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 unhealthy eating remain poorly understood. This paper provides novel evidence on the intergenerational transmission of dietary choices from parents to children by exploiting unique grocery transaction records matched with administrative data. We document a strong intergenerational persistence of diet that exceeds income transmission across all measures we consider. At the same time, substantial heterogeneities in the persistence of diet indicate that the socioeconomic background and location of children may be crucial to foster beneficial eating habits and to break unhealthy ones. We discuss potential mechanisms and show in a counterfactual analysis that only 12% of the intergenerational persistence in diet can be explained by the transmission of income and education. In line with these results, we introduce a habit formation model and argue that the formation of dietary habits during childhood and their slow alteration are key drivers of our findings.

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

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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, Bronnenberg et al., 2012, Atkin, 2013, 2016) and withstand major personal shocks and interventions (see Oster, 2018, Hut and Oster, 2022, Allcott et al., 2019a).

This paper studies 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 individuals (10% of the population of interest) 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.

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 0.227, and children whose parents spend one percentage point more on fruits and vegetables have a 0.231 percentage point higher spending themselves at the median of parents' consumption. Further, the children's probability of reaching the top quintile when parents are in the bottom quintile is

[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] Switzerland has a high density of grocery stores such that households travel on average 600 meters to the nearest one, and 80% of the population have a store within 2 kilometers (Swiss Federal Statistical Office). In comparison, the median distance to the nearest food store in the United States is 0.9 miles (1,450 meters), and only 40% of the population live no more than a mile ($\approx$ 1,600 meters) from the closest store (USDA). In addition, healthy eating is also relatively affordable in Switzerland. 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.

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 findings to income mobility suggests that intergenerational persistence of diet exceeds income transmission across all measures we consider, indicating that the development of dietary habits during childhood might be a persistent channel through which parents impact their children's future. Yet, the socioeconomic background of children may be crucial to foster beneficial habits and to break unhealthy ones. Therefore, we look at different sub-samples and observe that the parents' influence is stronger in rural areas and among children with lower education and income, while the transmission mechanism weakens as the distance between parents and children increases. Hence, high socioeconomic status and exposure to new environments seem to foster healthy eating.

Additional factors beyond the direct transmission of dietary habits influence children and their diet in many interconnected ways, and these could (partly) explain our findings. Such mechanisms include the transmission of socioeconomic status across generations, location and network effects, and unobserved family backgrounds, such as genetic variations in taste, genetic predispositions for diseases, or unobserved family shocks. For example, if highly educated and high-income individuals eat healthier, the transmission of these socioeconomic variables could (at least partially) drive our results. To understand the importance of these mechanisms, we apply the counterfactual analysis proposed in Chernozhukov et al. (2013) and find that the transmission of income and education can only explain 12% of the persistence in diet, while transmission of location preferences accounts for 5%. In addition, we analyze the lifestyle-related death of a parent to assess whether information on genetic predisposition impacts dietary choices, and we find no significant response.

These results indicate that parents impact their children's nutrition directly – for example, through the transfer of nutritional knowledge and dietary habits – rather than indirectly through socioeconomic variables. To this end, we introduce a model of dietary habit formation in which agents inherit a habit stock from their parents and childhood environment. These habits influence the agents' diet in two ways. On the one hand, agents want to eat healthily while, on the other hand, deviating from one's habit causes disutility. The solution of our model suggests that fruit and vegetable consumption is a weighted average of current habits and a known optimal diet. The most important determinants of these weights are the strength of habit formation and adaptation costs. The results from our model estimation suggest that sticky habits are an important determinant of dietary persistence. Further, we find that better-earning households are more efficient producers of healthy eating habits.

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) document the importance of social networks in fostering upward income mobility for low-income people.[3]

[3] See also Chetty et al. (2016, 2020), and Chetty and Hendren (2018). Rothstein (2019) tries to disentangle

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, a 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 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 total food expenditures and imputed consumption based on the PSID and 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 to exploit rich intergenerational consumption data and analyze the transmission of dietary habits across generations.

We further contribute to the literature on dietary choices. This strain of the literature primarily focuses on evaluating the impact of policies promoting healthier eating behavior, however, mostly finding results with limited economic or statistical significance. These policies include food subsidies (Bailey et al., 2023, Goldin et al., 2022, Hastings et al., 2021), food labels (Barahona et al., 2023, Araya et al., 2022, Cook et al., 2005), sin taxes (Dickson et al., 2023, Aguilar et al., 2021, Dubois et al., 2020, Allcott et al., 2019b), carbon pricing of food (Springmann et al., 2018), or school-food programs (Berry et al., 2021, Handbury and Moshary, 2021). In contrast, this paper contributes to the understanding of the origins of eating behaviors in the first place.

The paper is structured as follows. Section 2 introduces the data and presents summary statistics while Section 3 discusses our measures of intergenerational mobility. Section 4 documents the intergenerational patterns in diet and compares them to income mobility. Section 5 dives into heterogeneities and we discuss potential mechanisms in Section 6. Emphasizing the importance of dietary habits, Section 7 introduces and estimates a model framework on habit formation. Section 8 concludes.

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 for health, 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).

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 refer to individuals in the grocery data as *customers* and those in the administrative data as *residents*.

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 on average 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 (*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 fruits and vegetables are highly correlated with the healthy eating index in Allcott et al. (2019a) of 0.57 and 0.41. 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. The

[6] 1 Swiss franc (CHF) equals approximately USD 1.10 on July 19, 2023, meaning CHF 50 $\approx$ USD 55.

[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.

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 coded 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 for every resident for the years 2016 to 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 the years 2016–2020.

The *Structural Survey* for the years 2010–2020 provides information on housing, employment, mobility, and education. The survey selects a representative sample of 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 stabilizes for most individuals only after a certain age, we add the characteristics for

[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 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.

[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.

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 location grid cells, age, and gender. This generates 5.6 million matches between customers and residents. To isolate the unique matches, we take some additional steps.[14]

The refinement proceeds as follows: (i) Using the transaction data itself, we calculate the median road distance traveled in a given year, weighted by expenditures. Then, we require a customer to shop close enough to her home by excluding all pairs where this measure exceeds 20 kilometers during any year, as these residents are likely not the owners of the loyalty card they link 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 without changing their customer address. (v) As some consumers have moved recently without notifying the retailer, we check whether these movers uniquely match a resident 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 gives 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.

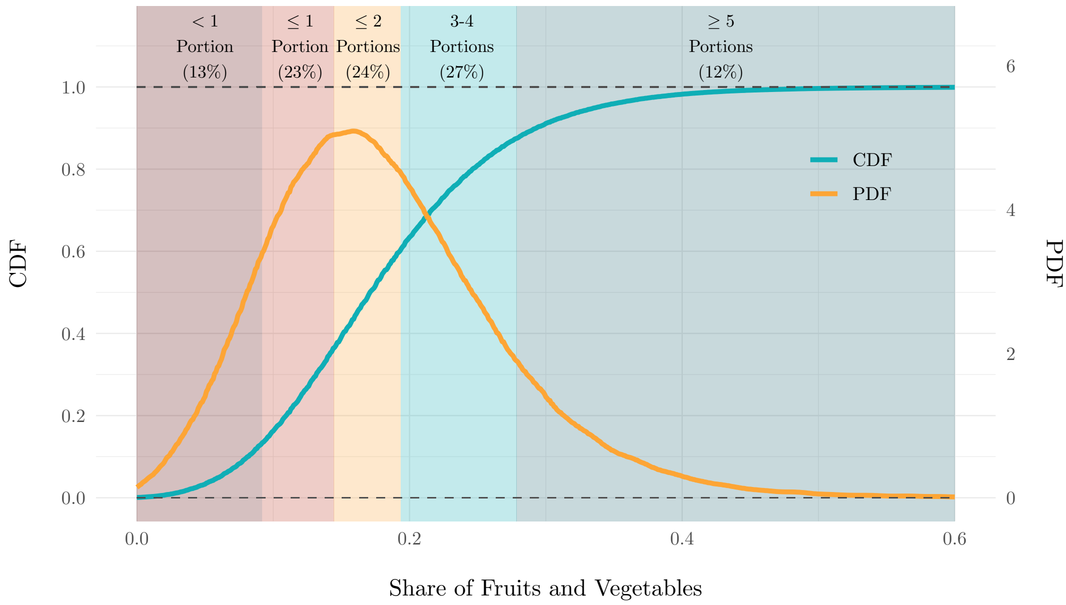
Dietary Variables – For households owning multiple loyalty cards, we first aggregate expenditures within the household before calculating the relative share over the sample period for each food product category at the household level. Additionally, some children moved out recently. In this case, we exclude their expenditures in the periods they still lived with their parents when aggregating the expenditures over time.[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 generate the intergenerational linkages, selecting pairs of children and parents observed in the data and living in different households. This substantially reduces our sample size to 350,000 children linking to 208,000 of their fathers and

[14] Some customers do not match any resident, which is most likely because their addresses in the grocery data are outdated or because they died. 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.

[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.

Figure 1: Distribution of Fruit and Vegetable Consumption



Notes: The figure shows the cumulative distribution function and the probability density function of the fruit and vegetable share in our data. The colored bars show independent data on the fruit and vegetable portion intake in Switzerland from the National Nutrition Survey menuCH.

280,000 of their mothers. 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 per capita. 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 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

Table 1 displays summary statistics for the consumers' monthly food expenditures and the share allocated to fruits and vegetables. The average customer spends 350 Swiss francs per month (380 USD) and allocates 18% of this money to fresh fruits and vegetables. To put this

[16]Because we detect minor 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.

into perspective, we plot in Figure 1 the entire distribution of fruit and vegetable intake and overlap it with data on portion intake from a representative administrative nutrition survey.[18] Only 12% of Swiss households fulfill the recommended fruit and vegetable intake of five daily portions. This implies that the mass of households in our data consume only between one and two portions of produce a day. The last two columns of Table 1 compare these expenditures to the administrative *Household Budget Survey*, showing that our transaction data covers 57% of the average household grocery expenditures on food and beverages.[19]

Looking at different household characteristics, we observe that 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 diet. 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, showing a nutritional inequality across different socioeconomic status as previously observed in Allcott et al. (2019a). Finally, we observe a larger fruit and vegetable share in urban than suburban or rural areas. One explanation could be that households in sparsely populated areas 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), and we do not expect this to affect our results.

In addition, we want to assess the representativeness of our data. Table A1 shows summary statistics for the 192,000 matched children and compares them to the 2.2 million children in the population fulfilling the same selection criteria, while Figure A2 plots municipality-level sample averages against the population values. 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. 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. Our 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 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 A1a 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

[18] The Federal Food Safety and Veterinary office conducted between 2014 and 2015 the *National Nutrition Survey* to document the diet of 2,000 Swiss adults.

[19] This survey continuously selects 2,500 households each year, and participants take for an entire month notes on their income and expenditure. Note that as we do not observe beverages, our actual coverage of food products is even higher.

Table 1: Summary Statistics for Kids' Expenditures

	Total Spending			% Fruit & Vegetable			Budget Survey	
	Mean	p50	SD	Mean	p50	SD	Spending	Share
Overall	350	280	254	0.18	0.17	0.09	616	0.57
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 Household Income								
< 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 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		

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.

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 A1b. In summary, our sample represents the target population well, and our expenditures cover a large share of grocery expenditures.

3 Measuring Moblity

In the literature, there is not one single measure of mobility. Instead, many different statistics caputre different aspects of mobility, which are not necessarily positively correlated.[20] For this paper, we need to consider that not all measures are interesting in our setting, as we focus 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 diet, there is an

[20] Deutscher and Mazumder (2023) provide an extensive discussion and clear classification of different mobility measures, discussing the relationship between them.

optimal level or interval of consumption of fruits and vegetables, and an increase in vegetable consumption beyond a certain threshold might not be beneficial. Yet, most of the population seems to be on the left of this threshold.[21] Differently, we usually assume a positive marginal utility of 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.

Papers analyzing intergenerational mobility face two challenges: (i) how to approximate the lifetime outcome well enough to handle transitory fluctuations and (ii) how to deal with lifecycle issues. The general approach in the recent literature is to average the outcome of children and parents over longer periods and to restrict the analysis to certain age bins of children and parents, ensuring that children, in the case of income, are old enough to be a regular part of the labor market and that parents are not yet retired to avoid lifecycle and attenuation biases.[22]

Figure 2 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 variables are normalized to the respective lifetime mean to make the results comparable. While income and diet exhibit both some variation over the lifecycle, the 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.[23] 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.[24] 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

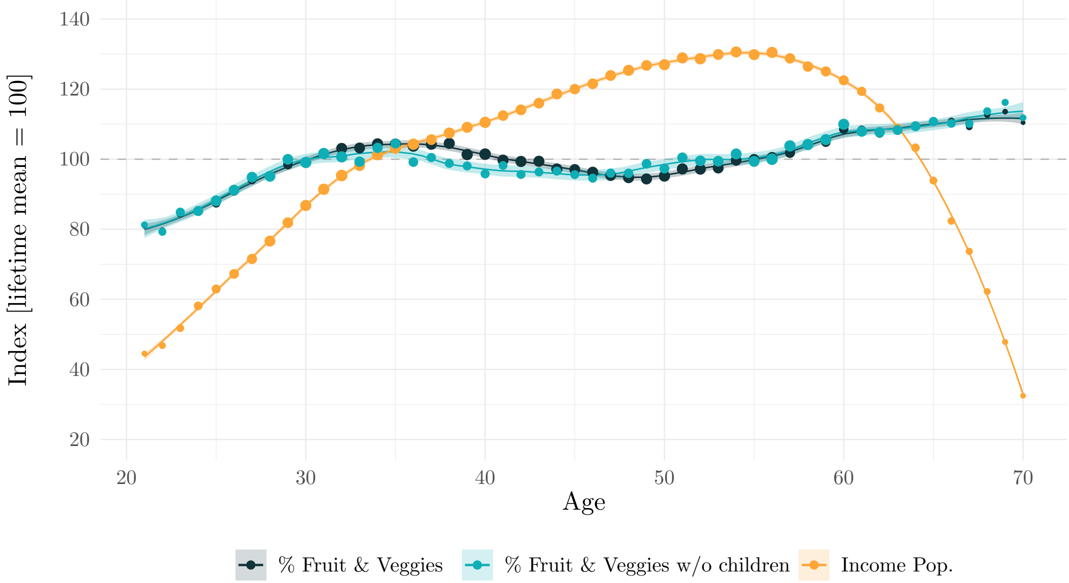
[21] According to governmental surveys, 87% the population does not follow the dietary recommendations to consume five portions of fruit and vegetables daily, and around 60% of the population eat two or fewer portions of fruits a day. In our data, 16% of the children spend less than 10% on fruit and vegetables, and 75% have a share smaller than 23%.

[22] There is a large variety of specific approaches. 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.

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

[24] 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 2: 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).

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, where the weights are proportional to the expenditure.

3.1 Rank-Rank Slope

Our first measure of intergenerational mobility is the rank-rank slope (RRS), where the percentile ranks of parents and children are computed within each age category. Let r_{ci} denote child i's percentile rank (from 1 to 100) among children conditional on their age. Similarly, let r_{pi} be the percentile rank of their parents within their parents' age group. The rank-rank regression is estimated by regressing the 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. 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 value of $\beta = 0.3$ tells that if you compare two sets of parents one decile apart, their children are expected to be three percentiles apart. A steeper slope reflects a less mobile society (meaning more persistence). For instance, 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.

3.2 Intergenerational Elasticity

As a second 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.[25] For our measure of diet, we do not take the logarithm, but we use a quadratic model since it better fits the data. 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 changes over s_{pi}, and we will report the slope at the $\{25, 50, 75\}$ percentiles of s_{pi}.

3.3 Transition Matrix

Transition matrices break down 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 compare children to their parents at a fixed part of the parents' distribution. As for the previous measures, we compute quintiles again for each generation and age group separately.

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

Table 2: Comparison of Moblity Measures

	(a) Rank-Rank Reg.		(b) IGE			(c) CER		(d) Transition Prob.		
	Intercept	Slope	25	50	75	25	75	Q1Q1	Q1Q5	Q5Q5
Diet	37.44	0.257	0.282	0.260	0.234	44.46	55.55	31.42	11.27	32.26
	(0.08)	(0.002)	(0.003)	(0.002)	(0.002)	(0.60)	(0.59)	(0.16)	(0.12)	(0.16)
Income	42.5	0.157	0.134	0.145	0.154	47.20	56.03	26.23	14.00	29.71
	(0.18)	(0.004)	(0.004)	(0.005)	(0.006)	(1.15)	(1.32)	(0.32)	(0.26)	(0.32)

Note:
The diet results are estimated using 319,982 observations. The income results are estimated using 93,277 observations as we restrict the sample to children between 32 and 38 and parents with an average age between 56 and 62. (We also restrict the mothers' age between 49 and 61 and fathers' age between 50 and 62 so that both parents are at least two years away from retirement). The IGE age analyzed using the log of father's income as an explanatory variable and the log of children's income as a dependent variable, and therefore, we drop 365 observations with zero values.

This implies that the bins p_j and p_k are age dependent.[26]

3.4 Conditional Expected Rank

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

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

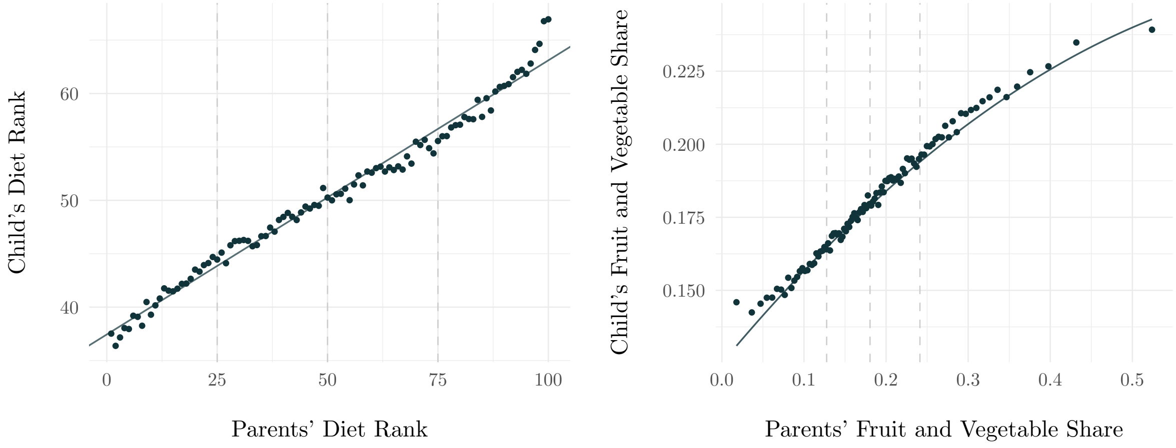
We focus on the CER at the 25th and 75th percentiles, denoted CER25 and CER75. The CER can be estimated parametrically (using directly the information from the rank-rank regression) or nonparametrically. Both have different advantages and disadvantages. On the one hand, the parametric CER for children 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 may be misspecified. 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 measure is resilient against misspecification, but susceptible to larger variance. We opt for a middle ground and use a nonparametric local linear regression evaluated at percentile p.

4 Main Results

This section presents results on the overall persistence of dietary habits across generations. Table 2 reports coefficients and standard errors for all our results. Across all the reported mobility

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

Figure 3: 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 3a shows the estimated the rank-rank regression line based on in Equation (1) and Figure 3b 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.

measures, we compute standard errors using 1,000 nonparametric bootstrap replications. Finally, to assess the magnitude of the persistence of dietary choices, we compare the findings to intergenerational mobility in income.

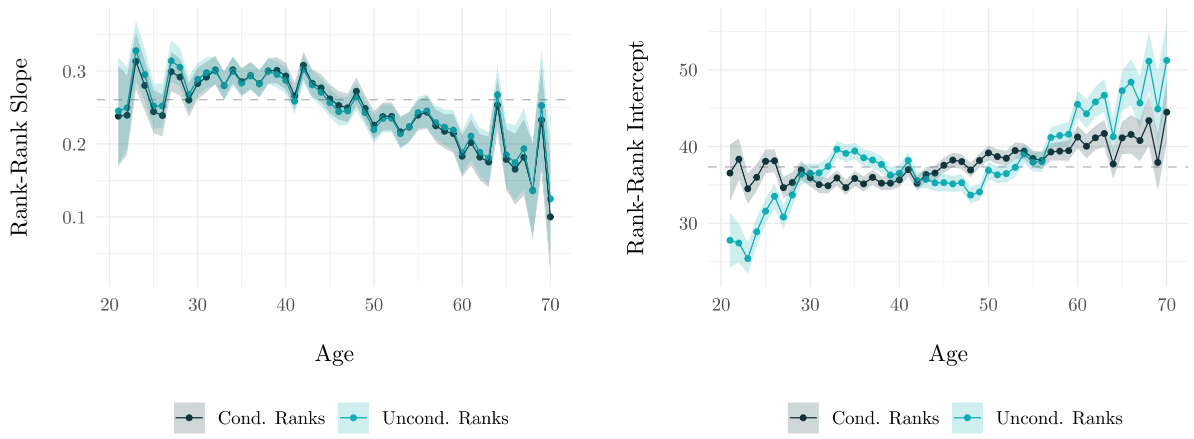
4.1 Dietary Mobility

Rank-Rank Regression – The estimated rank-rank slope in Panel (a) is 0.23, which shows that an increase in the parental percentile rank by one decile corresponds to an increase of 2.3 percentile ranks for the child. To put these results into perspective, it takes 2.98 generations to close the gap between two families at the first and the ninth decile.[27]

Figure 3 graphically illustrates the positional relationship between parents and children, plotting the estimated RRS regression line. The dots represent the average child percentile rank for each of the parents' percentile 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 percentile 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. While Figure 4a shows that the rank-rank slope is almost identical across both specifications, Figure 4b reveals that the intercept largely depends on the specification of the ranks, explaining the lifecycle observed in Figure 2. This observation supports our expectation that conditional ranks are a better measure of dietary mobility than their unconditional counterparts. The rank-rank slope

[27]The number of generations N to close the gap of $\Delta_{10,90} = 80$ percentile 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: Rank-Rank Slope: Life-Cycle



(a) Rank-Rank Slope

(b) Rank-Rank Intercept

Notes: Figure 4a 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 4b 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 2. Standard errors are estimated from 100 bootstrap replications.

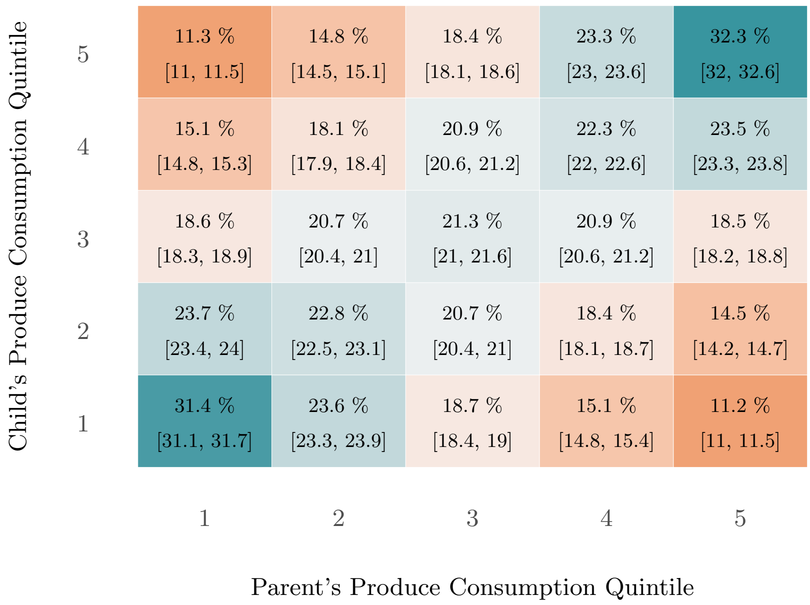
is remarkably constant in early adulthood at around 0.25, showing that dietary habits acquired at an early age carry on far into adulthood. The rank-rank slope starts declining at around age 40, which could be explained through habit adaptation that takes several periods to form. Yet, the relationship remains sizable until later in life.

Intergenerational Elasticity – Panel (b) of Table 2 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 3b 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 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 3 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 5 shows the estimated transition matrix with the corresponding

Figure 5: 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.

confidence interval. We show selected key results of the transition matrix in Table 2 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 probabilities reveal 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 supermarket data. 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 Comparison 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 the one used in Table A1). 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 2 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 2 shows that for these children, income only fluctuates slightly around the lifetime mean (all these age groups are 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 2 shows an estimated RSS of 0.17 and an IGE of 0.16 at the 50th percentile.[28] 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.[29] 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).[30]

Comparing our estimated mobility measures between diet and income in Table 2, we observe that intergenerational transmission is more pronounced in the case of eating habits than income across all measures. Figure 6 illustrates this graphically and shows that the slope of the rank-rank regression for diet is substantially steeper. This relationship suggests that the development of dietary habits during childhood is a persistent channel through which parents impact their children's future in a magnitude that exceeds the parental influence on the economic outcomes of their children.

Nevertheless, it is important to note that income is particularly mobile in Switzerland in comparison with most other Western countries, and the relative persistence of diet and income may differ in other countries.[31]

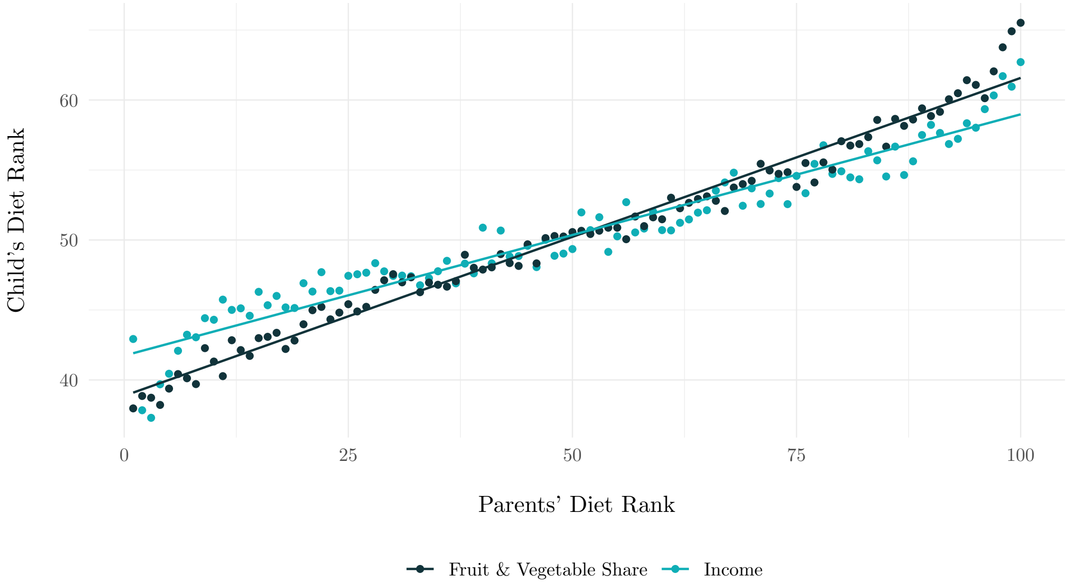
[28]We measure the intergenerational elasticity in income with a classical log-log specification, however, including a quadratic term.

[29]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.

[30]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.

[31]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).

Figure 6: 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.

5 Heterogeneities

Heterogeneities in the persistence of dietary habits across socioeconomic variables might enable dietary changes for some individuals while trapping others. This section unfolds heterogeneities between income classes, education levels, degrees of urbanization, and the distance to parents. To correct for a possible mechanical result that children belonging to an unhealthy group have a higher chance of making it to the top, we use percentile ranks based on the entire sample and reweight the observations in each group such that the parents' distribution imitates the one in the entire sample.[32]

Table 3 shows the rank-rank slopes, conditional expected ranks, intergenerational elasticities, and transition probabilities for the different subgroups. The second column contains the P-value of the Wald statistic testing for equality of the rank-rank slope between all the subgroups. Bootstrapped standard errors are in parentheses.

First, panel (a) shows the results for the three education levels: primary, secondary, and tertiary. The rank-rank slopes are close to 0.21 in all groups and not statistically different from each other. This means that a higher education for children does not impact how parents transfer their diet. Instead, Figure 7a reveals that the intercept increases with education such that higher-

[32] This happens because, in unhealthy groups, children are more likely to surpass their parents' outcomes through mean reversion. The reweighting procedure gives equal weights to all percentiles in the rank-rank regression and the conditional expected rank. For the transition matrix, the reweighting changes the distribution of children conditional on their parents' bins and, therefore, also changes the children's ranks. For an extensive discussion of weighting approaches in these settings, see Deutscher and Mazumder (2023).

Table 3: 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) 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, 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 1,000 replications. The number of observations in each subgroup is shown in the last column.

educated children consume more fruits and vegetables. Therefore, education allows children to break out of unhealthy dietary habits, not through a change in the transmission of these habits but through the simple fact that higher-educated households systematically follow a healthier diet, independent of their parents. Multiple reasons may explain this observation. For example, higher-educated individuals may have a more profound nutritional knowledge, a better assimilation of dietary information, or a higher patience. We discuss such channels in a conceptual framework in Section 7.

Second, panel (b) digs into differences between income groups. To account for the lifecycle in income, we condition income quartiles on age and keep only working-age children (25-64).[33] As

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

shown, the rank-rank slope and intergenerational elasticity monotonically decrease as children's income increases. For children in the first income quartile, we find a rank-rank slope of 0.25 compared to 0.185 for individuals in the fourth quartile. Thus, percentile ranks are statistically significantly more persistent over generations among low-income children, meaning that their parents' diet has a stronger and more persistent influence. Figure 7b shows the rank-rank slope and expected ranks for all four income quartiles. The differences in intercept and slopes suggest that high-earning children can better break out of unhealthy childhood habits and strengthen beneficial ones. In addition to the learnings on education, a higher income appears to incentivize households to allocate more money to a healthy consumption.

These findings also translate into geographical differences. Panel (c) shows that mobility is highest in urban areas and lowest in rural areas. The transition probabilities show that children living in urban areas have an outstanding probability of moving up in the distribution. Strikingly, a child born to parents in the first quintile of the distribution who lives in an urban area is more likely to find himself at the top of the distribution than in the first quintile. It appears that, in addition to higher education and income, moving to urban areas exposes individuals to new social networks and an abundant grocery supply that favor healthy behaviors.

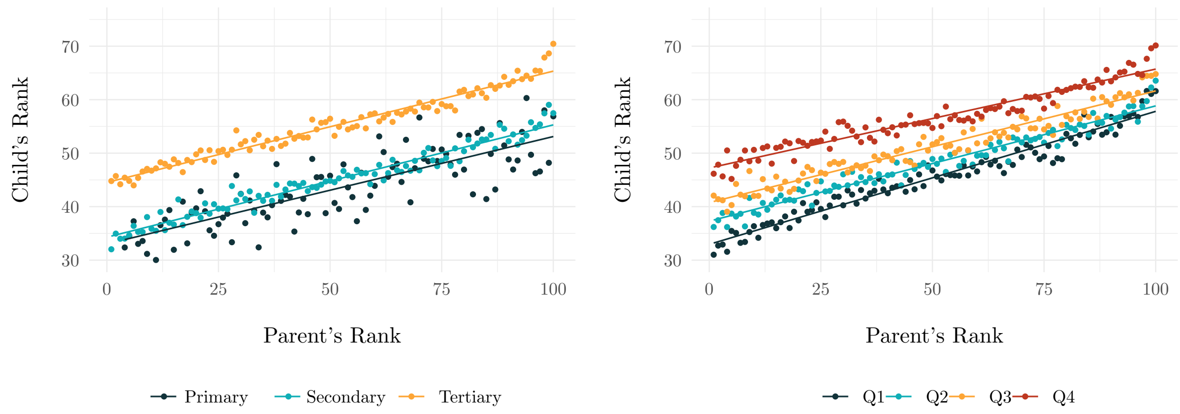
Lastly, panel (d) analyzes the role of the distance between the children's and parents' residences. We observe that nutritional persistence remains high even if children live far away from their parents. However, the further the children move away from their parents, the lower the patterns' persistence.[34] This result is not surprising as living away from one's family is often associated with moving away from one's childhood environment. However, it is striking that households are seven percentage points less likely to be trapped at the bottom if they live far away. This finding suggests that new social networks and environments play a decisive role in breaking old habits and is consistent with previous findings on diminishing social interactions and responses to family-related shocks with increasing distance (see, for example, Büchel et al., 2020 and Fadlon and Nielsen, 2019).

6 Mechanisms

The previous sections document a strong intergenerational persistence of diet across generations. In this part, we argue that habit formation is an important driver of these results. We do this in two steps. First, we focus on alternative explanations in this section and find that their explanatory power is limited. Second, we introduce a model in which children are endowed with a stock of eating habits when they form their own household. We argue that these habits are largely determined by childhood diet, but also other early life experiences likely play a role.

[34] We repeat this analysis for the sub-sample of children whose parents still live at the location their child grew up in. These individuals face a slightly higher rank-rank slope and higher transition probabilities in the Q1Q1 and Q5Q5 cells. Therefore, childhood networks beyond parents might play a role, but this role seems to be minor relative to parental diet.

Figure 7: 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 3. Figure 7a displays the RRS for different education levels and Figure 7b for different income levels. The dots in both graphs are the expected child's rank if their parents are at a given percentile.

The model considers agents maximizing their utility by choosing what to eat. This decision entails a trade-off between sticking to one's habits and following a healthy diet. Deviating from one's habits is costly in terms of taste, time, and money, as most dietary changes require either a time investment to discover new ingredients and recipes or a financial investment to purchase new equipment. Deviating from a healthy diet reduces utility as it increases, for example, the probability of developing obesity and diabetes.

Yet, additional factors influence children and their diet in many interconnected ways, and alternative explanations – rather than the direct transmission of dietary habits – could also (partly) explain our findings. Assessing the importance of these mechanisms is crucial to designing well-targeted policies. Such mechanisms include the transmission of socioeconomic status across generations, location and network effects, and unobserved family backgrounds, such as genetic variations in taste, genetic predispositions for diseases, or unobserved family shocks. In the following subsections, we analyze these factors in several ways. First, we consider a counterfactual scenario in which we shut down the indirect transmission of diet through income and education transmission. Second, we repeat this approach to look at the role of location. Third, we discuss the literature on the relationship between genes and diet and analyze the impact of the lifestyle-related death of a parent to assess whether information on genetic predisposition has an effect on diet. Having assessed these alternative factors, we then introduce and discuss the habit formation model.

6.1 Socioeconomic status

This subsection isolates and quantifies the component of intergenerational transmission in diet that cannot be attributed to the transmission of two important socioeconomic characteristics:

income and education. Isolating the influence of these channels is particularly important 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 that we document in this paper are due to the intergenerational transmission of these socioeconomic variables only. To this end, we compute counterfactual distributions in the spirit of Chernozhukov et al. (2013) to disentangle these socioeconomic drivers.[35] To identify the counterfactual distribution, we combine a population's conditional distribution function (cdf) with an alternative covariate distribution. In this subsection, 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.[36] Since the ranks are conditional on age, we include the children's and parents' age in the conditioning set. Once we have the counterfactual distribution, we can easily compute a counterfactual transition matrix, provided we observe the marginal distribution of the parents' diet conditional on age.

Let $F_{s_c|s_p,a_c,a_p}$ be the cdf of children's diet s_c conditional on the parents' diet s_p and the ages of children and parents, a_c and a_p. Let x_c denote a vector containing income and education of children, and let x_p contain the corresponding parents' variables. The main object of interest is the counterfactual distribution of the childrens' diet that we would observe if we change the covariate distribution $F_{x_c|s_p,a_c,a_p,x_p}(x_c|s_p,a_c,a_p,x_p)$ to a different distribution $F_{x'_c|s_p,a_c,a_p,x_p}(x_c|s_p,a_c,a_p,x_p)$. We denote this counterfactual distribution as $F_{s_c|s_p,a_c,a_p}\langle x_c|x'_c\rangle(s_c|s_p,a_c,a_p)$. Starting from the conditional cdf of children's diet conditional on (s_p,a_c,a_p,x_p,x_c) we can attain $F_{s_c|s_p,a_c,a_p,x_p}\langle x_c|x'_c\rangle(s_c|s_p,a_c,a_p,x_p)$ by integrating the conditional cdf over the alternative covariate distribution:

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

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

[35] A least squares regression of children's diet on parent diet controlling for socioeconomic variables does not disentangle this effect for several reasons. First, we need to model the distribution of children's diets to analyze directional mobility. Second, a least squares regression would fix a socioeconomic variable, whereas we want to consider a specific change in the covariate distribution. Third, comparing regressions that control for income and education with a regression without these controls provides meaningful results only under the strong assumptions of the correct specification. As we show in Section 5, diet transmission is heterogeneous across socioeconomic status, violating this assumption. While it would be possible to estimate a more flexible model that includes interactions between s_p and socioeconomic variables, such a model would become extremely tedious to compare. Instead, by estimating counterfactuals, even with a flexible model, results remain straightforward to interpret.

[36] 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. This assumption is consistent with the seminal work of Altonji et al. (1992), 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.

parents' covariates yields the desired result:

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

In the counterfactual scenario that we consider, children's income and education are independent of the parental socioeconomic variables. Further, we assume that parents' age and parents' diet do not affect children's characteristics. Hence, the counterfactual covariate distribution is the conditional distribution of x_c given a_c:

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

where children's age in the conditioning set accounts 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 estimation follows the plug-in approach. We obtain the conditional distribution function $F_{s_c|s_p,a_c,a_p,x_c,x_p}$ by inverting the conditional quantile function:[37]

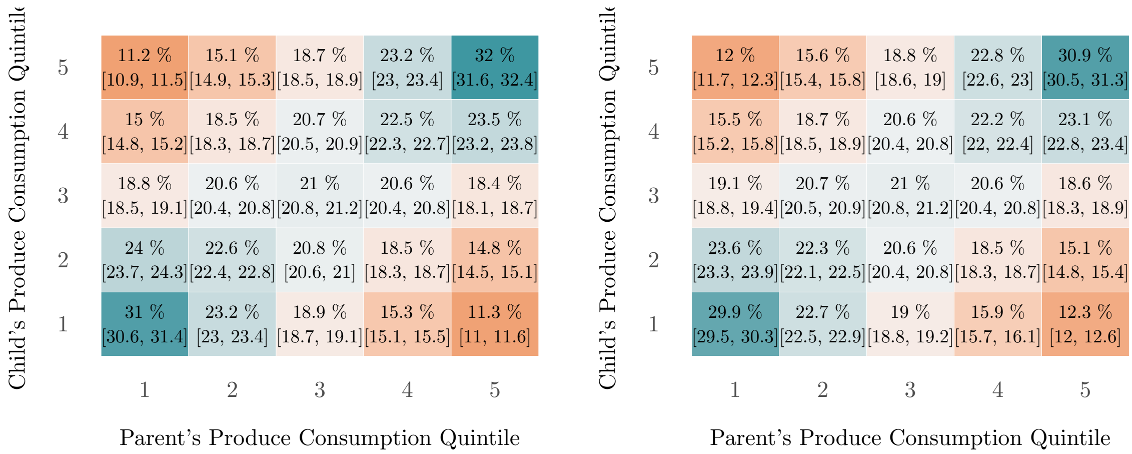
$$F_{s_c|s_p,a_c,a_p,x_c,x_p}(s_c|s_p,a_c,a_p,x_c,x_p) = \int_{(0,1)} 1\left\{Q(u,s_c|s_p,a_c,a_p,x_c,x_p) \leq s\right\}du, \quad s \in \mathcal{S} \tag{7}$$

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 $\tau = \{0.005, 0.015, \ldots, 0.995\}$. The regressors include a second-order polynomial of the parents' diet. Further, we include age and education dummies as well as household income (and its square) interacted with age and a dummy for age ≥ 65 for both parents and children. This last term allows income to have a different effect over the life-cycle, which is discontinuous after reaching retirement age.[38] All variables are also interacted with a second-order polynomial of the parents' diet.

[37]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.

[38]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.

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, we re-estimate the baseline transition probabilities in this smaller sample using the same linear quantile model to further ensure a meaningful comparison.

Figure 8 shows the estimated transition probabilities with the corresponding bootstrap confidence bands. Panel a) displays the transition probabilities estimated with the procedure described above, however, using the original covariates' distribution. These results are statistically indistinguishable from the transition probabilities computed nonparametrically for the entire sample in Figure 5. Panel b) shows the counterfactual transition probabilities. The transition matrix is similar to the one in Panel a). However, mobility is statistically significantly higher, mostly in the extremes. For example, the Q1Q1 and Q5Q5 probability decreases, and the Q1Q5 probability increases. Consider the Q5Q5 cell. In the original transition matrix, individuals whose parents are in the fifth quintile are 12 percentage points (= 32-20) more likely to be themselves in the fifth quintile than if there was no intergenerational transmission of diet. We 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 11 percentage points (= 31-20).

This change suggests that the transmission of income and education over generations explains less than 10% of this 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 single number, we compute the normalized anti-diagonal trace similarly to Jäntti and Jenkins (2015).[39] The normalization that we apply consists of subtracting the anti-diagonal trace of a completely mobile society. For the transition matrix in panel a), we find a normalized anti-diagonal trace of 25.2. In panel b), this number equals 22.1, suggesting that income and education 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.[40]

Overall, these results suggest that only between 10%-12% of intergenerational persistence of diet can be explained by intergenerational transmission of income and education. This result is surprising and indicates that even if income and education were completely mobile across generations, we would still see a large intergenerational persistence of dietary habits. Hence, policies such as income redistribution or income benefits might only have a minimal impact on nutritional inequality. This finding is also in line with the little effect of monetary incentives in promoting healthier food choices among SNAP recipients (see, for example, Verghese et al. (2019) and the references therein).

6.2 Current Location

Besides socioeconomic characteristics, the transmission of location preferences might partly explain our results. Yet, these variables are more difficult to measure than income or education, and more importantly, it is unclear which characteristics of a location are meaningful in determining diet. In this analysis, we use population density as a broader measure of location characteristic that happens to be persistent across generations. For instance, children who grew up in rural (urban) areas are more likely to live in rural (urban) areas later in life.[41] Hence, the transmission of location preferences may partially drive dietary persistence as people in urban areas eat healthier.

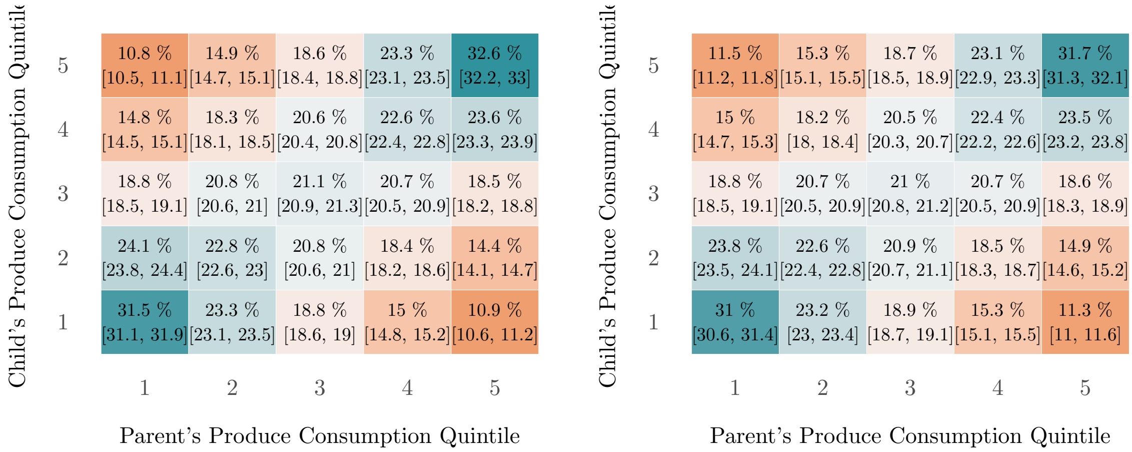
To assess the share of dietary persistence attributable to the transmission of location preferences, we perform the same exercise we used to assess the role of income and education, where we

[39] We compute the anti-diagonal trace as it measures how many children end up in the same quintile as their parents.

[40] The counterfactual analysis is not specific to the transition matrix. Instead, we can compute all mobility measures starting from the counterfactual distribution. The results are consistent across all mobility measures. To give an illustration, we find that after removing transmission of socioeconomic variables, the IGE decreases by 10%.

[41] 55% of individuals in our sample whose parents live in rural areas also live in a rural area, while only 9% of them reside in an urban area. Otherwise, 51% of individuals in our sample whose parents live in urban areas also live in an urban area, while only 12% of them reside in a rural area.

Figure 9: Intergenerational Diet: The Role of Location



(a) Transition Matrix (b) Counterfactual Transition Matrix

Notes: Figure 9a shows the transition matrix and Figure 9b shows the counterfactual transition matrix based on Eqaution (6) and Eqaution (5). The counterfactual considers the case where children's locations 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 and their parents' location.

now remove the link going through the transmission of location measured by the degree of urbanization. More precisely, we consider a counterfactual scenario where the probability that an individual lives in an urban, suburban, or rural environment is independent of her parents' location and other parental characteristics.

We again fit a flexible quantile regression model where we interact all variables with the degree of urbanization dummies. Figure 9 displays the original and the counterfactual transition matrix.[42] Comparing the normalized traces of the two matrices, we conclude that only 5% of the dietary transmission can be explained by children living in similar spatial environments as their parents (measured as urban, suburban, and rural areas). Notably, while the transmission of location plays a minor role as the two matrices are remarkably similar, some transition probabilities are statistically significantly lower in the counterfactual scenario.

Hence, this analysis suggests that while location is an important determinant of diet, transmission of the level of urbanization plays a minimal role in the intergenerational persistence of diet. These results align with previous papers discovering limited adaptations in diets in response to changes in spatial environments (for example, Atkin, 2013, Atkin, 2016, or Allcott et al., 2019a). Hence, while places impact the intergenerational transmission of dietary habits, the largest share remains unexplained.

[42] As before, we recompute the orginal transition matrix using the same flexible model. The marginal differences in the results are due to different samples and a slightly different model.

6.3 Genetic Family background

Genetic family background can influence our diet in at least two ways. First, genetic variations may determine how we taste and value different foods. Second, genetic predispositions to diseases could cause parents and children to adapt their diet. To give an illustration, a lifestyle-related death of a family member before the sample period could improve the diet for both parents and children. Here, we discuss these two channels, which could create a positive correlation between parents' and children's diets that is not explained by the direct transmission of dietary habits.

Taste – Genes determine how we perceive and interpret messenger signals sent from the taste receptors to the brain, and genetic variations in these taste receptor genes influence our individual sensitivity and preferences for flavors. Evidence is especially rich for receptor genes regulating the perception of bitter flavors (Gervis et al., 2023, Mennella et al., 2005), sweet flavors (Mennella et al., 2005, Mennella et al., 2016, Søberg et al., 2017), alcohol (Allen et al., 2014), and the olfactory perception of food in general (Cole et al., 2020).[43] These genetic variations shape food intake, and hundreds of genes are associated with our actual consumption of fruit, cheese, fish, tea, or alcohol (Cole et al., 2020), potentially affecting our results.

To assess the importance of genetic variations in taste, we analyze the transmission of diet for the subsample of children with divorced parents who never remarried.[44] In this way, we observe each parent's diet separately. Due to social norms, these children most likely grew up with their mothers.[45] Hence, if transmission is mostly due to genetic transmission of tastes, we should see no difference in the transmission of diet between their mother to their father, while a stronger link to the mother's diet indicates a stronger nurture channel. We find that the intergenerational link between children and their divorced mothers is significantly stronger than the link with the divorced fathers, suggesting an important role of nurture. Nonetheless, we cannot rule out that *nature* - meaning, the transmission of taste across generations - drives a share of the correlation between children's and parents' diet. However, taste receptors should not be regarded as an exogenous endowment. More precisely, as we explain later, what we eat can also alter the regulation of our genes.

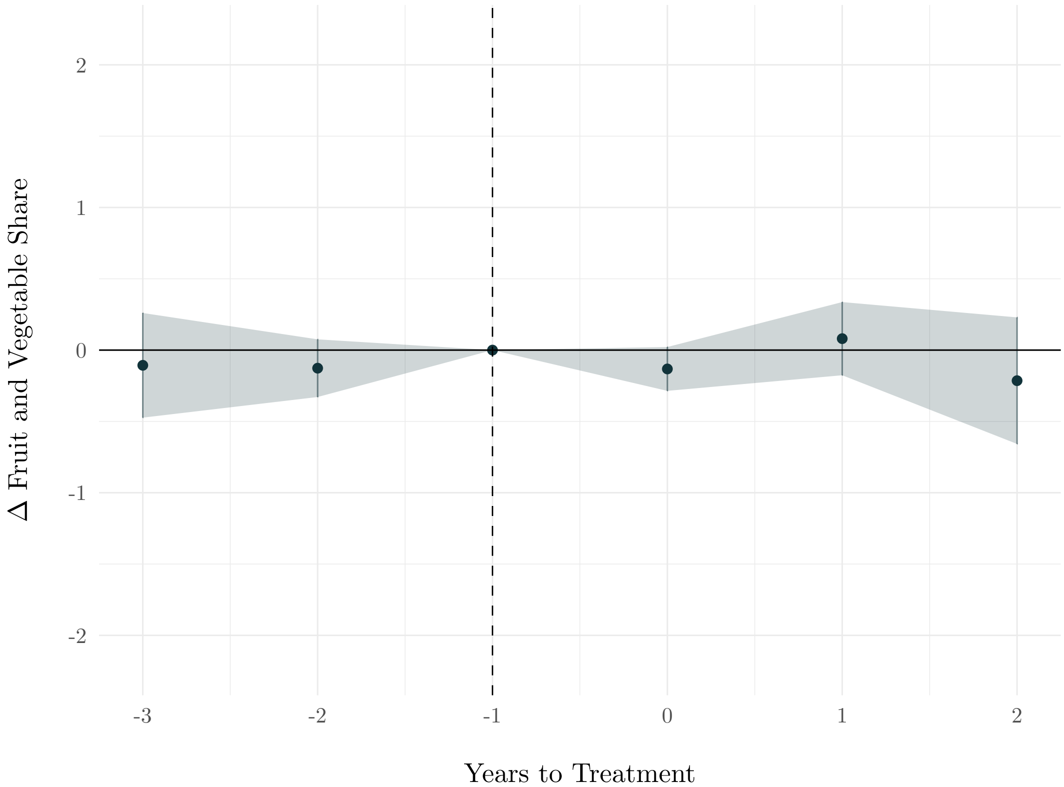
Predispositions to diseases – A genetic predisposition for a lifestyle-related disease may drive family members to change their eating behaviors consciously. To assess the importance of this channel, we analyze the effect of the death of a parent due to lifestyle-related diseases on their children's diet. Such shocks might be informative for children, as, for example, young men have an elevated risk of dying from a cardiovascular death if they have a family history of heart attacks (Barrett-Connor and Khaw, 1984).

[43] The effect of genes on diet may be polygenic in many cases, meaning, multiple genes work together, and a specific combination of variations implies a specific effect (See, for example, Gervis et al. 2023).

[44] We choose to focus on divorced parents who did not remarry to avoid possible contamination due to a new partner.

[45] We do not observe who the child lived with after the divorce. Yet, a report by the *Federal Department of Home Affairs* shows that 46% of children spend at least two-thirds of their nights at their mother's place compared to only 10% who spend more than two-thirds at their father's place.

Figure 10: Lifestyle-related death of a parent



Notes: Two-way fixed effects estimates of the lifestyle-related death of a parent's effect on the fruit and vegetable intake of children. We focus on deaths without any underlying health conditions and use annual consumption data. The estimation uses XXXX observations, coefficients are normalized to the year before the treatment, and standard errors are clustered at the individual level.

To conduct this analysis, we complement our data with the *Vital Statistics* administrative dataset for the years 2016-2021 that documents all deaths in Switzerland. The data includes the anonymized identifiers of all deceased residents and lists all underlying health conditions that either directly caused the death or may have contributed to it. Since sudden and unexpected deaths might provide the most additional information about one's risk of certain diseases and genetic predisposition might already be known due to a non-fatal shock or previous diagnosis, we consider only deaths of individuals without any other pre-existing condition.

If we find that children do not adjust their diet following the death of a parent, this channel is unlikely to play an important role in the transmission of diet. We use a staggered difference-in-differences design where we compare the diet of children whose parents die from a lifestyle-related disease (stroke and heart attack) to children who face the same shock in later years. We use the estimator proposed by Callaway and Sant'Anna (2021) and present the results in an event-study plot. Figure 10 shows that there is no change in fruit and vegetable intake for up to two years after the shock. This suggests that individuals might not perceive this shock as informative about their own risk for lifestyle diseases or simply do not respond to this information.

One weakness of our analysis is that we consider only one shock, and other events, such as diagnoses, might be more informative about one's genetic predisposition. For instance, a diabetes or hypertension diagnosis could have a stronger effect on diet as the affected person might receive nutritional advice from a physician or otherwise seek nutritional advice and pass the information to relatives. Yet, Oster (2018) finds only very small reductions in the caloric intake from unhealthy foods after a diabetes diagnosis, further suggesting that the predisposition to diseases is not a major channel.

6.4 Habits

We have seen that factors affecting both children's and parents' diets, such as income, education, location, and genes, do not explain much of the persistence in diet across generations. Based on this evidence, we argue that habit formation during childhood is potentially a sizable driver of our findings. This is consistent with the nutrition literature, which has long recognized the role of the family environment as a determinant of a child's diet (see, e.g., Birch, 1999, Scaglioni et al., 2018). These habits capture many different *nurture* components, such as diet-related knowledge and skills that parents pass on to their children.

Supporting the importance of this habit mechanism, evidence shows that food intake – even in utero and through breastfeeding – shapes a child's taste. For example, reducing sodium and sugar consumption sharpens the perception of saltiness and sweetness (Bertino et al., 1982, Wise et al., 2016), while infants show a higher initial acceptance of fruits and vegetables if their mother eats them regularly during pregnancy (Mennella et al., 2001) and breastfeeding (Forestell and Mennella, 2007). Hence, early over-consumption of unhealthy foods during childhood can reprogram our genes and numb our taste receptors, initiating a vicious cycle of bad habits and weight gain, obesity, and inflammation exacerbate these dysfunctions (May and Dus, 2021). Hence, parents' diet shapes children's taste preferences and consumption through many channels that we summarize in this paper by habits.

While parental diet is likely a major determinant of the endowment habit stock of their children, many different factors, including childhood networks and location, might contribute to building and shaping this habit stock (see, e.g. Story et al. (2008) for an overview). It is important to note that the presence of these factors does not invalidate our framework. Eventually, understanding the determinants of these habits and separating nurture from nature components is necessary to implement the most effective policies, and future research should contribute in this direction.

7 Model Setup

To discuss potential mechanisms explaining the origins of our findings, we introduce a simple framework on habit formation. We model the persistence in diet between generations as the result of a habit stock built during childhood and adjusting over a lifetime (see, for example, Fuhrer (2000), Carroll et al. (2000), and Campbell and Cochrane (1999) for some early work on habit formation models). Habit formation has been used to explain a variety of economic behaviors. For instance, there is evidence of habit formation in voting behavior (Fujiwara et al., 2016), digital addition (Allcott et al., 2022), health behaviors, handwashing (Hussam et al., 2022), as well as tastes of food. To give an illustration, Atkin (2013) finds that higher relative prices in the past shape current tastes, providing evidence of habit formation.

In our setting, individuals are born into families whose diet, skills, and nutritional knowledge exogenously determine their initial stock of habits for their adult life, h_1.[46] We think about the origin of h_1 as a Beckerian parental investment into their children's diet through the transfer of skills and knowledge (see, for example, Becker and Mulligan, 1997). Other factors outside the household, such as childhood networks, including extended family, friends, and school, might also determine habits without invalidating the framework.

Individuals enter adulthood and start their own household in period $t = 1$ and live on forever. They maximize their lifetime utility by choosing their relative intake of healthy foods $c_t \in [0, 1]$ given their initial endowment of habits h_1 and the degree of habit persistence mapping current consumption and habits into future habits:

$$h_{t+1} = h_t + \phi(c_t - h_t), \tag{9}$$

where $\phi \in [0, 1]$ measures the strength of habit formation. Hence, through their consumption behavior, agents continuously update their habits as a weighted average of current habits and consumption. Low values of ϕ imply a high degree of habit persistence and a low degree of learning, and deviations in c_t only have little effect on h_{t+1}. In the extreme case with $\phi = 0$, habits do not adapt, while with $\phi = 1$, the habit at time t equals consumption in the previous period, and there is no habit persistence.

Instantaneous utility in each period takes the form

$$u(c_t, h_t) = g(c_t - c^*) + h(c_t - h_t), \quad t = 1, 2, \tag{10}$$

where c^* denotes the optimal (healthy) intake of fruits and vegetables, which is assumed to be the same and known for all agents, and the functions $g(\cdot)$ and $h(\cdot)$ have the following properties:

$$\frac{\partial g(c_t - c^\star)}{\partial c} = g'(c_t - c^*) = \begin{cases} > 0, & if\ c_t < c^* \\ = 0, & if\ c_t = c^* \\ < 0, & if\ c_t > c^*, \end{cases} \tag{11}$$

[46] Other unobserved factors outside the household, such as childhood networks, extended family, friends, and school, might also affect habit formation within this setting.

and

$$\frac{\partial h(c_t - h_t)}{\partial c} = h'(c_t - h_t) = \begin{cases} > 0, & if\ c_t < h_t \\ = 0, & if\ c_t = h_t \\ < 0, & if\ c_t > h_t. \end{cases} \tag{12}$$

The two terms in Equation (10) account for two opposing forces. On the one hand, individuals want to eat healthily and be as close as possible to c^*. On the other hand, it is costly (painful) to deviate from one's habits h_t. Hence, any consumption different from $c_t = h_t$ causes disutility through adaptation costs.

To make the problem more concrete, we consider the following specification for the instantaneous utility function:

$$u(c_t, h_t) = -(c_t - c^*)^2 - \rho(c_t - h_t)^2, \tag{13}$$

where ρ is the importance of following one's habit relative to following a healthy diet. The quadratic specification means that small deviations from the optimal diet or one's habit cause little harm. However, large deviations are highly painful in utility terms. Intuitively, large deviations are costlier because large changes in diet require additional preparation and shopping time, skills and information that need to be acquired (for example, by reading recipes) and new utensils.

Summarizing, each agent solves the following maximization problem:

$$\begin{aligned} \max_{c_t, h_{t+1}} U(c_t, h_t) = \max_{c_t, h_{t+1}} & \sum_{t=1}^{\infty} \beta^{t-1} u(c_t, h_t) \\ \text{s.t. } & h_{t+1} = h_t + \phi(c_t - h_t), \\ & u(c_t, h_t) = -(c_t - c^*)^2 - \rho(c_t - h_t)^2, \\ & h_1 \text{ given} \end{aligned}$$

Solving the model, we find that the policy function $c_t(h_t)$ is a weighted average of the optimal diet c^* and the current habit stock h_t:

$$c_t(h_t) = wc^* + (1 - w)h_t, \tag{14}$$

where the weight w is

$$w = \frac{-\phi^2\beta + (1+\rho)(\beta-1) + \sqrt{-4\phi\beta(-1+\beta-\phi\beta)(1-\phi+\rho) + (-\phi^2\beta + (1+\rho)(\beta-1))^2}}{2\phi\beta(1-\phi+\rho)}. \tag{15}$$

Appendix B provides a detailed derivation of the solution.

7.1 Identification and Estimation

To estimate the model, we rely on the same cross-sectional data we use in the rest of the paper, treating children of different ages as people in different periods of their lives. We use data on children between the ages of 30 and 60, consider values for $\beta = \{0.9, 0.95, 0.99\}$, and set $c^* = 0.28$, which is the lowest fruit and vegetable share that meets the recommended consumption of five daily portions in Figure 1.

If we knew initial habits h_1, we could directly estimate $(1-w)$ in equation (14). Since we do not directly observe habits, we proxy them with parents' diet denoted $\tilde{h}_1$, introducing a measurement error. To deal with this challenge, we first express h_t and c_t as functions of initial habits h_1 for $t \geq 2$ by iterating backward the law of motions for habits in equation (9) and the policy function for consumption in equation (14):

$$h_t = h_1 (1-w\phi)^{t-1} + w\phi c^* \sum_{j=0}^{t-2} (1-w\phi)^j \tag{16}$$

$$\begin{aligned} c_t &= wc^* + (1-w)\left[h_1 (1-w\phi)^{t-1} + w\phi c^* \sum_{j=0}^{t-2} (1-w\phi)^j\right] \\ &= c^* \left[(1-w)w\phi \sum_{j=0}^{t-2} (1-w\phi)^j + w\right] + h_1(1-w)(1-w\phi)^{t-1}. \end{aligned} \tag{17}$$

A regression of c_t on $\tilde{h}_1$ identifies $\xi \cdot (1-w)(1-w\phi)^{t-1}\, \forall t$, where the term $\xi \in (0,1)$ arises from the measurement error and we identify $(1-w\phi)$ using data from different cohorts. We use a two-step estimator, where we first fit a saturated model of c_t on $\tilde{h}_1$ interacted with age fixed effects. In the second step, we impose the structure $\xi \cdot (1-w)(1-w\phi)^{t-1}$ on the coefficients by fitting a linear model in t on the logarithm of the first step slope coefficients. In this way, the slope captures $log(1 - w\phi)$.[47] We find a point estimate of

$$(1 - \hat{w}\hat{\phi}) = 0.989. \tag{19}$$

This expression does not separately identify ϕ and ρ because different values of the parameters are consistent with these results. As an example, assume $\beta = 0.95$, and consider an individual with $\rho = 1$ and $\phi = 0.02$, satisfying equation (19). This individual values following her habits and a healthy diet equally, and gives a weight of $w = 0.56$ to healthy eating. Yet, the values $\rho = 2$ and $\phi = 0.03$ are observationally equivalent. While this second individual values following a healthy diet less, she assigns a lower weight to healthy eating ($w = 0.41$) and alters her habits faster. Both of these individuals face the identical habit stock in the following period, as a smaller deviation in consumption coincides with more flexible habits such that equation (19) holds.

Figure 11 pictures the continuum of compatible values for ϕ and ρ that satisfy equation (19). We find that a higher valuation of a healthy diet (lower value of ρ) is consistent with our data if combined with stickier habits (lower ϕ). This explains why most individuals do not meet the dietary recommendations. On the other hand, if individuals value a healthy diet less, then habits are more amenable.[48] The results also show the role of discounting, as habits are less sticky if the discount rate is low, as people have lower incentives to invest in future habits and assign more weight to following their habits.

Reconciling the model with the empirical heterogeneities we derive in Section 5, we re-estimate our model for rich and poor households separately. Splitting the sample into income quartiles, we estimate $\hat{w}\hat{\phi} = 0.013$ for the top 25% and $\hat{w}\hat{\phi} = 0.011$ for the bottom quartile. Figure 12a shows that, therefore, better-earning households face a higher value of habit persistence across all parameterizations, implying that they are more efficient producers of healthy eating habits. Looking at the trajectories of habits in Figure 12b, richer households build over fifty periods a habit stock including 0.85 percentage points more fruits and vegetables.

A potential narrative for these behavioral differences is that agents with a higher socioeconomic status might enjoy more utility from consuming a healthy diet relative to the adaptation cost,

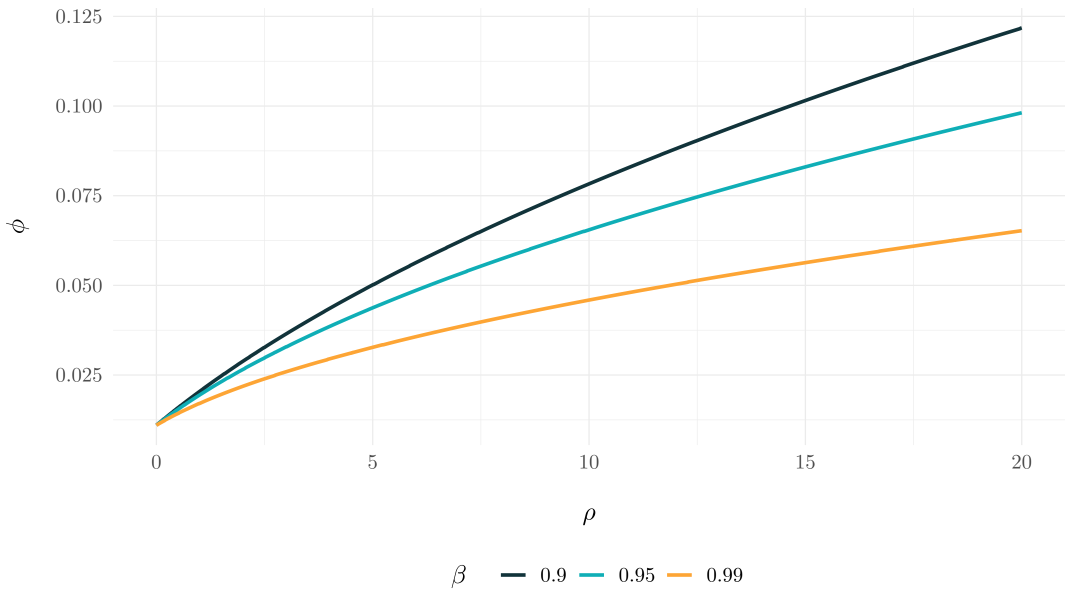
[47] One potential worry of this analysis is that the measurement error is not constant over time. More precisely, if the measurement error increases with age, it would imply that ξ is decreasing over time, consequently affecting the estimation of $log(1 - w\phi)$. An alternative approach to estimate $(1 - w\phi)$ would deal with the ratios of the coefficients:

$$\frac{Cov(c_{t+1}, \tilde{h}_1)}{Cov(c_t, \tilde{h}_1)} = (1 - w\phi), \ \forall t > 2, \tag{18}$$

and we can take the average of these ratios. In this way, only the coefficients of adjacent cohorts are compared, making this estimator more robust to potential cohort effects. However, this procedure does not entirely exploit the relationship between the coefficients implied by the model. Using this alternative approach, we find a coefficient of 0.991, suggesting that cohort effects should not invalidate the results.

[48] It is worth noting that even for extremely high values of ρ, our model still implies quite sticky habits. For example, at $\rho = 20$, $\phi = 0.11$ for $\beta = 0.99$ and $\phi = 0.17$ for $\beta = 0.9$.

Figure 11: Habit Persistence Parameters



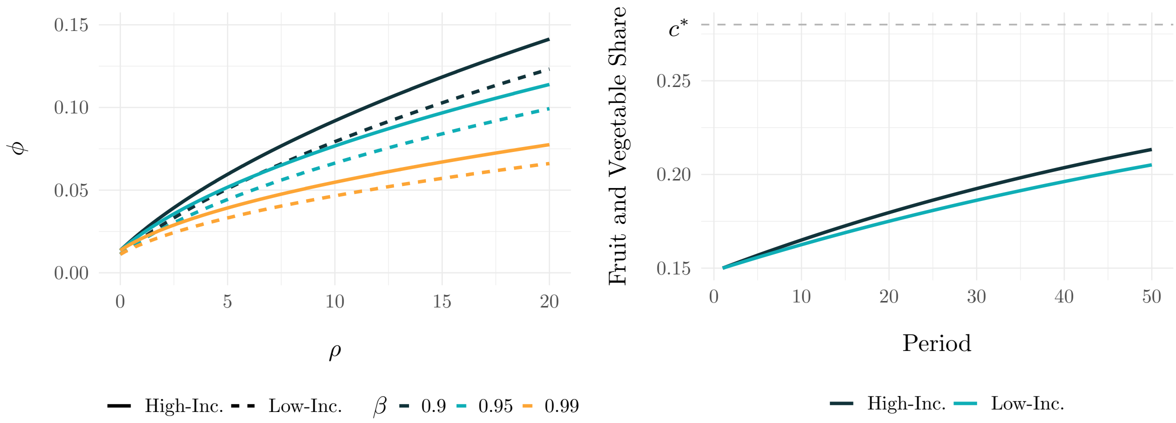
Notes: The figure shows the values of the habit persistence parameter ϕ and the relative utility weight ρ for different values of the discount factor β.

for example, because they assign a higher value to health. This is consistent with the finding of Cutler et al. (2006) that highly educated people are more likely to consume a healthy diet, exercise more, and take more preventive cases. Also, evidence shows that a higher socioeconomic status might reduce adaptation costs in other areas. For example, Lleras-Muney and Lichtenberg (2005) find that more educated individuals switch more easily to new drugs, suggesting their switching costs are lower. Overall, these model predictions support our empirical findings, suggesting that habits are indeed a major driver of the persistent dietary choices we document.

8 Conclusion

The detrimental consequences of bad dietary habits are responsible for a sizeable social and economic burden, while the origins of these harmful eating habits are so far greatly understudied. This paper sheds 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. Our results show that 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

Figure 12: Income Heterogeneities in the Model



(a) Habit Persistence Parameters

(b) Evolution of the Habit Stocks

Notes: Figure 12a shows the values of the habit persistence parameter ϕ and the relative utility weight ρ for the best- and lowest-earning quartile of households in the sample for different values of the discount factor β. Figure 12b shows the evolution of the habit stock over 50 periods for the two income groups. The dashed grey line shows the optimal level of fruit and vegetable intake c^*.

stuck in a cycle of unhealthy diets. Further, upward mobility is larger among children living in urban areas, and the transmission 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.

We then test and discuss potential mechanisms driving our findings. 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, and the transmission of location preferences explains around 5%. Although other unobserved variables of children likely influence eating habits throughout their lives, the direct effect of childhood diet is presumably large, and we argue that habit formation is an important mechanism, suggesting that not only does the apple not fall far from the tree but also that it does not roll far away afterward.

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. To optimally design such targeted policies, future research might focus on disentangling specific mechanisms, especially separating a nature form a nurture component. Houmark et al. (2024) present a promising approach in this direction, using genetic data to analyze the interaction of genes and parental investments in the formation of skills.

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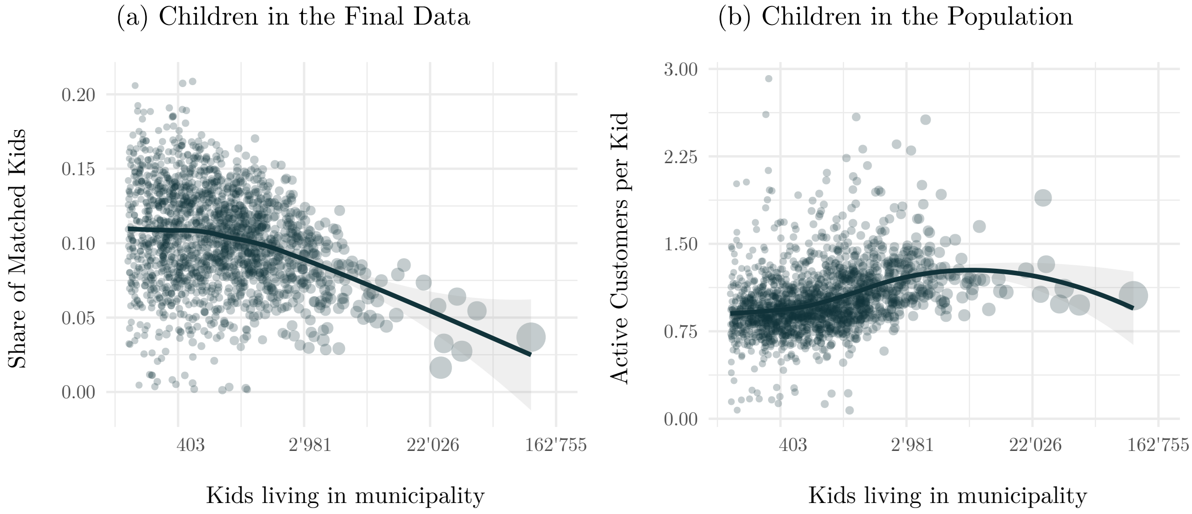
A Data: Additional Summary Statistics

Table A1: 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

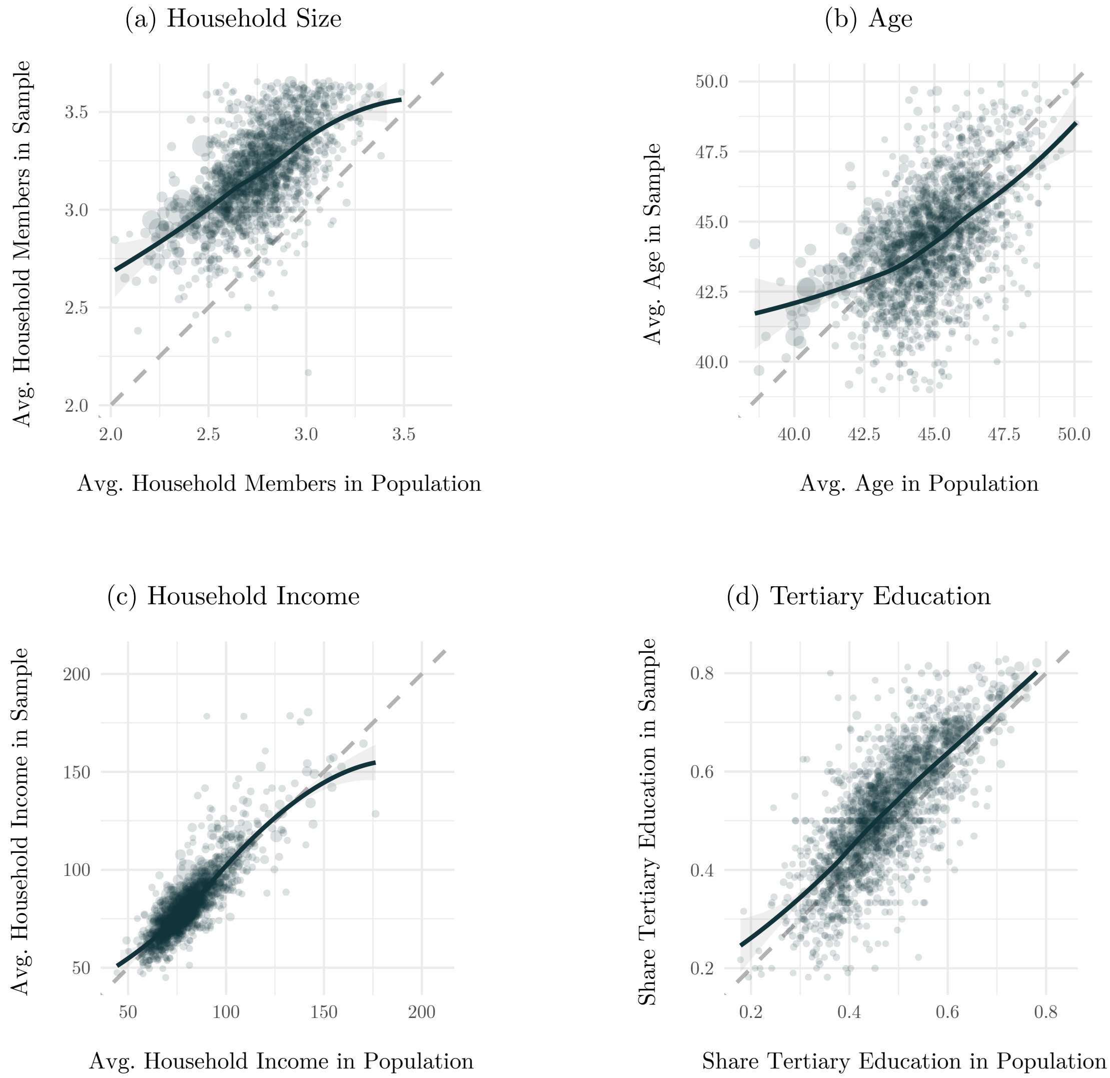
Notes: This table shows summary statistics for the customers uniquely linked to a kid in the administrative data and for the entire population of kids. *Income Total* is a household's average labor market income 2016-2020 in 1,000 CHF, and *Income Adjusted* adjusts household income by the square root 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.

Figure A1: Match Rate



Notes: The figure illustrates the representativeness of the retailer's loyalty program. To this end, Figure A1a shows the share of matched kids relative to all kids living in this municipality. Figure A1b 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.

Figure A2: 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.

B Model: Derivations

The Bellman equation $V_t(h_t)$ of the dynamic programming optimization problem takes the following form:

$$
\begin{aligned}
V_t(h_t) &= \max_{c_t} -(c_t - c^*)^2 - \rho\,(c_t - h_t)^2 + \beta V_{t+1}(h_{t+1}) \quad \text{ s.t. } \; h_{t+1} = h_t + \phi(c_t - h_t) \\
&= \max_{c_t} -\left(\frac{h_{t+1}}{\phi} - \frac{h_t}{\phi} + h_t - c^*\right)^2 - \rho\left(\frac{h_{t+1}}{\phi} - \frac{h_t}{\phi} + h_t - h_t\right)^2 + \beta V_{t+1}(h_{t+1}) \qquad (20)
\end{aligned}
$$

and the resulting first-order conditions for Equation (20) are:

$$0 = -\frac{2}{\phi}(c_t - c^*) - \frac{2\rho}{\phi}(c_t - h_t) + \beta V'_{t+1}(h_{t+1}), \qquad (21)$$

$$V'_t(h_t) = -\frac{2(\phi - 1)}{\phi}(c_t - c^*) - \frac{-2\rho}{\phi}(c_t - h_t). \qquad (22)$$

Shifting the second FOC one period ahead and combining the first-order conditions gives the following Euler equation:

$$(c_t - c^*) + \rho(c_t - h_t) = \beta(1 - \phi)(c_{t+1} - c^*) + \beta\rho(c_{t+1} - h_{t+1}). \qquad (23)$$

Based on our setting with a quadratic utility function and a linear constraint, we can use a guess-and-verify approach. We guess that the policy function for $c_t(h_t)$ is a weighted average of the optimal healthy diet c^* and the current habit stock h_t ($w \in [0, 1]$):

$$c_t(h_t) = wc^* + (1 - w)h_t \qquad (24)$$

Inserting the guess into the Euler equation yields

$$
\begin{aligned}
&[wc^* + (1 - w)h_t]\,\underbrace{(1 + \rho + \beta\rho\phi)}_{\alpha} = \\
&c^*[1 - \beta(1 - \phi)] + h_t\,[\rho - \beta\rho(1 - \phi)] + [c^*(w + \phi w - \phi w^2) + h_t(1 - w - \phi w + \phi w^2)]\,\underbrace{(\beta(1 - \phi) + \beta\rho)}_{\gamma}
\end{aligned}
$$

The method of undetermined coefficients provides the following two quadratic equations:

$$
\begin{aligned}
0 = {} & \phi\beta(1-\phi)w^2 + \phi\beta\rho w^2 + (1+\rho+\beta\rho\phi-\beta(1-\phi)-\beta\rho-\phi\beta(1-\phi)-\phi\beta\rho)w \\
& -1+\beta(1-\phi) && (25) \\
0 = {} & \phi\beta(1-\phi)w^2 + \phi\beta\rho w^2 + (1+\rho+\beta\rho\phi-\beta(1-\phi)-\beta\rho-\phi\beta(1-\phi)-\phi\beta\rho)w \\
& +\rho-\beta\rho(1-\phi)+\beta(1-\phi)+\beta\rho-1-\rho-\beta\rho\phi, && (26)
\end{aligned}
$$

which both simplify to:

$$
0 = (\phi\beta(1-\phi)+\phi\beta\rho)w^2 + (1+\rho-\beta-\beta\rho+\beta\phi^2)w - 1 + \beta(1-\phi) \tag{27}
$$

Solving this equation, we find for any meaningful calibration a single root $\in [0,1]$ such that it evaluates to zero:

$$
w = \frac{-\phi^2\beta+(1+\rho)(\beta-1)+\sqrt{-4\phi\beta(-1+\beta-\phi\beta)(1-\phi+\rho)+(-\phi^2\beta+(1+\rho)(\beta-1))^2}}{2\phi\beta(1-\phi+\rho)}. \tag{28}
$$

Under this value of w, the Euler equation and the resource constraint hold, justifying our initial guess. Therefore, the optimal weight w is independent of h_t and c^*.