financial means to follow a healthy diet in Switzerland. In comparison, this is the case for 1.5% of households in the United States, 12% in China, and 97% in Madagascar. The World Bank considers a healthy diet as unaffordable if the lowest-cost basket fulfilling national guidelines for a healthy diet costs more than 52% of a household's income.

findings to income mobility suggests that intergenerational persistence of income exceeds income transmission across all measures we consider.

One potential worry is that these patterns are due to the intergenerational transmission of income and education. More precisely, if highly educated and high-income individuals eat healthier, transmission of these socioeconomic variables could (at least partially) drive our results. To assess this possibility, we isolate the channel that does not pass through income and education with a counterfactual analysis proposed in Chernozhukov et al. (2013). The analysis shows that the transmission of these socioeconomic variables can explain only 12% of the persistence in diet between parents and children. Looking at different sub-samples, we observe that parents' influence is stronger among children with lower education and income, and the transmission mechanism weakens as the distance between parents and children increases. We find comparable results for mobility across language regions and the degree of urbanization. Finally, we document the spatial dispersion of dietary persistence, finding meaningful differences across labor market areas.

The existing literature on intergenerational mobility predominantly focuses on income. For example, Chetty et al. (2014) document strong transmissions of income from parents to their children in the United States. Related papers show substantial spatial variation in mobility and disproportional disadvantages for non-white groups and Chetty et al. (2022a,b) argue that having a high share of friends with a high socioeconomic status strongly increases upward income mobility for low-income people.[3] In recent years, various papers conducted comparable analyses for other high-income countries (Acciari et al. 2022, Corak 2020, Deutscher and Mazumder 2020, Bratberg et al. 2017), including Switzerland (Chuard and Grassi, 2020).[4]

Yet, much scarcer literature analyzes mobility in non-pecuniary dimensions like education, jobs, health, and consumption, which may partially be due to the limited data availability. For example, Halliday et al. (2020) analyze mobility in health and find striking gaps by race, region, and parent education, while Black et al. (2005) show that sons of better-educated mothers also attain higher education levels.[5] Nonetheless, the literature analyzing the behavior of consumers is surprisingly scarce. Exceptions rely all on self-reported survey data for small samples (less than 3,000 observations), including Charles et al. (2014) and Waldkirch et al. (2004) who use self-reported total food expenditures and imputed consumption based on the PSID. They find an intergenerational correlation in food expenditures from 0.14 to 0.20. Similarly, Bruze (2018), using the Danish Expenditure Survey, calculates an intergenerational elasticity of 0.41. To the best of our knowledge, our analysis is the first paper analyzing the transmission of dietary habits

[3] See also Chetty et al. (2016, 2020), and Chetty and Hendren (2018). Rothstein (2019) tries to disentangle the channels behind income persistence and concludes that job networks, as well as the local labor and marriage markets drive income mobility rather than a transmission of education or human capital.

[4] Some studies show that also accumulated wealth is persistent within families, even after four to five generations (Clark and Cummins 2015, Adermon et al. 2018, or Charles and Hurst 2003).

[5] Halliday et al. (2020) find a rank-rank slope of 0.11-0.15, while Andersen (2021) estimates a higher rank-rank slope of 0.28 from Danish register data. Further, intergenerational persistence has been documented for labor force participation (Fernandez et al., 2004) and tax evasion (Frimmel et al., 2019).

across generations.

This paper also contributes to the literature focusing on diet. This strain of the literature primarily focuses on evaluating the impact of policies promoting healthier eating behavior. These policies include food subsidies (Hastings et al. 2021, Goldin et al. 2022, Bailey et al. 2023), food labels (Barahona et al. 2023, Araya et al. 2022, Cook et al. 2005), sin taxes (Allcott et al. 2019b, Dubois et al. 2020, Aguilar et al. 2021, Dickson et al. 2023), carbon pricing of nutrition (Springmann et al., 2018), or school-food programs (Berry et al. 2021, Handbury and Moshary 2021). However, such studies find results with low economic or statistical significance. Contrarily, we contribute to the understanding of eating behaviors' origins in the first place.

The paper is structured as follows. Section 2 introduces the data and presents summary statistics. Section 3 discusses our measures of intergenerational mobility and Section 4 provides the associated results. Section 7 concludes.

2 Data

We analyze the intergenerational transmission of diet by combining (i) individual transaction data from the largest Swiss retailer with (ii) administrative data from the Federal Statistical Office. Throughout this paper, we refer to *children* as adult residents for which we observe at least one parent in the administrative data. They are our population of interest, and we treat their parents' characteristics as observable covariates. To introduce the data, we will refer to individuals in the grocery data as *customers* and those in the administrative data as *residents*. This section discusses the different data sources and explains the construction of the data as well as the sample selection process. Then, we present summary statistics and discuss the representativeness of our data.

2.1 Data Sources

Grocery Transaction Data – The consumption data is from the loyalty program of the largest Swiss grocery retailer, holding a market share of 32.7% in 2020. The program participants identify themselves at the in-store checkout with their loyalty card in exchange for exclusive offers and discounts. 2.8 million individuals hold this loyalty card (i.e., 42% of all Swiss residents above legal age), and 2.1 million are active users spending at least 50 Swiss francs monthly.[6] The program is substantive and captures 79% of the retailer's sales. Also, the retailer charges the same prices throughout the country, independent of local purchasing power, wages, and costs, and stores of comparable size generally offer similar goods, except for local products.

The grocery data provides information on every consumer-linked purchase, including expenditures divided into 41 product categories. In this paper, we focus on the food product categories

[6] 1 Swiss franc (CHF) equals approximately USD 1.10, meaning CHF 50 $\approx$ USD 55.

(*fruits and vegetables*, *meat and fish*, *milkproducts and eggs*, *conservables*, and *other food products*). The outcome of interest throughout this analysis is a child's share of fresh fruits and vegetables relative to total food expenditures. This is a suitable measure for a healthy diet because of four reasons. First, fruits and vegetables have a high correlation with the healthy eating index in Allcott et al. (2019a) of 0.57 and 0.41 and capture a more complex aggregation of individual products. Second, a diet low in fruits or vegetables is among the most frequent reasons for nutrition-related mortality in Afshin et al. (2019). Third, we observe that our measure correlates strongly with the intake of important micronutrients across age groups.[7] Fourth, this measure provides a transparent and objective approximation of dietary quality as it requires no weighting of different nutrients or products.

We use the universe of 1.5 billion customer-linked purchases for the period 2019-2021Q2. The grocery data also contains customer characteristics, including their residence location, age, gender, and household type.[8] The residence locations are coded on a grid of 100×100–meter cells. The grid contains 350'000 cells with a median population of 11 residents.

Administrative Data – We enrich this unique consumption data with administrative records for the Swiss population (8.7 million inhabitants in 2020). Pseudo social security numbers allow linking residents across different administrative data sets. We use three different data sets. The *Population and Households Statistics* provides socio-demographic characteristics for each resident for the years 2016–2020. This includes, among others, information on gender, age, marital status, residence location, household identifiers, and the pseudo-identifiers of spouses and kids. The residence locations are again approximated on the same 100×100–meter grid as in the grocery transaction data. Family linkages, including pseudo-identifiers for mothers and fathers, have been collected since 2005. This information is available for all individuals unless their parents never lived in Switzerland, died before 2005, or if there was no civil status change either for them or their parents since the 1990s (for example, wedding, divorce, or birth). Consequently, the *Population and Households Statistics* includes information on the parents of 84% of the Swiss residents under age 60, and of 22% above age 60.[9] For the analysis, we consider all registered residents in 2020, plus those who moved away or died since 2019 or those who immigrated in 2021 (a total of 9 million people).[10]

The *The Old-Age and Survivors Insurance* dataset contains annual gross labor market income

[7] We compare the dispersion of our measure across age groups to the administrative National Nutrition Survey, inquiring 2,000 participants between the age of 18 and 75 about their previous day's diet. The expenditure share of fruits and vegetables has a correlation across age groups of 0.4 with the intake of fibers, 0.38 with phosphorus, 0.33 with zinc, 0.22 with Vitamin A, and 0.29 with magnesium.

[8] The household types include the categories *small households*, *young families*, *established families*, *golden agers*, and *pensioners*. To be a family, you have to register your children. This registration implies additional benefits related to family products.

[9] The coverage for foreigners is lower because many of their parents live abroad. Yet, we include foreigners with known parents in our analysis.

[10] Some customers who died or moved away before August 2021 will still be in the customer database, and we can analyze their diet in the previous period. In the same way, people who immigrated in 2021 may already be customers in our data but not yet residents in the 2020 administrative data.

for every resident for the years 2016 and 2020.[11] Throughout this paper, we adjust average household income by the square root of household size.[12] Further, to reduce biases in estimating permanent income due to transitory shocks, we average annual household income for 2016–2020.

The *Structural Survey* for the years 2010–2020 provides information on housing, employment, mobility, and education. The representative survey selects 200'000 people above age 15 every year, and participation is mandatory. From this survey, we attain the highest completed education in a household and take the most recent survey they participated in for every individual. Education is categorized as either primary, secondary, or tertiary education.[13] As education and jobs stabilize for most individuals only after a certain age, we add the characteristics for individuals above age 25 at the time of the survey to the *Population and Households Statistics*.

2.2 Sample Construction

Matching – In a first step, we combine the food transaction data and the administrative data sets based on grid cells, age, and gender. This generates 5.6 million matches between customers and residents. To identify the unique matches, we take some additional steps.[14]

The refinement proceeds as follows: (i) Using the transaction data itself, we calculate for every pair the median road distance traveled to spend one Swiss franc in a given year. Then, we require a customer to shop close enough to her home by excluding all pairs where the resident traveled more than 20 kilometers for an entire year, as this resident is likely not the owner of the loyalty card she links to. This step excludes 258,000 pairs. (ii) A customer can only be registered in the loyalty program as a family if she has kids younger than 25. Thus, we exclude the 530,213 customer-resident pairs where the customer is registered for the family program, but the resident has no kids fulfilling this criterion. (iii) From the remaining customer-resident combinations, we select customers that link to exactly one household (multiple residents can live in this household). This gives 1,244,071 unique customer-resident matches. (iv) The minimum age to register for the loyalty program is 18. Hence, we exclude households linking to more customers than household members aged 18 and older. This can happen if someone moved

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

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

[13]Primary (or compulsory) education ends at the latest after around eleven mandatory years of school (including kindergarten). Individuals who completed high school or an upper-secondary specialized school have a secondary education. The completion of any degree at a university, university of applied Sciences, or university of teacher education results in a tertiary degree.

[14]Some customers do not match any resident, which is only possible if their location in the grocery data is outdated or due to measurement errors (for example, if the customer died or moved abroad). This is the case for 400'000 of the 2.8 million customers (14%), of which 330'000 are active customers, spending more than 50 Swiss francs monthly over our sample period.

without changing their customer address. (v) As some consumers have moved recently without notifying the retailer, we check whether these movers uniquely match a customer at their old location. This procedure uniquely identifies 43,336 additional pairs. (vi) Removing the movers matched in the previous step, we find additional 4,093 matches at their actual location in the last step. This leaves a final sample of 1.4 million customers uniquely linked to a resident, accounting for 66% of active customers and 19% of Swiss adult residents.

Dietary Variables – For households owning multiple loyalty cards, we first aggregate expenditures within the household before calculating the relative share for each food product category at the household level. Additionally, some children moved out recently. In this case, we exclude their expenditures in the periods they still lived with their parents.[15] Then, we assign the aggregated transaction data to all adult residents in the household. This provides grocery expenditures for 2.2 million residents in 1.2 million households.

Sample Selection – In the final step, we keep pairs of children and parents that are both observed in the data and live in different households. This substantially reduces our sample size to 350,000 children linking to 208,000 of their fathers and 280,000 of their mothers. We drop children living less than 500 meters from their parents because they are more likely to shop for their parents or share regular meals together. We adjust both household incomes and grocery expenditures by the square–root of household size. We restrict the sample to children and parents with average monthly grocery expenditures between CHF 50 and 1,000. This is because too-small monthly baskets might not capture the overall consumption accurately, while too-large monthly baskets are unlikely to suit personal use but are rather from business customers. We keep households with at most ten members to exclude, for example, large cohabiting arrangements and retirement homes. Ultimately, we focus on children between the ages of 21 and 70 and parents between the ages of 48 and 97 to avoid too small age groups in our estimation.[16] Further, we generate parents' variables as the average value of the father and mother weighted by their respective food expenditures.[17] This gives a final sample of 220,000 children.

2.3 Summary Statistics

Columns (1) and (2) of Table 1 show the summary statistics for all 192,000 matched children. To assess the representativeness of the final data, columns (3) and (4) compare the sample to the 2.2 million children fulfilling the same selection criteria imposed on the sample data. Hence, our final data includes around 10% of our population of interest. Columns (2) and (4) in panel

[15]These children may contaminate our measure of diet for their parents in the periods before they moved out. Excluding them entirely leaves our estimates unchanged.

[16]Because we detect potential life cycles in diet, we provide all our results conditional on age groups and want to ensure that groups are large enough (see Section 3, for details).

[17]If parents live together, their household characteristics and consumption behavior are identical, while individual variables vary. If parents have separate living arrangements, household characteristics, and consumption behavior differ, and we average all characteristics in the same way we average the shares of fruit and vegetables.

Table 1: Summary Statistics for Kids

	Final Sample		Population	
Panel a)	Mean	SD	Mean	SD
Age	44.10	10.85	43.82	11.70
Age father	72.05	9.81	71.18	10.35
Age mother	71.45	10.66	70.97	11.36
Income Total	144.20	129.54	129.68	109.05
Income Adjusted	83.30	79.61	81.60	64.85
Panel b)	Pct.	N	Pct.	N
Gender		192,814		2,276,376
Female	54.4	104,844	50.8	1,155,500
Male	45.6	87,970	49.2	1,120,876
Marriage		192,814		2,276,376
Married	65.1	125,443	50.3	1,144,923
Not Married	34.9	67,371	49.7	1,131,453
Highest Education		138,477		1,554,457
Tertiary	53.6	74,264	50.0	777,526
Secondary	42.8	59,222	44.6	694,008
Elementary	3.6	4,991	5.3	82,923
Language Region		192,622		2,273,913
French	19.5	37,647	22.0	500,058
German	76.7	147,815	72.3	1,643,900
Italian	3.7	7,160	5.7	129,955
Pop. Density		192,622		2,273,913
Rural	26.3	50,571	21.6	490,575
Suburban	57.2	110,098	52.2	1,186,021
Urban	16.6	31,953	26.3	597,317
Household Size		192,814		2,276,376
1	8.5	16,465	21.0	478,402
2	26.4	50,994	33.1	754,521
3-4	51.7	99,773	37.2	846,187
5+	13.3	25,582	8.7	197,266
Observations		192,814		2,276,376

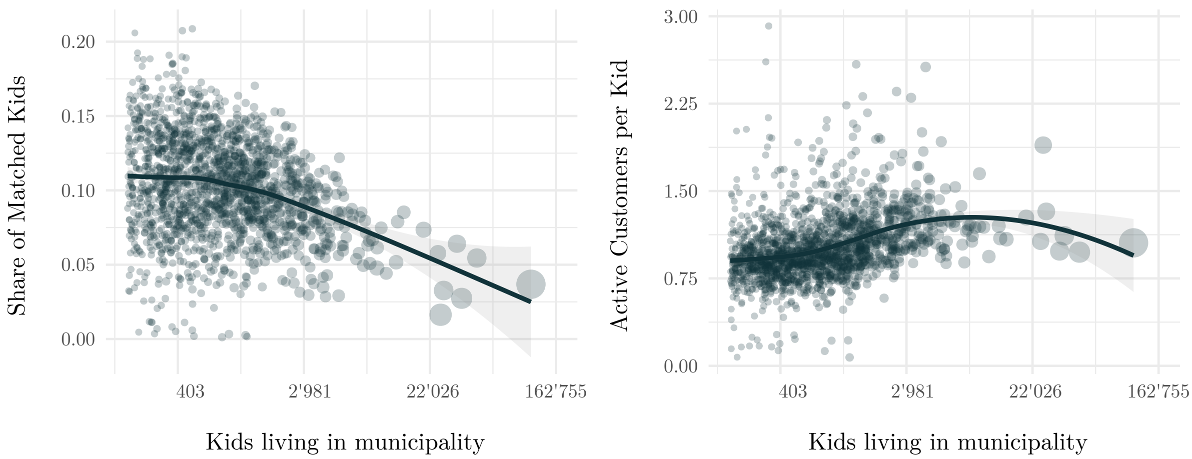
Notes: This table shows summary statistics for the customers uniquely linked to a kid in the administrative data and for the entire population of kids. *Income Total* is a household's average labor market income 2016-2020 in 1,000 CHF, and *Income Adjusted* adjusts household income by the square root of household size. *Highest Education* is the highest education anyone within the household completed, and *Pop. Density* is defined by the municipality's population density.

b) include the number of observations for each variable. The average child in the final dataset is 44.1 years old with an adjusted household income of 83,000 Swiss francs. 54% of them are female and 65% married. Further, 53% hold a tertiary degree, and more than 90% live in multi-person households. The education variable is available for the 138,000 individuals that participated in the Structural Survey since 2010. Regarding geographical characteristics, 19% of the children in our sample live in the French-speaking part of Switzerland, 76% in the German- and 4% in the Italian-speaking region.

Column (3) shows that the final sample resembles the population of children well, with some differences in marital status and the degree of urbanization. In the population, only 50% are married, compared to the 65% in the sample, and while 26.3% of the population live in densely populated areas, this only holds for 16.6% in our sample. The latter discrepancy is because

Figure 1: Match Rate

(a) Children in the Final Data (b) Children in the Population



Notes: The figure illustrates the representativeness of the retailer's loyalty program. To this end, Figure 1a shows the share of matched kids relative to all kids living in this municipality. Figure 1b shows for the full customer data the number of active customers relative to their municipality's number of children. Each dot represents a municipality's value, while the size indicates the municipality's population. The solid line shows a local regression.

we are less likely to identify unique combinations of customers and residents the more people live in a raster cell. We illustrate this in Figure 1a by plotting the share of residents in a municipality linked to a child against the number of children living within this municipality. While we link more than 10% of residents in smaller municipalities to a customer, this share declines as the population grows and lies around 5% for the largest cities. This result is not driven by the difference in penetration rates of the loyalty program across municipalities, as shown in Figure 1b.

In addition, Figure A1 in the appendix shows the representativeness of our sample in more detail by plotting average children's household characteristics per municipality in our sample against the corresponding values of the administrative data. We replicate the spatial distribution of household income and tertiary education well. However, the children in our sample live, on average, in slightly larger households and are somewhat older.

Next, we want to assess whether the transaction data represents a household's shopping behavior accurately since households also shop at other grocery retailers and eat out-of-home. Table 2 displays summary statistics for the aggregated transactions in the sample. We display the mean, median and standard deviation of the total monthly food expenditures in columns (1)–(3) and of the share of fruits and vegetables in columns (4)–(6). In addition, we show these summary statistics for different subgroups based on individual- and household-level characteristics separately. In column (7), we add the average grocery expenditures for food and beverages from the administrative *Household Budget Survey* wherever available.[18] Column (8) shows the expendi-

[18]This survey continuously selects 2,500 households per year, and participants take for an entire month notes

Table 2: Summary Statistics for Kids' Expenditures

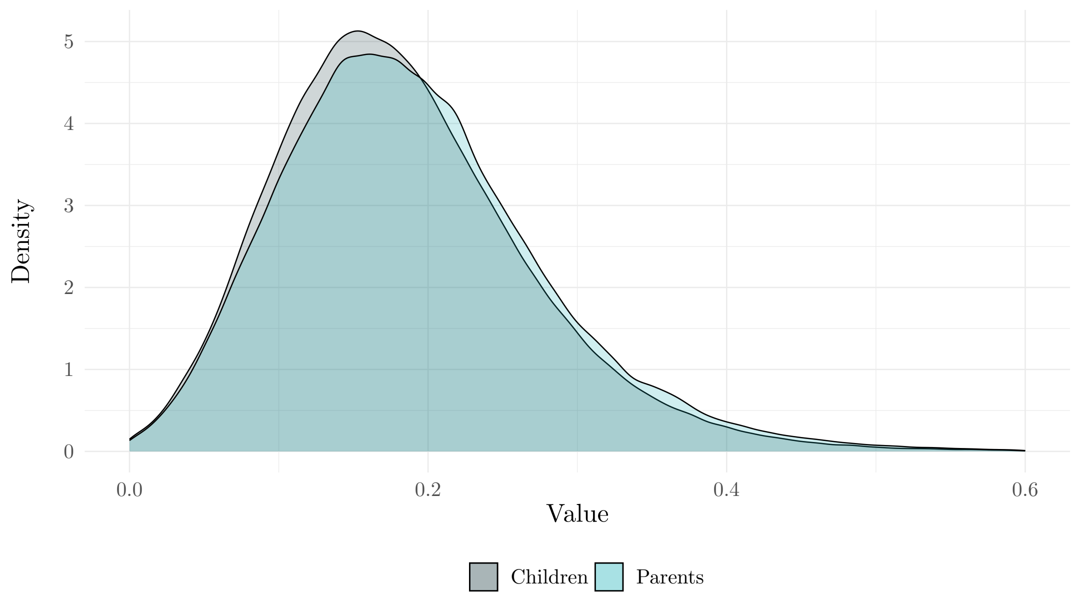
	Total Spending			% Fruit & Vegetable				
By Gender	Mean	p50	SD	Mean	p50	SD	Spending	Share
Overall	350	280	254	0.18	0.17	0.09	616	0.57
By Gender								
Female	348	279	252	0.18	0.17	0.09		
Male	352	281	257	0.18	0.17	0.09		
By Age								
< 34	262	209	183	0.18	0.17	0.09	459	0.57
35–44	374	311	256	0.19	0.18	0.08	654	0.57
45–54	403	330	289	0.18	0.17	0.08	728	0.55
55–64	343	277	245	0.19	0.18	0.09	663	0.52
65+	300	241	213	0.20	0.19	0.09	616	0.49
By Income Adjusted								
< 4,530	237	186	170	0.17	0.16	0.10	409	0.58
4,530–6,717	263	206	195	0.17	0.15	0.09	485	0.54
6,718–9,288	329	267	233	0.17	0.16	0.08	604	0.54
9,289–12,855	365	301	253	0.18	0.17	0.08	713	0.51
12,856+	400	326	282	0.20	0.19	0.08	869	0.46
By Highest Education								
Elementary	246	193	179	0.15	0.14	0.08		
Secondary	330	264	238	0.17	0.16	0.08		
Tertiary	387	315	272	0.20	0.19	0.08		
By Household Size								
1	164	136	104	0.18	0.16	0.10		
2	258	209	174	0.19	0.17	0.09		
3–4	395	332	259	0.18	0.18	0.08		
5+	481	412	308	0.18	0.17	0.08		
By Household Type								
Couple w/ children	422	357	275	0.18	0.17	0.08	900	0.47
Couple w/o children	263	213	179	0.19	0.17	0.09	635	0.41
Single w/ children	292	249	179	0.17	0.16	0.08	618	0.47
Single w/o children	165	136	105	0.18	0.16	0.10	344	0.48
By Pop. Density								
Rural	333	269	235	0.17	0.16	0.08		
Suburban	358	289	259	0.18	0.17	0.08		
Urban	349	269	266	0.21	0.20	0.09		
By Language Region								
French	333	262	246	0.18	0.17	0.08	650	0.51
German	357	288	258	0.18	0.17	0.09	608	0.59
Italian	293	226	215	0.18	0.17	0.08	565	0.52

Notes: This table shows summary statistics for the transaction records of food expenditures of customers uniquely linked to a kid in the administrative data. The columns titled *Survey* show the average grocery expenditures for food and beverages from the administrative Household Budget Survey, 2015–2017, and the relative share between spending in our data and the survey. *Income Adjusted* adjusts household income by the square root of household size. *Highest Education* is the highest education anyone within the household completed, and *Pop. Density* is measured with the municipality's population density. *Age* and *Income Adjusted* use the respective quintiles in the Household Budget Survey for comparabilty.

tures in our data relative to the survey's expenditures and measures our coverage of total food expenditures.

on their income and expenditure. The most recent data available are for the period 2015–2017. We do not adjust for inflation as consumer prices increased by only 0.6% between 2017 and 2020.

Figure 2: Kernel Densities of the Share of Fruit and Vegetable Consumption



Notes: The figure illustrates the kernel densities of the share of fruit and vegetable consumption of children and parents.

The average customer in our final data spends 350 Swiss francs per month (380 USD) and allocates 18% of this money to fresh fruits and vegetables. These expenditures cover 57% of the average household grocery expenditures on food and beverages (note that our data does not include any beverages). Looking at different subgroups, the broad picture shows that we cover around 50% of the typical expenditures. There are a couple of notable aspects to consider here. Households increase their grocery expenditures throughout their life from a young age (262 Swiss francs) until age 45-54 (403 Swiss francs) before decreasing them again towards retirement (300 Swiss francs). Meanwhile, the share of these expenditures allocated to fruits and vegetables increases with age from 18% to 20%. This gives a first indication of a potential lifecycle in our measure of diet, which we will discuss further in the next section. The coverage of food expenditures in our data decreases with age from 57% to 49%. Food expenditures also grow with income and education, such that, for example, the top income quintile spends 400 Swiss francs per month compared to 237 Swiss francs for the bottom quintile. Wealthier and better-educated households also consume relatively more fruits and vegetables. An important point to note here is that the share spent on fruits and vegetables is larger for urban than suburban or rural areas. This could be due to different consumption levels or because, in sparsely populated areas, households are more likely to buy fresh products from a farmer or own their own garden. Yet, households in rural areas spend with 333 Swiss francs only marginally less on grocery products than households in urban areas (349 Swiss francs). Therefore, we do not expect this to affect our results.

Finally, Figure 2 shows the kernel density of the share of fruit and vegetable consumption for both parents and children. Both variables are slightly right-skewed, and most households spend less than 40% on fruits and vegetables. Further, we see that for children, the density is somewhat shifted to the left, indicating that children tend to eat fewer vegetables. This difference is likely driven by age. Nonetheless, densities for the two generations share many similarities. Overall, our sample represents the target population well, and our expenditures cover a large share of groceries expenditures.

3 Measuring Moblity

In the literature, there is not one single measure of mobility. Instead, many different statistics measure different aspects of mobility, which are not necessarily positively correlated (Deutscher and Mazumder, 2023). Broadly speaking, mobility measures can be divided between global and local as well as absolute and relative. Global measures provide one single coefficient for the entire distribution, which is often easy to communicate, while relative measures zoom in on particular parts of it, providing a more detailed but also more complex picture. An absolute mobility measure responds in the same way to a change in child income regardless of who attains it. They capture welfare gains and improvements in living conditions if one cohort is uniformly better off than the previous one. Differently, relative measures' response to a change in child outcome depends on whose outcome changes. In the extreme case, if we would distribute the same amount of money or improve diet for everyone, relative measures would remain unchanged in contrast to absolute ones. Doing the same thing for only the top or bottom decile influences relative measures in the opposite direction, while absolute measures respond identically in both cases.[19]

As with most papers, we use different measures of mobility. However, we need to consider that not all measures are interesting in our setting, as this paper focuses on diet and not income, and the two outcomes exhibit important differences. First, our measure of diet is bounded from below and above, while income is not. Second, with our measure of diet, there is an optimal level or interval of consumption of fruits and vegetables, and an increase in vegetable consumption might not be beneficial above a certain threshold. However, most of the population seems to be on the left of this unknown threshold.[20] Differently, we usually assume a positive marginal utility of additional income so that more real income leads to better living standards and higher welfare. Hence, having a higher real wage than your parents seems to be a good thing in most cases, while this is not necessarily the case for the share of fruits and vegetables. Third, a poor diet causes externalities via the health care system, while one's living standards might depend on others' income only through general equilibrium effects.

Previous papers analyzing intergenerational income mobility faced two challenges: (i) how to

[19]See Deutscher and Mazumder (2023) for an extensive discussion and clear classification of different mobility measures. They provide empirical comparisons of measures within and between countries and discuss the relationship between them.

[20]According to governmental surveys, 87% the population does not follow the dietary recommendations to consume five portions of fruit and vegetables daily. In our data, 16% of the children spend less than 10% on fruit and vegetables, and 75% have a share smaller than 23%.

approximate the lifetime outcome well enough to handle transitory fluctuations and (ii) how to deal with lifecycle issues. The general strategy in the recent literature is to average the income of children and parents over some period and to restrict the analysis to certain age bins of children and parents. But there is a large variety of specific approaches. Lifetime income may be approximated either by a single year's income or multi-year averages, and the age bins selected vary strongly. While some papers compare individual income between generations, others aggregate to the household or family level. Further, some papers deal with lifecycles through conditioning, while others simply run robustness checks. In all these cases, the challenge is to have old enough children who are, in the case of income, already part of the labor market and young enough parents who are not yet retired to avoid lifecycle and attenuation biases.[21]

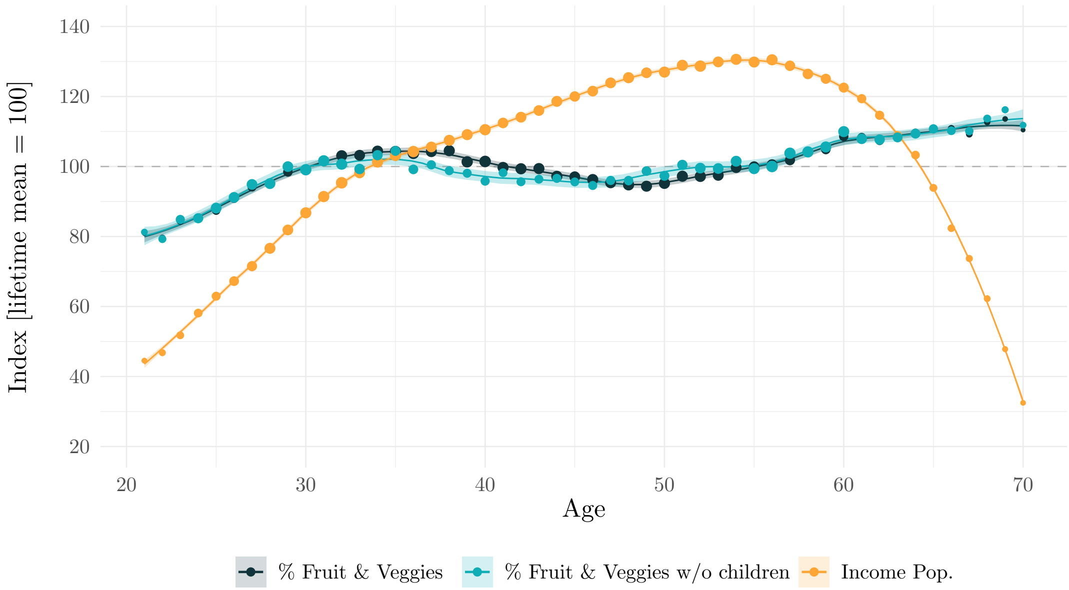
Figure 3 compares the lifecycle variation of diet and income, displaying the average income and the share of fruit and vegetable consumption as a function of age. Both are normalized to the respective lifetime mean to make the results comparable. While income and diet exhibit some variation over the lifecycle, this variation in diet is substantially smaller than for income. Income more than doubles from age 21 to 60 before declining again towards retirement age. Diet exhibits an s-shaped pattern. Young people tend to have a relatively poor diet, which improves by 30 percent until age 35. After that, there is a small decline of 10 percent until age 50, which then ameliorates again.[22] If we exclude instead households with children, the curve flattens, providing interesting insights. At the age where many households have small children, their diet improves above the lifetime mean. At the same time, they eat unhealthier around the age where they live together with older kids.[23] Given the visible, albeit small, lifecycle in diet, and since we observe children and parents at the same point in time, we will estimate ranks conditional on age as in Chetty et al. (2014) for the positional measures, and we control for age if the measure directly relies on the share of fruits and vegetables. If not indicated otherwise, we always compare a child's household diet to the weighted average of their parent's household diet. In the following, we introduce the set of mobility measures we find interesting for the case of diet.

[21]For example, Chetty et al. (2014) rank children's income at ages 29 and 30 within birth cohorts of children and compare it to their parents' five–year average family income when the children were 15 to 19 years old. Chetty and Hendren (2018) use children's income at the household level at age 26. Parents' income is measured as the five–year average household income from 1996 to 2000 (independent of their children's age), and ranks are conditional on birth cohorts. Corak (2020) measures children's individual income at age 38–45, arguing this age approximates average lifetime income very well. He compares this to parents' income as a five–year average when the child was 15–19 years old. Parents' income is defined as the father's and mother's income together. He addresses lifecycle concerns with robustness using children at ages 31 and 32. Acciari et al. (2022) restrict their analysis for Italian children's income at age 34–38 in 2016. Both parents' and children's income is measured as the average from 2016 to 2018. They compare the children's income to parents jointly and fathers and mothers separately. Acciari et al. (2022) address lifecycle issues with an error component model, simulating lifetime income. Similar strategies are also used in papers that do not concern income. For example, Andersen (2021) documents mobility in health, measuring parental health between the age of 60 and 70 and child's age between 36 and 50.

[22]This effect toward the end of life could also be driven by higher survival rates of individuals following a healthy diet.

[23]For both variables, the graph shows the values of the variable at a point in time. Thus the changes could also be due to differences in diet across cohorts and not age effects.

Figure 3: Life Cycle in Income and Diet of Children



Notes: The figure shows the average of three household variables for each age group between 21 and 70: (i) annual household income in the target population adjusted by the square root of household members (2.2 million observations), (ii) the households' expenditure share of fruits and vegetables in the sample (190,000), and (iii) the households' expenditure share of fruits and vegetables for households in the sample who currently do not live together with their children (72,000). All values are normalized to 100 for the lifetime average of each variable, and the points' size indicates the relative number of observations for this age group. The regression lines are estimates from a local regression with uniform confidence bands (with weights for the age groups' sizes).

3.1 Rank-Rank Slope

Our first measure of intergenerational mobility is the global relative rank-rank slope (RRS). To take into account a potential lifecycle in diet, we consider the rank of parents and children within each age category. Let r_{ci} denote child i's rank (from 1 to 100) among children conditional on their age. Similarly, let r_{pi} bet the rank of their parents within their parents' age group. The rank-rank regression is estimated by regressing children's rank on the parents' rank:

$$r_{ci} = \alpha + \beta r_{pi} + \epsilon_i, \tag{1}$$

where β is the rank-rank slope which provides a measure of transmission of the parents' position in their generation. For example, a $\beta = 0.3$ tells that if you compare two sets of parents one decile apart, their children are expected to be three percentiles apart. Then, the intercept α is the average rank for the lowest percentile ($r_{ci} = 1$). Without any correlation between r_{ci} and r_{pi}, the slope coefficient would be zero, and the intercept corresponds to the median rank. A steeper slope reflects a less mobile society (meaning more persistence). Hence, if each child were in the same percentile as their parents, the slope would be one, and the line would correspond to the 45-degree line. The rank-rank slope measures positional mobility as it measures mobility in the ranks instead of mobility in the distribution of the outcome itself (Deutscher and Mazumder, 2023). Positional measures are usually more robust to measurement errors than measures based on levels since only the relative position matters. Still, they do not consider level shifts and changes in dispersion within generations. Hence, if everyone were to eat healthier within one cohort, the rank-rank slope would ignore this, although welfare is clearly higher.

3.2 Intergenerational "Elasticity"

As a second global relative measure, we directly examine the relationship between children's diet and their parents. This measure is similar to the well-established intergenerational elasticity computed by regressing the logarithm of children's income on the logarithm of parents' income.[24] For our measure of diet, we do not take the logarithm, but we fit a quadratic model since it better fits the data.[25] Further, we control for the lifecycle in diet by including parent and child age as well as their squares in the following regression:

$$s_{ci} = \delta_1 s_{pi} + \delta_2 s_{pi}^2 + x_i' \gamma + \nu_i \tag{2}$$

where s_{ci} and s_{pi} are, respectively, the child's and parents' fruit and vegetable share, and x_i contains the age control variables. Since we fit a polynomial regression, the slope will change for different values of s_{pi}, and we will report the slope at $s_{pi} = \{25, 50, 75\}$.

3.3 Transition Matrix

Another commonly used measure in the literature are transition matrices. The idea is to break down both the children's and parents' distribution into groups of equal size. We group children and parents into quintiles, and the conditional probability that a child is in bin p_j given her parents are in bin p_k is defined as

$$TP_{j,k} = Pr(s_{ci} \in p_j | s_{pi} \in p_k). \tag{3}$$

This transition matrix answers questions like, *"What is the probability that an individual whose parents are in the bottom quintile of the distribution is in the top quintile?"* or "*What is the probability that this individual stays at the bottom of the distribution?"*. Hence, transition probabilities are a local absolute measure comparing children to their parents at a fixed part of the parents' distribution.[26] As for the previous measures, we compute quintiles again for each

[24]With a slight abuse of terminology, we refer to this measure as the *intergenerational elasticity*.

[25]Compared to income, our variable is only minimally skewed (see again Figure 2).

[26]Therefore, they would capture uniform intergenerational growth while the previous measures would not.

Table 3: Comparison of Mobility Measures

	(a) Rank-Rank Reg.		(b) IGE			(c) CER		(d) Transition Prob.		
	Intercept	Slope	25	50	75	25	75	Q1Q1	Q1Q5	Q5Q5
Diet	38.87	0.227	0.252	0.231	0.206	45.41	53.79	30.27	12.16	30.66
	(0.1)	(0.002)	(0.004)	(0.003)	(0.002)	(0.81)	(0.79)	(0.21)	(0.16)	(0.21)
Income	41.81	0.171	0.128	0.126	0.124	43.67	54.43	28.73	15.30	27.96
	(0.19)	(0.004)	(0.005)	(0.005)	(0.006)	(1.20)	(1.13)	(0.30)	(0.26)	(0.27)

Notes: The diet results are estimated using 192,814 observations for children. The income results are estimated using 93,277 observations for children as we restrict the sample to children between the age of 32 and 38 and parents with an average age between 56 and 62 (We also restrict the mothers' age to be between 49 and 61 and the fathers' age between 50 and 62, such that both parents are at least two years away from retirement). The IGE for income uses the log of father's income as an explanatory variable and the log of children's income as a dependent variable. Therefore, we drop 365 observations with zero values.

generation and age group separately. This implies that the bins p_j and p_k are age dependent.[27]

3.4 Conditional Expected Rank

The *Condtional Expected Rank* (CER) is the expected rank of children having parents at population percentile p:

$$CER(p) = \mathbb{E}(r_{ci}|r_{pi} = p). \tag{4}$$

We focus on the CER at the 25th and 75th percentiles, denoted CER25 and CER75. The CER can be estimated parametrically (using directly the information from the rank-rank regression) or nonparametrically. Both have different advantages. On the one hand, the parametric CER for children with parents at the 25th percentile also depends on the observations with parents at the top of the distribution as these observations influence both the intercept and slope of the regression. Hence, the parametric CER is, in fact, a global relative measure, and it may be misspecified.[28] On the other hand, with a large enough data set, one can calculate the CER directly from the subsample of parents at the percentile of interest, which is a fully nonparametric model. This gives a local absolute measure, resilient against misspecification, but susceptible to larger variance. We opt for a middle way and use a nonparametric local linear regression evaluated at percentile p fits our analysis best.

[27]We omit here the dependence of p_j and p_k on age to simplify notation.

[28]By definition, using the entire distribution to measure a linear model gives $CER50 = 50.5$. Hence, it will not change with a level shift of the dependent variable, which is the definition of a global measure.

4 Main Results

In the following, we present results on the overall persistence of dietary habits across generations. We start with the global measures introduced in the previous section (the rank-rank slope and the intergenerational elasticity). Both these measures summarize one specific aspect of mobility into a single number. Next, we discuss the relative measures, zooming in on specific parts of the distribution (using conditional expected ranks and transition matrices). Across all the reported mobility measures, We compute standard errors using the nonparametric bootstrap with 100 replications. Table 3 reports coefficients and standard errors for all our results. Finally, to assess the magnitude of the persistence of dietary choices we compared the findings to intergenerational mobility in income.

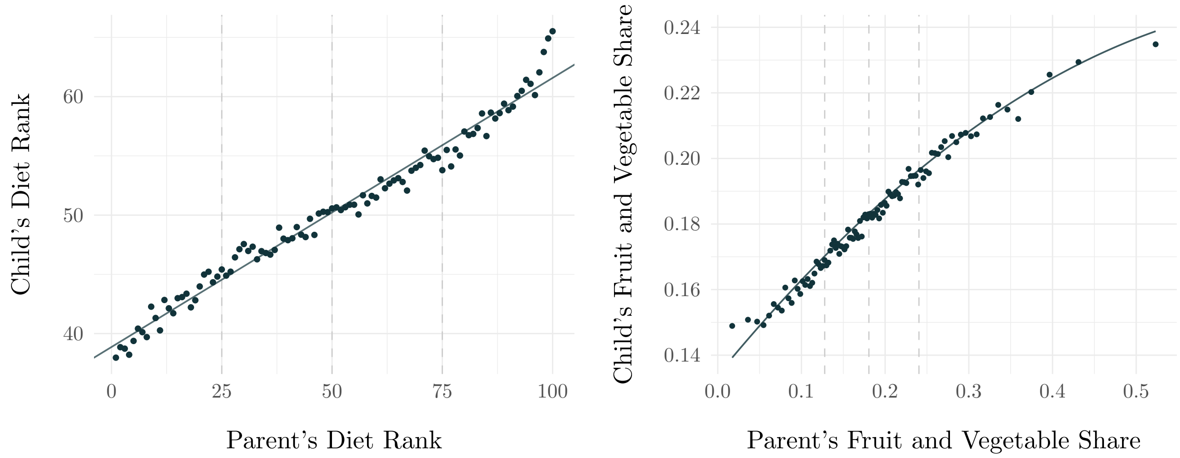
4.1 Dietary Mobility

Rank-Rank Regression – The results of the rank-rank regression are displayed in panel (a) of Table 3. The estimated rank-rank slope is 0.23, which suggests that an increase in the parental rank by one decile corresponds to an increase of 2.3 ranks for the child. To put these results into perspective, this number implies that it takes 2.98 generations to close the gap between two families at the first and the ninth decile.[29] Figure 4 graphically illustrates the positional relationship between parents and children, plotting the estimated RRS regression line. The dots represent the average child rank for each of the parents' ranks. The linear model approximates dietary patterns particularly well in the rank-rank model, which aligns with previous findings on income mobility. To show that conditioning the ranks on age solves the lifecycle issues, we allow the intercept and the slope to change over the lifecycle by saturating the model in children's age. Figure 5 shows the results using both unconditional and conditional ranks. The slopes are remarkably similar, and both decline with age. This latter result is unsurprising as one would expect the intergenerational association to weaken later in life. Differently, the intercept largely depends on the specification of the ranks, consistent with the life cycle in Figure 3. These findings support our expectation that conditional ranks are a better measure of diet than their unconditional counterparts.

Intergenerational Elasticity – Panel (b) of Table 3 shows our estimates for the intergenerational elasticity in diet at different parental percentiles according to model (2) (namely, at the 25th, 50th, and 75th percentile). We observe in Figure 4b that the estimated slope decreases as the parents' share increases, following the data closely. The decreasing slope suggests that increasing the fruit and vegetable consumption of a parent with a low consumption has a stronger effect on their children's diet. For example, a one percentage point increase in parents' fruit and vegetable consumption is associated with a 0.26 percentage point increase in child consumption

[29] The number of generations N to close the gap of $\Delta_{10,90} = 80$ ranks between the first and ninth decile solves $\beta^N \Delta_{10,90} = 1$, such that $N = \frac{log(1/\Delta_{10,90})}{log(\beta)}$.

Figure 4: Intergenerational Diet: RRS and IGE



(a) Rank-Rank Slope

(b) Intergenerational Elasticity

Notes: This figure shows the global measures for intergenerational mobility in diet. Figure 4a shows the estimated the rank-rank regression line based on in Equation (1) and Figure 4b shows the estimation results for the intergenerational elasticity in Equation (2). The dots in both graphs are the average child's rank at each parent's percentile.

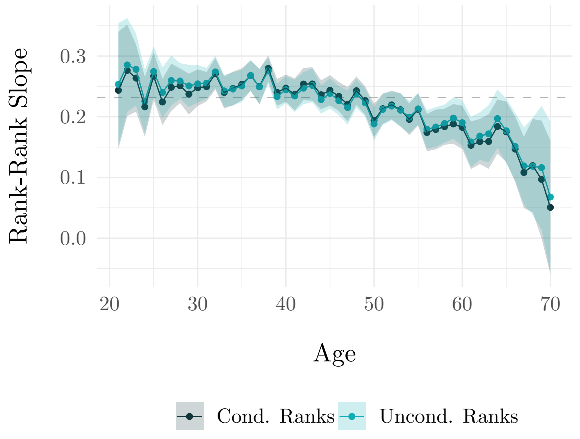
for parents at the 25th percentile. This relationship decreases to 0.21 when the parents are at the 75th percentile. Therefore, targeted policy interventions might have the largest benefits for unhealthily eating families, resulting in sizeable improvements in children's diets.

Conditional Expected Ranks – Panel (c) in Figure 4 shows the conditional expected rank estimated nonparametrically. We estimate a CER25 and CER75 of 45.6 and 54.1, respectively. Hence, a child with parents at the 25th percentile of the parents' distribution of fruits and vegetables is, on average, at the 46th conditional percentile of children. In contrast, children with parents at the 75th percentile can expect to reach the 54th percentile. Hence, although we observe strong persistence across generations in diet, there is still substantial reversion to the mean.

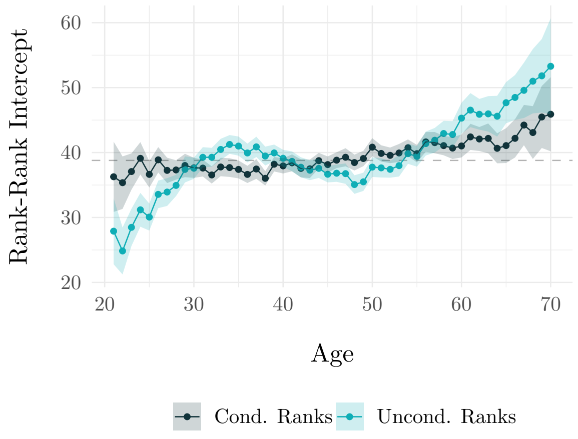
Transition Matrix – Figure 6 shows the estimated transition matrix with the corresponding confidence interval. Selected key results of the transition matrix are also displayed in Table 3 panel d). Without intergenerational persistence of diet across generations, the transition probabilities would not depend on parents' ranks, and we would observe 20% of children in each cell. The estimated transition matrix suggests a strong persistence in diet between generations as children are most likely to be in the same quintile as their parents. Focusing on the cells in the tails of the parents' distribution, 30.8% of children whose parents buy the least fruits and vegetables are also in the lowest quintile of children (corresponding to a Q1Q1 transition), while only 11.7% move up to the highest quintile (Q1Q5). If, on the other hand, a household's parents are among their generation's top 20% fruits and vegetable consumers, their children are most likely also in the fifth quintile (in 31.2% of the cases, Q5Q5). The estimation matrix is precisely estimated, and the confidence intervals are small.

Overall, we find a compelling persistence in healthy food consumption from our extensive super-

Figure 5: Rank-Rank Slope: Life-Cycle



(a) Rank-Rank Slope



(b) Rank-Rank Intercept

Notes: Figure 5a shows the rank-rank slope for a given age. The estimation uses ranks for kids and parents conditional on their age according to Equation (1) (with interactions for age groups). The blue line adds the results from the same estimation using unconditional ranks. Figure 5b shows the intercepts (the expected rank for a child with parents at rank zero) from the respective regressions. The dashed lines show the average RRS slope and intercept reported in Table 3. Standard errors are estimated from 100 bootstrap replications.

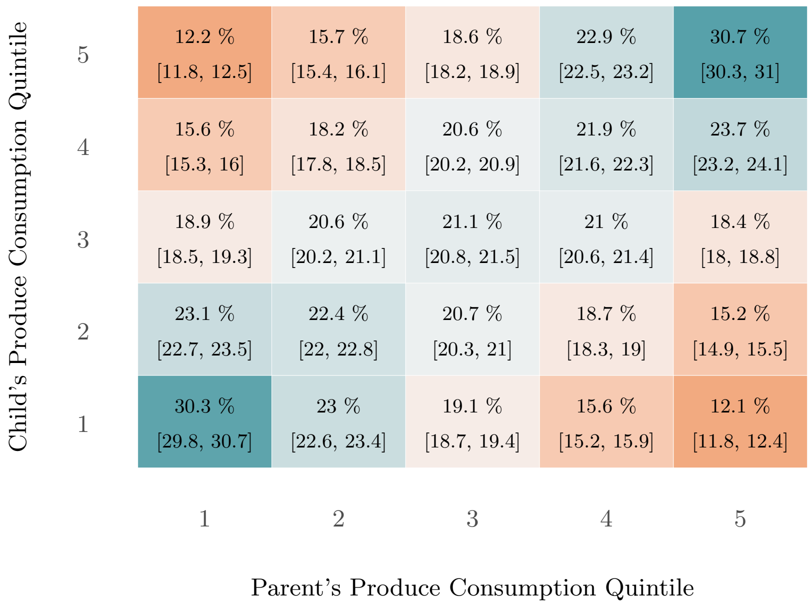
market data, and our coefficients are in the range of previous findings on total expenditures.[30] Especially the "extreme" transition probabilities face the highest persistence, meaning that the so-called cycles of poverty and privileges are pronounced. At the same time, there is more mobility around the median of the distribution.

4.2 Comparion to Income Mobility

To put the magnitude of our findings into perspective, we compare them to intergenerational mobility in income. To this end, we generate a data set for all Swiss children fulfilling the sample restriction criteria applied to the final data (this sample corresponds to one used in columns 3 and 4 of Table 1). We focus on the relationship between children and parents' income. Further, we average income between 2016 and 2021 to smooth out transitory fluctuations. Observations without income throughout this period have zero income, and if the parents are separated, we average their income. Figure 3 shows that lifecycle issues are far more pronounced for income than for diet. Thus, we follow the procedure of the previous literature trying to select a subgroup of children and parents with stable income (see, among others, Chetty et al. 2014, Corak 2020, or Acciari et al. 2022), and decide to restrict our analysis to children between the age of 30 and 40 with parents between 52 and 60. This restriction ensures that most children are already participating in the labor market and parents are not yet retired. Figure 3 shows that for these children, income only fluctuates slightly around the lifetime mean (all these age groups are

[30] see Charles et al. (2014), Waldkirch et al. (2004), and Bruze (2018).

Figure 6: Intergenerational Diet



Notes: The figure shows the transition probabilities for children's ranks of fruit and vegetable consumption conditional on their parents' ranks based on Equation (3). We analyze transitions between quintiles and calculate the ranks for children and parents conditional on their age group within the respective subsample of parents and children. 95% confidence intervals in parenthesis are estimated from 100 bootstrap replications.

within a maximum deviation from the average lifetime income of 10%), and parents' income is also stable. We estimate for income the same measures for intergenerational income mobility we use for diet, again calculating the ranks within children and parents conditional on age.

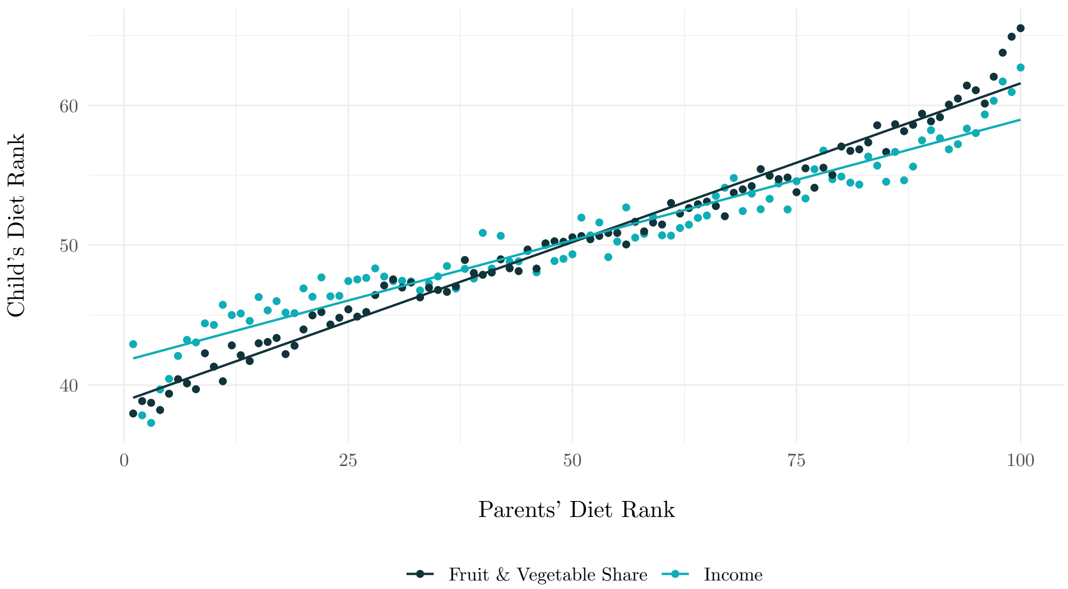
Table 3 shows an estimated RSS of 0.17 and an IGE of 0.16 at the 50th percentile.[31] The conditional expected ranks at the 25th and 75th percentile are 45.78 and 54.63. 28.5% of children with parents at the bottom quintile stay at the bottom, and 13.6% move up to the top.[32] Our estimates on income mobility in Switzerland are in the range of comparable analyses based on the same administrative data source (Chuard and Grassi, 2020).[33] Comparing our estimated mobility measures between diet and income, we observe that intergenerational transmission is more pronounced in the case of eating habits than income. This conclusion is identical across all our mobility measures, suggesting that parents have a more considerable influence on their children's diet than economic outcomes. Figure 7 illustrates this graphically and shows that the slope of the rank-rank regression for diet is substantially steeper, associated with less mobility. Nevertheless, it is important to note that income is particularly mobile in Switzerland

[31] We measure the intergenerational elasticity in income with a classical log-log specification, however, including a quadratic term.

[32] Different sample selection procedures and income definitions lead to comparable findings. Hence, we are confident that lifecycle issues are also contained for income after conditioning on age groups (as a covariate or in the form of conditional ranks), and our measures are robust to different sample selections.

[33] They use the administrative data for a different and longer time horizon and derive an RRS of 0.14 and an IGE of 0.22. They follow Chetty et al. (2014) and measure the parental income at child age 15 to 19.

Figure 7: Intergenerational Diet vs. Income: RSS



Notes: The figure shows the estimation results for the rank-rank regression in Equation (1) for intergenerational diet and income. The dots in both graphs are the expected child's rank if their parents are at a given percentile.

in comparison with most other Western countries, and the relative persistence of diet and income may differ in other countries.[34]

5 Counterfactual Analyis

The goal of this section is to isolate the component of intergenerational transmission in diet that does not pass through the transmission of two important socioeconomic characteristics across generations, namely income and education. Isolating this channel is particularly interesting as Table 1 shows that better-earning and higher-educated individuals tend to consume more fruits and vegetables. Consequently, it is natural to ask whether and how much of the patterns we document in this paper are due to the intergenerational transmission of these socioeconomic variables only. To this end, we apply the method proposed in Chernozhukov et al. (2013) and compute counterfactual transition matrices to disentangle these socioeconomic drivers. The idea is to identify the counterfactual distribution by combining a population's conditional distribution function (cdf) with an alternative covariate distribution. Here we are interested in the conditional distribution of children's diet (conditional on parents' diet) that we would observe if their income and education were independent of their parents' socioeconomic variables.[35] Since

[34]Previous literature estimates, for example, a rank-rank slope income mobility of 0.34 for the United States (Chetty et al., 2014), 0.24 for Canada (Corak, 2020), 0.22 for Sweden and Norway (Bratberg et al., 2017), 0.25 for Italy (Acciari et al., 2022), and 0.21 for Australia (Deutscher and Mazumder, 2020).

[35]We expect no direct channel from parents' income or education on their children's diet. Instead, such effects are more likely to pass through the parents' diet directly. This assumption is consistent with Altonji et al. (1992),

the ranks are conditional on age, we include the children's and parents' age in the conditioning set.

Let $F_{s_c|s_p,a_c,a_p}$ be the cdf of the children's diet s_c conditional on the parent's diet s_p as well as the age of children and parents, a_c and a_p. Further, note that from this distribution function, we can construct a transition matrix, provided we observe the marginal distribution of the parent's diet conditional on age. Let x_c denote a vector containing income and education of children, and let x_p contain the corresponding parents' variables. Our main object of interest is the counterfactual distribution of the children's diet that we would observe if we change the covariate distribution $F_{x_c|s_p,a_c,a_p,x_p}$ to $F_{x'_c|s_p,a_c,a_p,x_p}$ denoted $F_{s_c|s_p,a_c,a_p}\langle x|x'\rangle(s_c|s_p,a_c,a_p)$. Starting from the conditional cdf of children's diet conditional on (s_p,a_c,a_p,x_p,x_c) we can attain $F_{s_c|s_p,a_c,a_p,x_p}\langle x|x'\rangle(s_c|s_p,a_c,a_p,x_p)$ by integrating the conditional cdf over a different covariates distribution:

$$F_{s_c|s_p,a_c,a_p,x_p}\langle x|x'\rangle(s_c|s_p,a_c,a_p,x_p) = \\ \int_{\mathcal{X}'_c} F_{s_c|s_p,a_c,a_p,x_c,x_p}(s_c|s_p,a_c,a_p,x_c,x_p)dF_{x'_c|S_p,a_c,a_p,x_p}(x_c|s_p,a_c,a_p,x_p), \quad (5)$$

where $\mathcal{X}_j$ denotes the support of the covariates x_j for $j = \{c,p\}$ conditional on the other variables. Then, integrating $F_{s_c|s_p,a_c,a_p,x_p}\langle x|x'\rangle(s_c|s_p,a_c,a_p,x_p)$ over the distribution of the parents' covariates yields the desired result:

$$F_{s_c|s_p,a_c,a_p}\langle x|x'\rangle(s_c|s_p,a_c,a_p) = \\ \int_{\mathcal{X}_p} F_{s_c|s_p,a_c,a_p,x_p}\langle x|x'\rangle(s_c|s_p,a_c,a_p)dF_{x_p|s_p,a_c,a_p,x_p}(x_c|s_p,a_c,a_p). \quad (6)$$

In the counterfactual scenario that we consider, children's income and education are independent of the parental variables. Also, we assume that parents' age and parent's diet do not affect children's characteristics. Thus,

$$F_{x'_c|s_p,a_c,a_p,x_p}(x_c|s_p,a_c,a_p,x_p) = F_{x'_c|a_c}(x_c|a_c),$$

where we include age in the conditioning set to account for the lifecycle changes in income and different education distribution over cohorts. Thus, this counterfactual scenario closes the path going from the parents' to the children's diet through the intergenerational transmission of education and income.

The implementation follows the plug-in approach. We obtain the conditional distribution func-

which shows that the economic resources of the extended family have no impact on an individual's consumption. This rejects the classical altruism theory of perfect risk and consumption sharing within the extended family.

tion $F_{S_c|S_p,a_c,a_p,x_c,x_p}$ by inverting the conditional quantile function:[36]

$$F_{s_c|s_p,a_c,a_p,x_c,x_p}(s_c|s_p,a_c,a_p,x_c,x_p) = \int_{(0,1)} 1\{Q(u,s_c|s_p,a_c,a_p,x_c,x_p) \leq s\}\,du, \quad s \in \mathcal{S} \tag{7}$$

where $Q(\tau, s_c|s_p, a_c, a_p, x_c, x_p)$ is the τ conditional quantile function of s_c given the covariates. For this first step, we estimate flexible quantile regressions for $\tau = \{0.0001, 0.01, 0.02, \ldots, 0.99, 0.9999\}$. The regressors include a second-order polynomial of parents' diet, and for both parents and children we include age and education dummies as well as household income (and its square) interacted with age and a dummy for age ≥ 65. This last term allows income to have a different effect over the life-cycle, which is discontinuous after reaching retirement age.[37] For the estimation of the covariate distribution $F_{x_c'|a_c}$, we use the empirical distribution function:

$$\hat{F}_{x_c'|a_c=k} = \frac{1}{n_k}\sum_{i=1}^{n_k} 1\{X_{ci} \leq x\}, \tag{8}$$

where n_k is the number of children in a given age group.

For this analysis, we restrict the sample to the 138,477 children for which we observe their as well as their parents' education. The procedure in this section relies on the correct specification of the conditional quantile function. While we fit a flexible model, to further ensure a meaningful comparison, we re-estimate the transition probabilities in this smaller sample using the same linear quantile model.

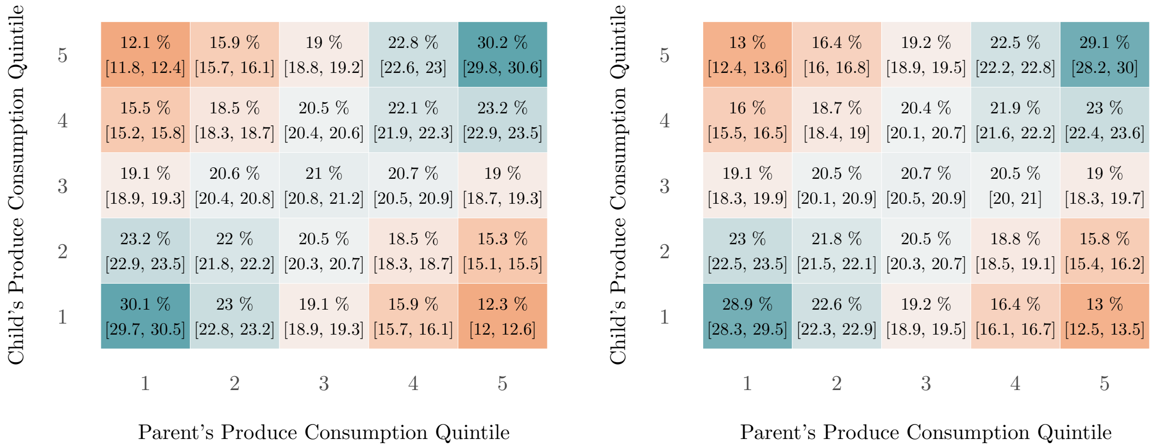
Figure 8 shows the estimated transition probabilities with the corresponding bootstrap confidence bands. First, Panel a) displays the transition probabilities estimated with the procedure described above, however, without changing the covariates' distribution. The results in panel a) are not statistically different from the transition probabilities computed nonparametrically for the entire sample in Figure 6. This observation provides some evidence that our estimated quantile regression is flexible enough. Second, Panel b) shows the counterfactual transition probabilities. The transition matrix is similar to the one in Panel a). However, the matrix suggests a statistically significant higher mobility, mostly in the extremes. For example, the Q1Q1 and Q5Q5 decrease, and the Q1Q5 probability increases.

Consider the Q5Q5 cell. The data suggests that individuals whose parents are in the fifth quintile are ten percentage points (= 30-20) more likely to be themselves in the fifth quintile than if there

[36]For this step, both a quantile regression or a distribution regression can be used (see Chernozhukov et al., 2013). One of the main advantages of a distribution regression is that it does not require a continuous outcome and allows for mixed and discrete ones. However, this does not pose a problem in our case, as our outcome variable exhibits a smooth conditional density. On the other hand, the quantile regression coefficient provides a more natural interpretation.

[37]During the sample period, the retirement age in Switzerland is 65 for men and 64 for women.

Figure 8: Intergenerational Diet: The Role of Income and Education



(a) Transition Matrix

(b) Counterfactual Transition Matrix

Notes: Figure 8a shows the transition matrix and Figure 8b shows the counterfactual transition matrix based on Eqaution (6) and Eqaution (5). The counterfactual considers the case where children's income and education are assigned independently from their parents' values. Bootstrap confidence intervals are in parenthesis. The results are estimated using the sample of 138,477 children for which we observe their as well as their parents education.

was no intergenerational transmission of diet. We will refer to this as an excess probability. In the counterfactual scenario where we close the channel going through income and education, this number declines to nine percentage points (= 29-20). This change suggests that transmission of income and education over generations explains around 10% of the excess probability. A similar calculation indicates that around 10% of the excess probability of remaining trapped at the bottom of the distribution can be attributed to income and education transmission.

In order to break down these transition matrices into a unique number, we compute the normalized trace similarly to Jäntti and Jenkins (2015).[38] For the transition matrix in panel a), we find a normalized (off-diagonal) trace of 25.04 which is 5.04 percentage points from the 20 of a perfectly mobile society. For panel b) we have a normalized trace of 24.42. This means that even after closing the path going through education and income, there is a gap of 4.42 percentage points, again suggesting that income and education might drive only 12% of the intergenerational transmission of diet. If we do the same exercise for the diagonal elements, we find that only 10% can be explained by education and income.

Overall, these results suggest that only between 10% and 12% of intergenerational persistence of diet can be explained by intergenerational transmission of income and education.

[38]Note that in our case, the normalized trace would be computed using the opposite diagonal elements.

6 Heterogeneities

The transmission of dietary habits across generations may be heterogeneous for different subgroups. Thus, this section unfolds the heterogeneous patterns (i) between individuals with different socioeconomic backgrounds (e.g., income, education, place of residence) and (ii) across regions. We estimate all results using parents' and children's ranks within the national distribution. Parental distributions may differ across groups, so the ranks are not uniform within the groups. As a consequence, children belonging to an unhealthy group will mechanically have a lower chance of making it to the top. To account for these differences, we follow Deutscher and Mazumder (2023) and reweight the parents' distribution in each group to imitate the distribution in the national population. For example, when we work with ranks, reweighting makes the ranks uniform in each group. Without this reweighting of the observations across groups, absolute mobility measures may simply reflect that some groups are particularly healthy and unhealthy.[39]

6.1 Heterogeneities Based on Children Characteristics

This section discusses the heterogeneities in intergenerational diet transmission. Table 4 shows the RRS, CER, IGE, and transition probabilities for different subgroups based on income and education, as well as residence, language region, and distance to their parents. The second column contains the P-value of the Wald statistic testing for equality of the RRS between all the subgroups, and the number of observations in each subgroup is in the last column. Bootstrapped standard errors are in parentheses.

First, panel (a) shows the results for three education levels: primary, secondary, and tertiary. The rank-rank slopes are close to 0.21 in all groups indicating that there is no heterogeneity in this mobility measure. However, when looking at the conditional expected ranks, it is clear that higher-educated children eat more fruits and vegetables. While, on the one hand, a child with parents at the 25th percentile can expect to reach the 37th percentile if she has an primary education, a tertiary education increases this number to 51 (a difference of 14 ranks). On the other hand, a child can expect to reach the 51st or 59th percentile conditional on having a primary and tertiary education if her parents are at the 75th percentile (a smaller difference of 8 ranks). Thus, although the estimated rank-rank slopes are not economically nor statistically different, the gap in diet seems to narrow towards the top of the distribution. Figure 9a illustrates this, plotting the rank-rank slope and the expected child's rank given her parents' rank.

Second, panel (b) provides the results for different income groups. To account for the lifecycle in

[39]This is because, in unhealthy groups, children are more likely to surpass their parents' outcomes through mean reversion. For our measures of intergenerational elasticity, the rank-rank slope, and the conditional expected rank, the reweighting procedure gives equal weights to all groups. For the transition matrix, the reweighting changes the distribution of children conditional on their parents' bins and, therefore, also changes the children's (nationally estimated) ranks. Relative measures are almost unaffected by the reweighting in most cases. For an extensive discussion of the topic, see Deutscher and Mazumder (2023).

Table 4: Heterogeneities

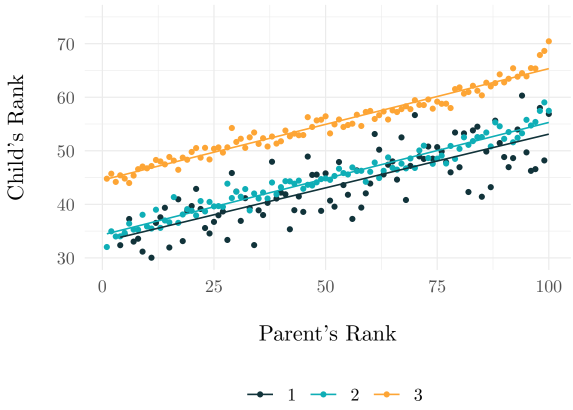
	Rank-Rank		IGE			CER		Transition Prob.			
	RRS	P-value	25	50	75	25	75	Q1Q5	Q1Q1	Q5Q5	N
(a) Kid's Education											
Primary	0.217	0.876	0.264	0.229	0.190	36.76	51.02	7.69	42.71	22.33	4,991
	(0.019)		(0.023)	(0.018)	(0.021)	(4.30)	(4.40)	(1.06)	(1.17)	(1.73)	
Secondary	0.210		0.233	0.208	0.179	39.81	48.80	8.89	36.46	23.77	59,222
	(0.004)		(0.006)	(0.004)	(0.004)	(1.37)	(2.32)	(0.33)	(0.40)	(0.45)	
Tertiary	0.208		0.220	0.208	0.193	50.64	59.39	16.35	22.77	35.34	74,264
	(0.004)		(0.008)	(0.005)	(0.004)	(1.28)	(1.44)	(0.34)	(0.39)	(0.34)	
(b) Kid's Income											
1th Quartile	0.246	0.000	0.261	0.240	0.217	40.21	48.58	8.39	39.65	26.54	45,962
	(0.004)		(0.007)	(0.005)	(0.005)	(1.56)	(1.91)	(0.28)	(0.42)	(0.49)	
2nd Quartile	0.218		0.233	0.214	0.194	45.26	53.36	9.82	31.34	26.22	45,954
	(0.005)		(0.006)	(0.005)	(0.005)	(1.62)	(1.61)	(0.32)	(0.41)	(0.41)	
3rd Quartile	0.203		0.223	0.202	0.178	46.57	53.09	13.19	26.00	30.68	45,940
	(0.004)		(0.007)	(0.005)	(0.005)	(1.85)	(1.60)	(0.37)	(0.47)	(0.46)	
4th Quartile	0.193		0.213	0.201	0.187	52.68	58.04	19.17	21.87	36.99	45,934
	(0.005)		(0.007)	(0.005)	(0.005)	(1.89)	(1.76)	(0.45)	(0.47)	(0.48)	
(c) Kid's place of residence											
Rural	0.217	0.000	0.247	0.219	0.186	41.73	48.75	8.32	34.99	24.25	50,571
	(0.004)		(0.007)	(0.005)	(0.005)	(1.42)	(1.58)	(0.25)	(0.44)	(0.50)	
Suburban	0.211		0.230	0.212	0.192	45.59	53.78	12.12	29.77	28.58	110,098
	(0.003)		(0.005)	(0.004)	(0.003)	(1.16)	(0.97)	(0.21)	(0.26)	(0.28)	
Urban	0.186		0.203	0.192	0.180	53.68	60.33	23.38	20.90	41.65	31,953
	(0.006)		(0.010)	(0.007)	(0.006)	(2.22)	(1.79)	(0.62)	(0.60)	(0.52)	
(d) Language Region											
Italian	0.189	0.009	0.202	0.178	0.151	42.70	58.11	9.10	29.85	23.56	4,297
	(0.007)		(0.015)	(0.012)	(0.009)	(1.70)	(1.32)	(0.67)	(0.59)	(1.51)	
Germany	0.231		0.259	0.236	0.211	46.77	54.05	12.35	30.28	31.32	153,239
	(0.014)		(0.018)	(0.016)	(0.018)	(2.50)	(2.15)	(1.02)	(1.01)	(1.97)	
French	0.223		0.237	0.218	0.196	43.79	51.88	11.26	30.73	28.64	34,898
	(0.019)		(0.031)	(0.022)	(0.023)	(4.01)	(4.66)	(1.34)	(1.75)	(2.31)	
(e) Distance to Parents											
1th Quartile	0.254	0.000	0.271	0.252	0.231	44.21	52.85	9.83	33.17	29.48	48,204
	(0.004)		(0.007)	(0.005)	(0.004)	(1.59)	(1.41)	(0.30)	(0.51)	(0.50)	
2nd Quartile	0.239		0.266	0.243	0.216	45.57	52.90	10.52	31.48	29.40	48,204
	(0.005)		(0.007)	(0.005)	(0.005)	(1.64)	(1.66)	(0.29)	(0.45)	(0.48)	
3rd Quartile	0.213		0.240	0.218	0.193	45.01	53.73	13.09	29.91	30.29	48,203
	(0.005)		(0.007)	(0.005)	(0.005)	(1.57)	(1.37)	(0.31)	(0.46)	(0.46)	
4th Quartile	0.193		0.219	0.199	0.176	47.68	56.11	15.52	26.48	32.82	48,203
	(0.005)		(0.008)	(0.006)	(0.005)	(1.64)	(1.65)	(0.39)	(0.53)	(0.48)	

Note: The table shows the results for difficult subsamples defined by education, income, residence, language region, and distance to their parents. The second column gives the P-value of the null hypothesis that the rank-rank slope is the same for all subgroups. Bootstrap standard errors in parenthesis are computed using 100 replications. The number of observations in each subgroup is shown in the last column.

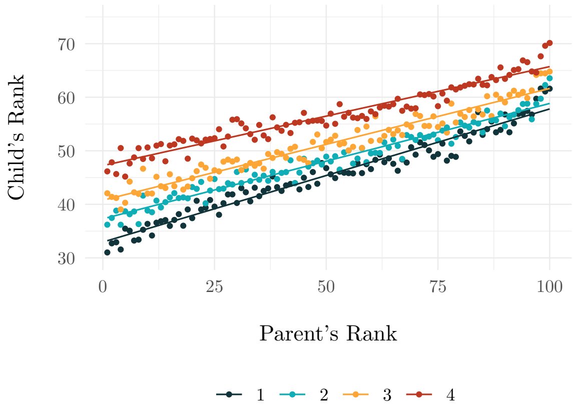
income, the income quartiles are conditional on age, and we keep only children of working age (25-64).[40] As shown, the RRS and IGE monotonically decrease as children's income increases. For children in the first income quartile, we find a RRS of 0.25 compared to 0.185 for individuals in the fourth quartile. Thus, ranks are more persistent over generations among low-income children,

[40]The results are not affected if we use all observations.

Figure 9: Intergenerational Diet: Heterogeneous RRS



(a) RRS: Education



(b) RRS: Income

Notes: This figure shows estimation results from a rank–rank regression (Equation (1)) for different subpopulations, complementing the results in Table 4. Figure 9a displays the RRS for different education levels and Figure 9b for different income levels. The dots in both graphs are the expected child's rank if their parents are at a given percentile.

meaning that their parents' diet has a stronger influence. This difference is also statistically significant. Figure 9b shows the rank-rank slope and expected ranks for all four income quartiles. In addition, the transition probabilities in Table 4 say that richer children are also more likely to move up or stay at the top of the diet distribution, and they are less likely to move down. In contrast, low-income individuals have a high probability of remaining trapped in the lowest quintile. We observe sizeable heterogeneities between income and education levels, although Section 5 we showed they only explain 12% of intergenerational persistence in diet.

Panel (c) shows that mobility is higher in urban areas and lower in rural areas, where people also seem to eat better. The transition probabilities show that children in urban areas have an outstanding possibility of moving up in the distribution. strikingly, a child born to parents in the first quintile of the distribution is more likely to find himself at the top of the distribution than in the first quintile. Panel (d) shows heterogeneities across languages region. The Italian speaking has higher mobility while the lowers are among German-speaking children. At the same time, the children in Italian-speaking regions have lower values of CER, suggesting a poorer average diet among those children compared to other regions. Last, parental transmission of diet may weaken if households move away from their family and the social network in which they grew up. Hence, panel (e) analyzes the role of the distance between the children's and parents' residences. We observe that nutritional persistence remains high even if children live far away from their parents. However, the further the children move away from their parents, the lower the patterns' persistence. Striking is especially that households are seven percentage points less likely to be trapped at the bottom if they live far away. This finding seems plausible as social interactions and the responses to family-related shocks diminish with increasing distance (see, for example, Büchel et al., 2020 and Fadlon and Nielsen, 2019).

Table 5: Regional Heterogeneities

Measure	Mean	p10	Median	p90	SD
Rank-Rank Regression					
Intercept	39.841	36.908	39.327	44.613	3.289
	(0.272)	(0.412)	(0.374)	(0.824)	(0.279)
Slope	0.219	0.178	0.226	0.260	0.037
	(0.004)	(0.012)	(0.007)	(0.009)	(0.005)
IGE					
IGE25	0.234	0.156	0.251	0.289	0.063
	(0.008)	(0.027)	(0.010)	(0.014)	(0.010)
IGE50	0.218	0.154	0.232	0.266	0.049
	(0.005)	(0.017)	(0.007)	(0.010)	(0.006)
IGE75	0.200	0.151	0.206	0.236	0.036
	(0.005)	(0.010)	(0.006)	(0.008)	(0.005)
CER					
CER25	44.367	35.804	46.238	51.783	7.122
	(2.386)	(3.378)	(2.172)	(4.076)	(1.610)
CER75	54.488	48.684	54.881	59.148	4.403
	(1.810)	(2.665)	(1.756)	(3.105)	(1.272)
TP					
Q1Q1	28.467	22.470	28.453	33.712	4.698
	(0.490)	(1.604)	(0.781)	(0.875)	(0.555)
Q1Q5	12.244	9.712	12.331	14.923	2.669
	(0.352)	(0.709)	(0.530)	(0.639)	(0.459)
Q5Q5	30.743	27.371	30.801	36.095	4.443
	(0.392)	(1.049)	(0.640)	(0.744)	(0.336)

Note: The table shows the regional variation in mobility measures for the 26 administrative cantons. We observe for 106,131 children the place where they grew up. The mean canton has 4,082 individuals, a value that ranges from 532 to 17,802. Standard errors in parenthesis are estimated from 100 boostrap replications.

6.2 Regional Heterogeneities

Children's behaviors may be influenced differently by their parents depending on where they grow up. This can be the case if one's childhood neighborhood makes it particularly easy for a kid to eat either healthy or unhealthy, independent of their parents. For example, cheap takeaways and stores selling ice cream or sweets likely influence children differently than local farmers' markets. Therefore, we document the spatial dispersion of intergenerational mobility measures. We again estimate ranks on the national level and reweight the observations.[41] To identify the place a child had grown up, we select parents that had not moved since the child was at most fourteen years old and treat this location as the child's place of origin. Table 5 displays for each of our mobility measures the mean, median, as well as the 10th and 90th percentile for the 26 Swiss cantons.[42] The rank-rank slope ranges from 0.18 to 0.26. The conditional expected rank at the 25th percentile lies between 35 and 51 (a difference of 16 ranks), and the expected rank at the 75th percentile is between 48 and 59 (11 ranks). Hence, the spatial dispersion is lower for

[41] Reweighting regional estimates ensures that we compare apples with apples. If everyone in a region suddenly ate better, this would not change the region's estimates but the national ranks.

[42] The 26 Swiss cantons are the highest administrative regions and their population ranges from 16,000 to 1.5 million.

children from healthier-eating households. Children from parents at the bottom quartile reach the top quartile in 9.7% to 14.9% of the cases while they are stuck at the bottom in 22.5% to 33.7%. Hence, we observe significant spatial variation in the parents' impact on their children's diet.

7 Conclusions

The detrimental consequences of bad dietary habits are responsible for a huge social and economic burden, while the origins of these harmful eating habits are so far greatly understudied. In this paper, we shed light on the intergenerational transmission of dietary habits from parents to their children. We do so by combining unique supermarket transaction data with administrative records, including family linkages. We contribute to the literature with novel evidence showing that one's family background is, in fact, a crucial determinant of persistent eating patterns, suggesting that the diet consumed early on in life at one's parents' dinner table shapes our nutritional tastes and preferences throughout our lives. Isolating the part of diet transmission going through education and income, we show that these socioeconomic variables only explain 12% of the intergenerational persistence in diet. Although other unobserved variables of children likely influence eating habits throughout their lives, the direct effect of childhood diet can be expected to be large. Further, we show the intergenerational transmission of diet varies across observable covariates. Higher-educated and better-earning children generally eat better, independent of their parents. While the transmission mechanism (in terms of the rank-rank slope) does not vary between educational levels, it grows significantly weaker as income rises. Hence, low-income individuals are particularly vulnerable to getting stuck in a cycle of unhealthy diets. Further, our results show even larger upward mobility among children living in urban areas. Among those living in urban areas, children with parents in the first quintile have a higher probability of reaching the highest quintile than remaining trapped in the lowest quintile themselves. We also observe that the transmission also becomes weaker as the distance between children and their parents increases, suggesting that breaking out of one's childhood environment can be a valid way to break unhealthy patterns. Ultimately, we document spatial differences in our mobility measures, identifying particularly vulnerable regions and showing that one's place of origin is an important factor for intergenerational mobility.

These findings have important implications for public health and policymakers. Recognizing the influence of family on dietary choices helps to design targeted interventions and formulate policy recommendations aimed at promoting healthier eating habits. By understanding the origins of unhealthy eating patterns and the mechanisms through which they are transmitted across generations, policymakers and healthcare professionals can develop effective strategies to combat the rising prevalence of diet-related diseases. For example, policy interventions targeting school-food programs, nutritional education for children, and information campaigns at schools and doctors' offices may be particularly effective.

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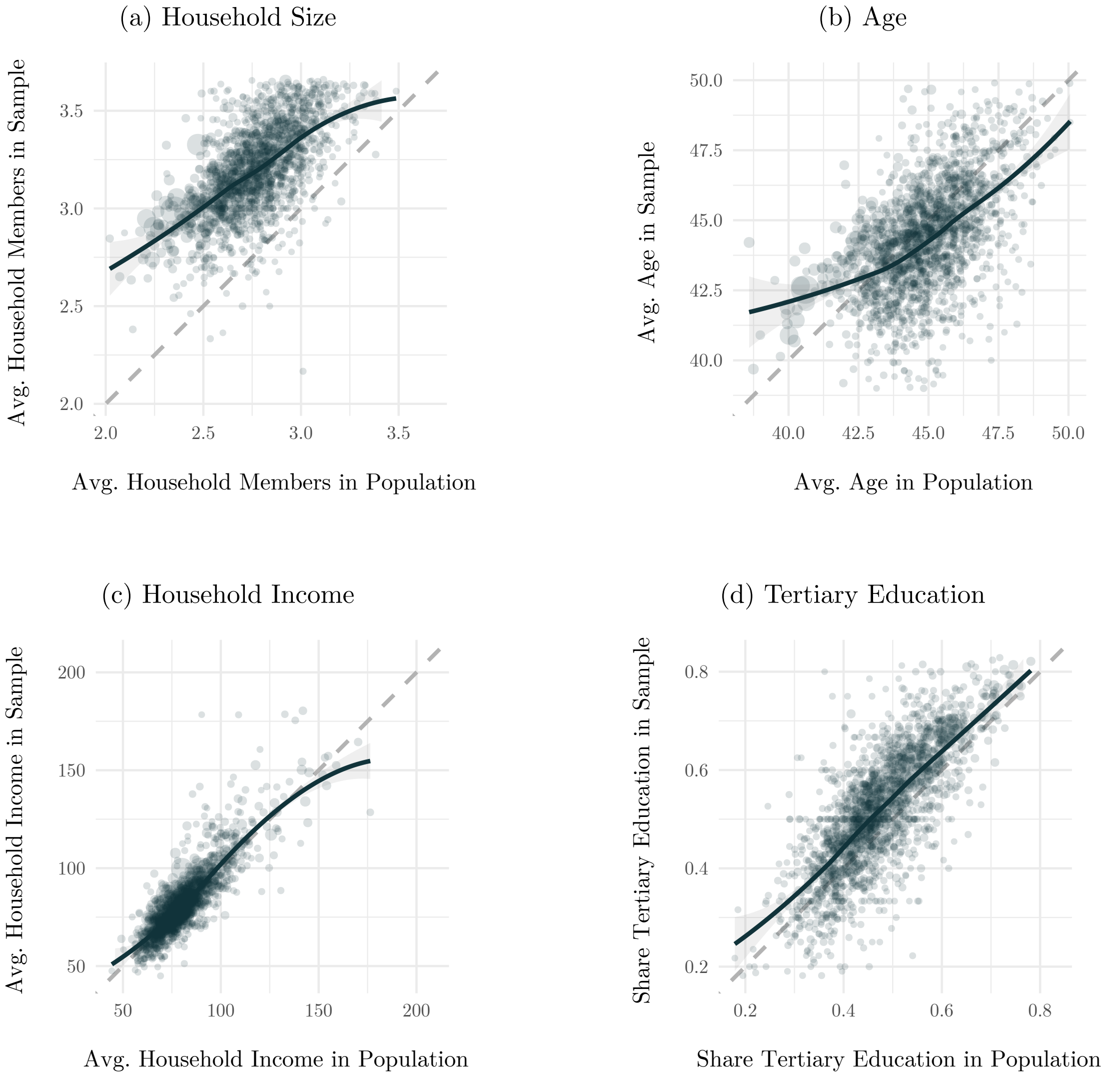
A Appendix

Figure A1: Municipality Averages: Kids in the Sample vs. Population



Notes: The figure illustrates the representativeness of the matched final data. To this end, we compare kids that could be uniquely matched between the administrative and consumption data to the entire Swiss population of kids. Each dot represents a municipality's average, while the dot's size indicates the municipality's population. The blue line shows a local regression. The dashed line is the 45-degree line. *Household Size* is the count of members living in an average household, *Age* is the average age of all kids in this municipality, *Household Income* is the average household labor market income, and *Tertiary Education* is the average share of households with at least one member having a tertiary degree.