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

Frédéric Kluser †
University of Bern

Martina Pons ‡
University of Bern

First Version: October 2022
This Version: January 3, 2025
Link to the newest version

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 fostering beneficial eating habits and breaking unhealthy ones. We discuss potential mechanisms and show in a counterfactual analysis that only 10% 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: health behaviors, inequality, intergenerational mobility, intergenerational diet.
JEL-codes: D12, I12, J12.

*We are grateful to Blaise Melly, Maximilian von Ehrlich, and Jessie Handbury for their invaluable support. We thank David Atkin, Jean-Michel Benkert, Simon Büchler, Gilles Duranton, Marcel Henkel, Benjamin Lockwood, and seminar participants at the University of Bern, the ETH Zurich, and the University of Pennsylvania for their helpful comments and suggestions. We gratefully acknowledge the support from two UniBE Doc.Mobility grants to visit the Massachusetts Institute of Technology (Martina) and the University of Pennsylvania (Frédéric) and a grant from the Swiss National Science Foundation with ref. 187443 (NRP 77). We thank the Migros Genossenschafts Bund, the Federal Statistical Office, and the Central Cooperation Office for sharing their data.

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

‡University of Bern, Department of Economics, Schanzeneckstrasse 1, CH-3001 Bern, martina.pons@unibe.ch.

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). 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 Bronnenberg et al., 2012, Atkin, 2013, 2016, Hut, 2020, Hut and Oster, 2022) and withstand major personal shocks and interventions (see Oster, 2018, Allcott et al., 2019a, Hut and Oster, 2022).

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.[1]

Our data contains customer-linked spending by product categories from 1.7 billion shop visits between 2019Q1 and 2021Q2 at the largest Swiss retailer.[2] 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 270,000 individuals (12% 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 0.250, and children whose parents spend one percentage point more on fruits and vegetables have a 0.252 percentage point higher spending themselves at the median of parental consumption. Further,

[1] Switzerland has a high density of grocery stores, households travel on average 600 meters to the nearest one, and 80% 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 1,450 meters, and only 40% of the population lives less than a mile 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.

[2] Our findings are robust if we concentrate our analyses on the pre-COVID-19 period.

the children's probability of reaching the top quintile when parents are in the bottom quintile is 11.5%. This is substantially smaller than the probability that children with parents at the top quintile remain at the top of the distribution (31.9%). A comparison of our findings to income mobility suggests that the 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 children's socioeconomic background may be crucial to fostering beneficial habits and breaking 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 geographical 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 to 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 10% of the persistence in diet, while the transmission of location preferences accounts for 6%. In addition, we analyze the impact of 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 by creating a trade-off. 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] In recent years, various papers conducted comparable analyses for other countries (Bratberg et al., 2017, Corak, 2020, Deutscher and Mazumder, 2020, Acciari et al., 2022, Asher et al., 2024), 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 health mobility 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 Waldkirch et al. (2004) and Charles et al. (2014) 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 for consumption. While informative, these studies do not address the composition of consumers' shopping baskets. In comparison, our study is the first to analyze the intergenerational transmission of specific dietary choices rather than aggregate expenditures, offering novel insights into dietary behaviors and their persistence 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, but most papers find results with limited economic or statistical significance. These policies include food subsidies (Hastings et al., 2021, Goldin et al., 2022, Bailey et al., 2024), food labels (Cook et al., 2005, Araya et al., 2022, Barahona et al., 2023), sin taxes (Allcott et al., 2019b, Dubois et al., 2020, Aguilar et al., 2021, Dickson et al., 2023), 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.

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

[4]Some studies show that wealth is also persistent within families, sometimes even after four to five generations (Charles and Hurst, 2003, Clark and Cummins, 2015, Adermon et al., 2018, or Belloc et al., 2024).

[5]A series of papers examines the transmission of health and estimates rank-rank slopes for the United States of 0.11-0.15 (Halliday et al., 2020), of 0.22 for Taiwan (Chang et al., 2024), and of 0.28 for Denmark (Andersen, 2021). Furthermore, intergenerational persistence has been documented for longevity (Black et al., 2024), 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 stems from the loyalty program of the largest Swiss grocery retailer. We observe expenditures on 41 product groups for 1.7 billion customer-linked purchases between 2019Q1 and 2021Q2, and customer characteristics include their residence location, age, and household type. Locations are coded on a grid of 350,000 100×100–meter cells with a mean population of 25 residents.[6] In this program, participants identify themselves at the checkout with their loyalty cards in exchange for exclusive offers and discounts. The program has substantive coverage, tracking expenditures of 2.1 million active users (32% of all Swiss residents above legal age), spending on average at least 50 Swiss francs monthly (USD 56 on July 29, 2024), and capturing 79% of the retailer's total sales. Notably, 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.

Our analysis focuses on a child's share of fresh fruits and vegetables relative to total food expenditures. This is a suitable measure for a healthy diet because (i) fruits and vegetables are highly correlated with the healthy eating index in Allcott et al. (2019a) (0.57 and 0.41, respectively), (ii) a diet low in fruits or vegetables is among the most frequent reasons for nutrition-related mortality in Afshin et al. (2019), and (iii) our measure correlates strongly with the intake of important micronutrients across age groups.[7] Furthermore, this measure provides a transparent and objective approximation of dietary quality as it requires no weighting of different nutrients or products.

Administrative Data – We enrich this unique consumption data with administrative records

[6]The retailer holds a market share of 32.7% in 2020. The major product groups include, among others, *fruits and vegetables*, *meat and fish*, *milk products and eggs*, and *bakery and convenience*. The household types include the categories *small households*, *young families*, *established families*, *golden agers*, and *pensioners*. To be a family, consumers have to register their children. This registration gives access to additional benefits related to family products.

[7]We compare our data's fruit and vegetable shares to the micro-nutrient intake reported in the *National Nutrition Survey* (by age group). This survey inquired in 2014 and 2015 2,000 participants between the ages of 18 and 75 about their previous day's diet. We find that the expenditure share of fruits and vegetables has a correlation 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.

for the entire Swiss population (8.7 million inhabitants in 2020). Pseudo social security numbers allow linking residents across three different administrative data sets. The *Population and Households Statistics* provides socio-demographic characteristics for each resident for the years 2016–2021. This includes, among others, information on gender, age, marital status, residence location, household identifiers, and the pseudo-identifiers of spouses and children.[8] The residence locations are coded on the same 100×100–meter grid as in the grocery transaction data. The *The Old-Age and Survivors Insurance* dataset contains annual gross labor market income for every resident for the years 2016 to 2021.[9] We average annual household income for the years 2016–2021 to reduce biases in permanent income from transitory shocks and adjust, in most cases, average household income by the square root of household size.[10] Finally, the *Structural Survey* gives information on the highest completed education in a household for the years 2010–2021.[11]

2.2 Sample Construction

We restrict our analysis to customers that we can uniquely match to a resident based on the common variables of age and location. Appendix A describes the individual steps of the matching procedure. The matching links 337,000 children to at least one of their parents. We focus on children and parents with average monthly grocery expenditures adjusted by the square root of household size between 50 and 1,000 Swiss francs. This is because too-small monthly baskets might not accurately capture the overall consumption, while too-large monthly baskets are unlikely to suit personal use but are 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.[12] Further, we generate parents' variables as the

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

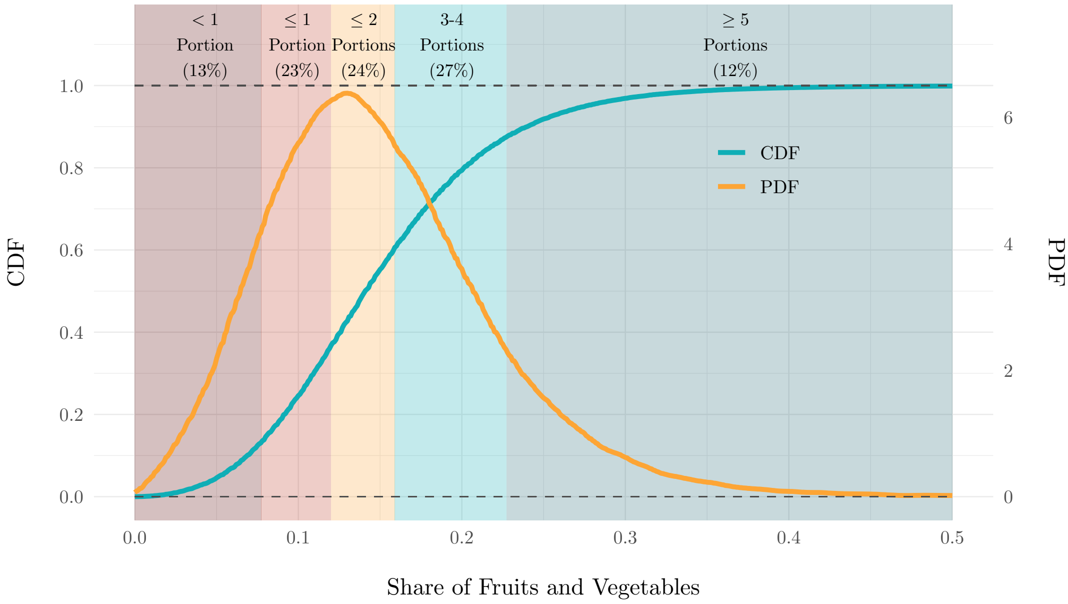
[9]Contribution to this insurance is mandatory for everyone except for individuals younger than 25 with an annual income below 750 Swiss Francs. The contributions amount to a fixed share of the gross labor market income, including official awards, gifts, and bonuses, and are also mandatory for self-employed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

[10]The calculation is $income\_adjusted = \frac{income\_total}{\sqrt{\#household\_members}}$, where we consider all household members, including small children. 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.

[11]The survey questions a representative sample of 200,000 people above age 15 every year on housing, employment, mobility, and education. Participation is mandatory. Education is categorized as either primary, secondary, or tertiary education. Primary (or compulsory) education ends at the latest after eleven mandatory school years (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. As education stabilizes for most individuals after a certain age, we use educational variables only for individuals above age 25 at the time of the survey.

[12]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).

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 final data. The colored bars show additional data on the fruit and vegetable portion intake in Switzerland from the *National Nutrition Survey*.

average value of the father and mother weighted by their respective food expenditures.[13] This results in a final sample of 271,000 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 household spends 399 Swiss francs per month (450 USD on July 29, 2024) and allocates 15% of this money to fresh fruits and vegetables. To put the latter observation into perspective, we plot in Figure 1 the distribution of fruit and vegetable expenditures and overlap it with data on portion intake from a representative administrative nutrition survey.[14] Only 12% of Swiss households fulfill the recommended fruit and vegetable intake of five daily portions, while 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 expenditures in our data to the administrative *Household Budget Survey*, showing that our transaction data covers 65% of the average household grocery expenditures on food and beverages.[15]

[13] 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.

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

[15] This survey continuously selects 2,500 households each year, and participants take notes on their income and expenditure for an entire month. Note that as we do not observe beverage expenditures, our actual coverage of

Table 1: Summary Statistics for Children's Expenditures

	Total Spending			% Fruit & Vegetable			Budget Survey	
	Mean	p50	SD	Mean	p50	SD	Spending	Share
Overall	399	323	284	0.15	0.14	0.07	616	0.65
By Age								
< 34	298	239	207	0.15	0.14	0.07	459	0.65
35–44	425	357	287	0.15	0.14	0.07	654	0.65
45–54	459	382	316	0.14	0.14	0.07	728	0.63
55–64	393	325	274	0.16	0.15	0.08	663	0.59
65+	345	286	237	0.17	0.16	0.08	616	0.56
By Household Income								
< 4,530	269	212	191	0.14	0.13	0.08	409	0.66
4,530–6,717	294	230	215	0.14	0.13	0.08	485	0.61
6,718–9,288	374	305	259	0.14	0.13	0.07	604	0.62
9,289–12,855	422	354	283	0.15	0.14	0.06	713	0.59
12,856+	458	384	312	0.16	0.16	0.07	869	0.53
By Highest Education								
Primary	275	222	190	0.13	0.12	0.07		
Secondary	376	304	264	0.14	0.13	0.07		
Tertiary	442	368	303	0.16	0.16	0.07		
By Pop. Density								
Rural	386	317	266	0.14	0.13	0.06		
Suburban	407	332	288	0.15	0.14	0.07		
Urban	389	303	289	0.17	0.16	0.08		

Notes: This table shows summary statistics for the transaction records of food expenditures in our final data. The columns titled *Budget Survey* show the average grocery expenditures for food and beverages from the administrative Household Budget Surveys (2015–2017) and the average expenditures in our data relative to the survey. *Household Income* is a household's average gross labor market income 2016-2020 in 1,000 CHF. *Highest Education* is the highest education completed by anyone within the household, and *Pop. Density* is the municipality's population density.

Looking at different household characteristics, we observe that households increase their grocery expenditures throughout their life from a young age (298 Swiss francs) until age 45-54 (459 Swiss francs) before decreasing them again towards retirement (345 Swiss francs). Meanwhile, the share of these expenditures allocated to fruits and vegetables increases with age from 15% to 17%. 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 458 Swiss francs per month compared to 269 Swiss francs for the bottom quintile. Wealthier and better-educated households also consume relatively more fruits and vegetables, providing evidence of 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 386 Swiss francs only marginally less on grocery products than households in urban areas (389 Swiss francs), and we do not expect this to affect our results.

food products is even higher.

To assess the representativeness of our data, Table A1 shows summary statistics for the 271,000 matched children and compares them to the 2.3 million children in the population fulfilling the same selection criteria. Figure A2 plots municipality-level sample averages against the population values. The average *child* in the final dataset is 43.7 years old with an adjusted household income of 83,000 Swiss francs. 54% of them are female and 62% married. Further, 53% hold a tertiary degree, and 90% live in multi-person households. Regarding geographical characteristics, 76% of the children in our sample live in the German-speaking part of Switzerland, 19% in the French- 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. The latter discrepancy is because we are less likely to identify unique combinations of customers and residents when more people live in a raster cell.[16] Our findings remain qualitatively unchanged if we re-weight undersampled locations. In summary, our sample represents the target population well, and our expenditures cover a large share of grocery expenditures.

3 Measuring Mobility

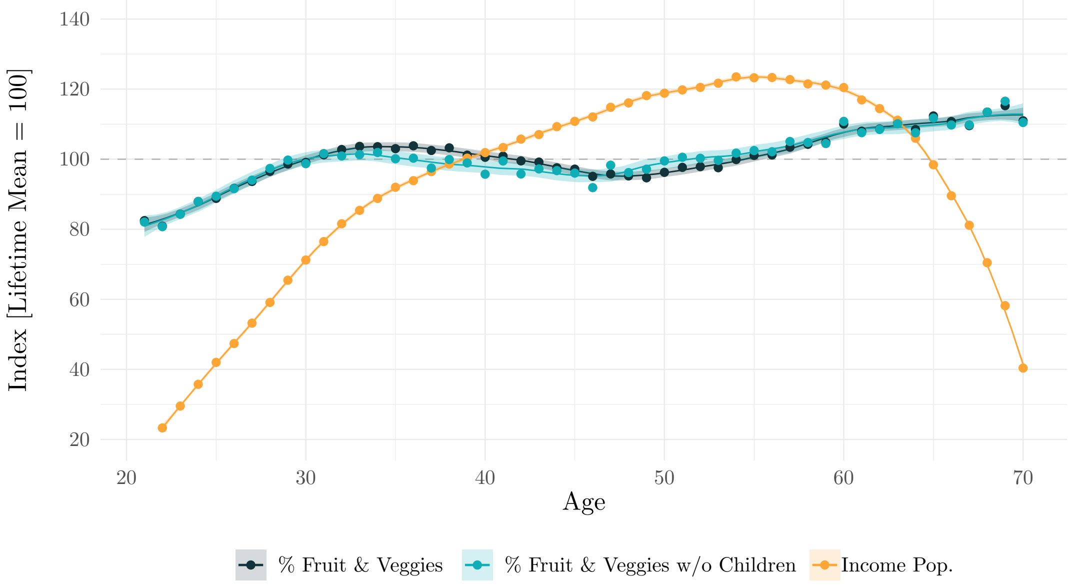
Different statistics capture different aspects of mobility, which are not necessarily positively correlated (see Deutscher and Mazumder (2023) for an extensive discussion and classification of different mobility measures). For this paper, we need to consider that the focus is on diet and not income, and the two outcomes exhibit important differences. First, our measure of diet is bounded from below and above, while income is not. Second, 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 is a good thing in most cases. Differently, with diet, there is an optimal level or interval for fruit and vegetable shares, and an increase beyond a certain threshold might not be beneficial. Yet, Figure 1 shows that most of the population seems to be on the left of this threshold.

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.[17]

[16] 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. The final data set includes more than 10% of residents in smaller municipalities; 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. Further, Figure A2 shows that the representativeness of the matched customers is not different for larger cities. See further discussion of the data in Kluser (2024) and Kluser et al. (2024), studying spatial consumer mobility from quasi-experimental shocks.

[17] 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 and compare it to their parents' five–year average family income when the

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 (3.1 million households), (ii) the households' expenditure share of fruits and vegetables in the sample (270,000), and (iii) the households' expenditure share of fruits and vegetables for households in the sample who currently do not live together with their children (105,000). All values are normalized to 100 for the lifetime average of each variable. The regression lines and uniform confidence bounds are estimated by a local regression weighted by the size of the age groups.

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.[18] After that, there is a decline of 10 percent until age 50, when diet ameliorates again.[19] If we exclude instead households with children, the curve

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 measured by a five–year average when the child was 15–19 years old. 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. The parents' and children's income is 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 at ages 60–70 and the children's health at ages 36–50.

[18] Note that both age and cohort effects could drive these differences.

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

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 children.[20] Given the visible, albeit small, lifecycle in diet, and since we observe children and parents at the same point in time, we will estimate ranks conditional on age as in Chetty et al. (2014) for the positional measures, and we control for age if the measure directly relies on the share of fruits and vegetables. If not indicated otherwise, we always compare a child's household diet to the weighted average of their parent's household diet, 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.[21] 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

[20] 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.

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

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 compute the conditional probability that a child is in bin p_j given her parents are in bin p_k:[22]

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

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. This implies that the bins p_j and p_k are age-dependent.

3.4 Conditional Expected Rank

The *Conditional 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

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

Table 2: Comparison of Mobility Measures

	(a) Rank-Rank Reg.		(b) IGE			(c) CER		(d) Transition Prob.		
	Intercept	Slope	25	50	75	25	75	Q1Q1	Q1Q5	Q5Q5
Diet	37.75	0.250	0.274	0.252	0.226	44.97	56.07	31.26	11.47	31.89
	(0.1)	(0.002)	(0.003)	(0.002)	(0.002)	(0.67)	(0.68)	(0.17)	(0.13)	(0.17)
Income	43.22	0.143	0.117	0.120	0.122	47.84	54.22	26.48	14.12	28.45
	(0.12)	(0.002)	(0.003)	(0.003)	(0.004)	(0.81)	(0.80)	(0.22)	(0.18)	(0.22)

Notes: The diet results are estimated using 270,957 observations. The income results are estimated using 161,504 observations and we restrict the sample to children between 32 and 38 and fathers between 50 and 62. The IGE uses the log of the father's income as an explanatory variable and the log of the children's income as a dependent variable. Standard errors are computed using 1,000 bootstrap replications.

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

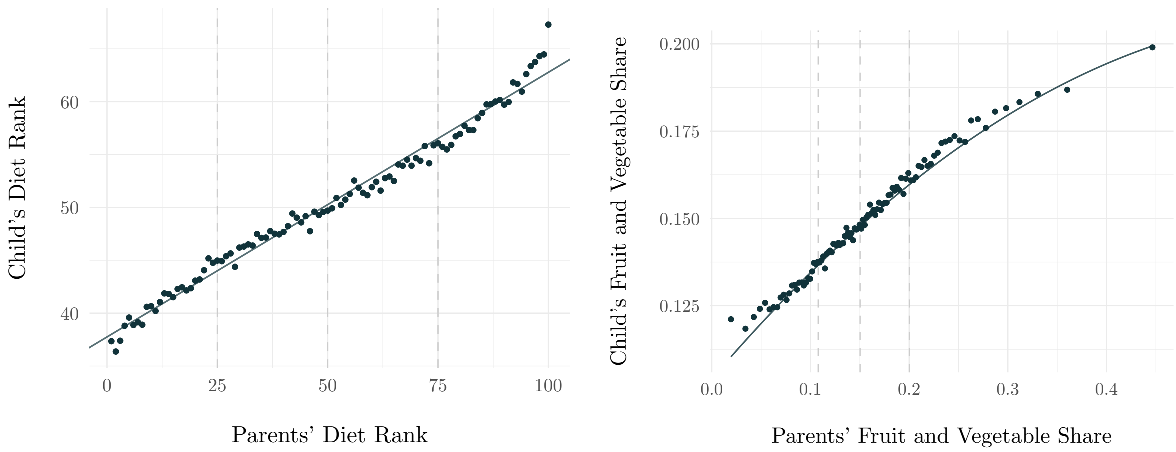
4.1 Dietary Mobility

Rank-Rank Regression – The estimated rank-rank slope in Panel (a) of Table 2 is 0.250, which shows that an increase in the parental percentile rank by one decile corresponds to an increase of 2.5 percentile ranks for the child. To put these results into perspective, it takes 3.16 generations to close the gap between two families at the first and the ninth decile.[23]

Figure 3a 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 parental rank. The linear model approximates dietary patterns particularly well, which aligns with previous findings on income mobility. To show that conditioning the percentile ranks on age solves the lifecycle issues, we compare the results using conditional and unconditional

[23]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 3: Intergenerational Diet: RRS and IGE



(a) Rank-Rank Slope

(b) Intergenerational Elasticity

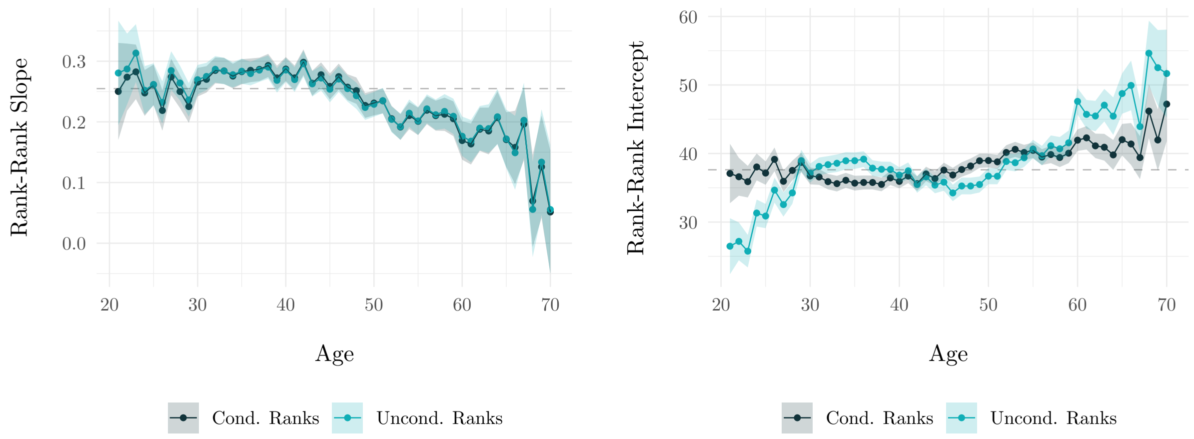
Notes: Figure 3a shows the estimated rank-rank regression line based on Equation (1) and Figure 3b shows the estimation results for the intergenerational elasticity in Equation (2). The dots in both graphs are the average children's ranks and values at each of the parents' percentiles.

ranks where 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, and in the specification using unconditional ranks, the intercept captures 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 is large and roughly constant in early adulthood at around 0.27, showing that dietary habits acquired at an early age carry on far into adulthood. The slope starts declining at around age 45, which could be explained by habit adaptation, taking several periods to form. Yet, the relationship remains sizable until later in life.[24]

Intergenerational Elasticity – Panel (b) of Table 2 shows our estimates for the intergenerational elasticity in diet at different parental percentiles and Figure 3b shows that the estimated slope decreases as the parents' share increases and that the quadratic model fits the data well. The decreasing slope suggests that the intergenerational persistence in diet is larger in the lower tail of the parents' distribution. For example, a one percentage point increase in the parents' fruit and vegetable consumption is associated with a 0.274 percentage point increase in child consumption for parents at the 25th percentile. This relationship decreases to 0.226 when the parents are at the 75th percentile. Therefore, targeted policy interventions might have the largest benefits for unhealthily eating families, resulting in more sizeable improvements in children's diets.

[24]Note that the more noisy estimates for higher age groups are due to the smaller sample as for most individuals in these age groups, we cannot observe their parents' consumption since they might be deceased or live in a retirement home.

Figure 4: Rank-Rank Slope: Lifecycle



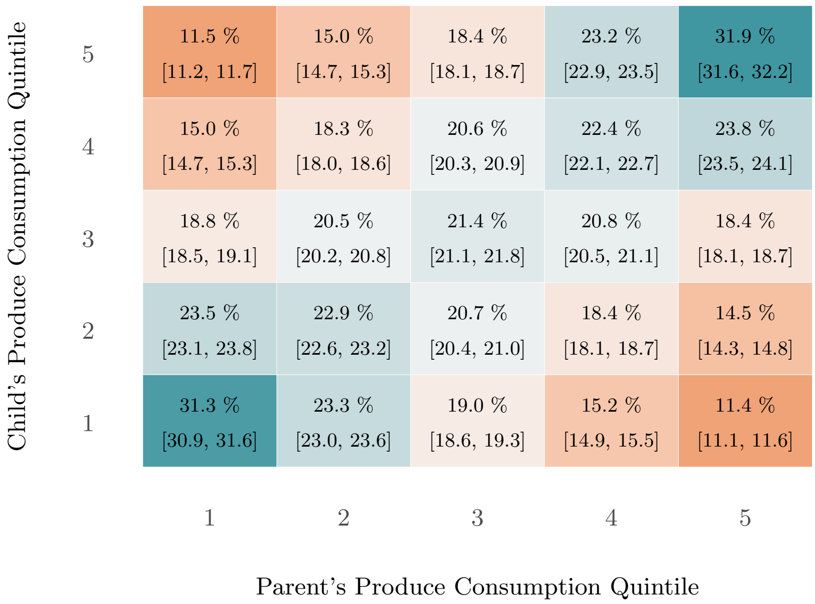
(a) Rank-Rank Slope (b) Rank-Rank Intercept

Notes: Figure 4a shows the rank-rank slope by age group. The grey line uses ranks for children and parents conditional on their age in a variation of Equation (1) fully saturated in the children's age. The blue line provides the results of 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. 95% confidence bands are computed using bootstrapped standard errors (1,000 replications).

Conditional Expected Ranks – Panel (c) in Table 2 shows the nonparametric estimates of the conditional expected rank. We estimate a CER25 and CER75 of 45.0 and 56.1, respectively. Hence, a child with parents at the 25th percentile of the parents' distribution of fruits and vegetables is, on average, at the 45th conditional percentile of children. In contrast, children with parents at the 75th percentile can expect to reach the 56th 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 confidence interval. We include 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, we see that 31.3% 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 11.5% 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 also most likely to be in the fifth quintile (Q5Q5). These particularly strong results in the "extreme" transition probabilities provide evidence that the so-called cycles of poverty and privileges are pronounced. At the same time, mobility appears larger around the center of the distribution.

Figure 5: Intergenerational Diet



Notes: The figure shows the transition probabilities for children's ranks conditional on their parents' ranks (Equation 3). We analyze transitions between quintiles and calculate the ranks conditional on age groups within the respective sub-sample of parents and children. 95% confidence intervals in parentheses are estimated using 1,000 bootstrap replications.

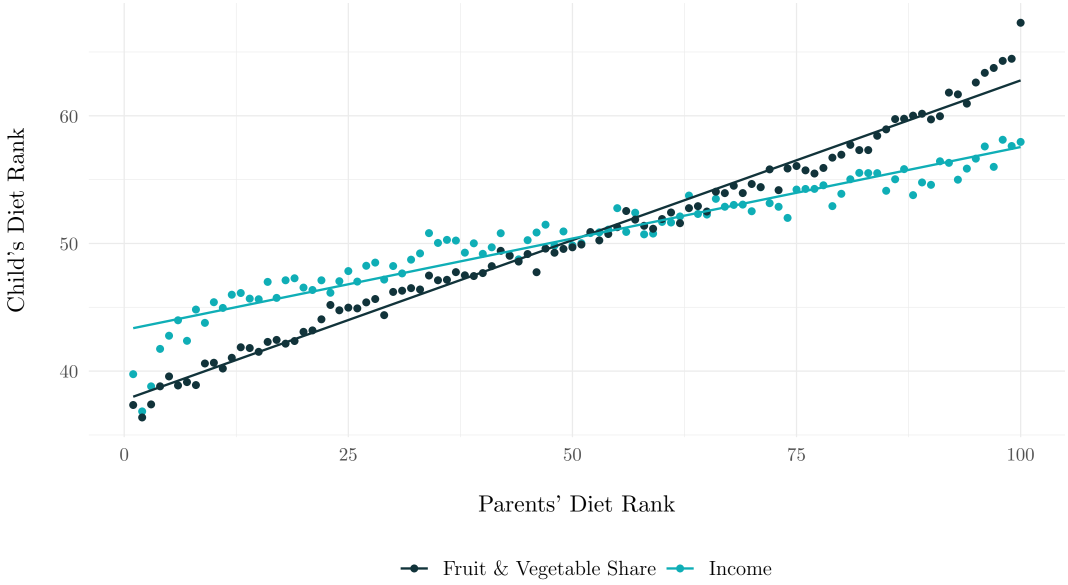
4.2 Comparison to Income Mobility

To put the magnitude of our findings into perspective, we compare them to intergenerational mobility in income. More specifically, we focus on the relationship between children's and their fathers' income. To this end, we generate a data set for all Swiss children fulfilling the sample restriction criteria applied to the final data. To deal with lifecycle variation in income, we follow the procedure of the previous literature and focus on a subgroup of children and fathers 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 fathers between 50 and 62. This restriction ensures that most children are already participating in the labor market and fathers are not yet retired. Figure 2 shows that for these children, income only fluctuates slightly around the lifetime mean, and the fathers' income is also stable. Further, we average income over the years 2016-2021 to smooth out transitory fluctuations. We estimate 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 RRS of 0.143 and an IGE of 0.120 at the 50th percentile.[25] The conditional expected ranks at the 25th and 75th percentile are 47.84 and 54.22. Also, more than one in four children with fathers' at the bottom quintile stay at the bottom, and 14.1% move up to the top.[26]

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

[26] Different sample selection procedures and income definitions (for example, using the average of parents' income) lead to comparable findings. Particularly, focusing on the sub-sample of households present in the diet

Figure 6: Intergenerational Diet vs. Income: RRS



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 children's ranks at each of the parents' percentiles.

Comparing our estimated mobility measures between diet and income in Table 2, we observe that intergenerational transmission is more pronounced in the former across all the different metrics we consider. 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.[27]

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.

as well as the income sample leaves our conclusions unchanged. Furthermore, our estimates on income mobility in Switzerland are in the range of those in Chuard and Grassi (2020), who measure the parental income as the average of the father's and mother's income when the child is between 15 and 20 years old. They find an RRS of 0.14 and an IGE of 0.22.

[27] Previous literature estimates, for example, a rank-rank slope for income 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).

Table 3: Heterogeneities

	Rank-Rank		IGE			CER		Transition Prob.			
	RRS	P-value	25	50	75	25	75	Q1Q5	Q1Q1	Q5Q5	N
(a) Child's Education											
Primary	0.242	0.457	0.289	0.255	0.215	39.04	49.19	7.66	43.78	24.16	7,272
	(0.012)		(0.018)	(0.013)	(0.013)	(3.69)	(4.33)	(0.66)	(1.23)	(1.28)	
Secondary	0.234		0.249	0.226	0.200	40.35	50.77	8.18	37.68	24.61	82,763
	(0.004)		(0.005)	(0.004)	(0.004)	(1.09)	(1.30)	(0.20)	(0.33)	(0.35)	
Tertiary	0.229		0.242	0.226	0.208	49.00	60.65	15.46	23.43	36.66	103,676
	(0.003)		(0.005)	(0.004)	(0.003)	(1.08)	(1.07)	(0.24)	(0.30)	(0.31)	
(b) Child's Income											
1th Quartile	0.279	0.000	0.296	0.273	0.246	39.87	51.59	8.00	40.98	28.46	64,881
	(0.004)		(0.006)	(0.004)	(0.004)	(1.25)	(1.47)	(0.23)	(0.40)	(0.40)	
2nd Quartile	0.239		0.253	0.231	0.205	42.77	52.30	9.22	32.83	27.07	64,873
	(0.004)		(0.006)	(0.004)	(0.004)	(1.16)	(1.34)	(0.24)	(0.39)	(0.41)	
3rd Quartile	0.228		0.246	0.225	0.200	46.78	55.77	12.04	27.91	31.40	64,863
	(0.004)		(0.006)	(0.004)	(0.004)	(1.42)	(1.30)	(0.29)	(0.40)	(0.42)	
4th Quartile	0.208		0.230	0.217	0.201	51.81	61.90	18.18	20.86	38.73	64,852
	(0.004)		(0.007)	(0.005)	(0.004)	(1.47)	(1.22)	(0.35)	(0.37)	(0.40)	
(c) Child's Place of Residence											
Rural	0.236	0.013	0.260	0.234	0.203	42.02	51.84	8.02	35.43	24.67	58,732
	(0.004)		(0.006)	(0.004)	(0.004)	(1.34)	(1.46)	(0.21)	(0.38)	(0.43)	
Suburban	0.235		0.255	0.234	0.210	43.95	55.09	10.98	31.57	29.34	157,660
	(0.002)		(0.004)	(0.003)	(0.003)	(0.83)	(0.89)	(0.17)	(0.25)	(0.25)	
Urban	0.221		0.242	0.227	0.210	53.83	62.74	20.28	22.80	41.82	54,319
	(0.005)		(0.008)	(0.006)	(0.005)	(1.69)	(1.38)	(0.47)	(0.47)	(0.41)	
(e) Distance to Parents											
1th Quartile	0.281	0.000	0.298	0.277	0.254	41.55	55.70	8.57	34.77	30.60	63,842
	(0.004)		(0.006)	(0.004)	(0.004)	(1.28)	(1.47)	(0.24)	(0.39)	(0.42)	
2nd Quartile	0.252		0.273	0.249	0.222	44.07	54.82	10.44	31.43	30.71	63,841
	(0.004)		(0.007)	(0.005)	(0.004)	(1.37)	(1.28)	(0.27)	(0.41)	(0.40)	
3rd Quartile	0.225		0.246	0.226	0.203	43.80	53.99	12.88	29.90	30.77	63,841
	(0.004)		(0.006)	(0.004)	(0.004)	(1.38)	(1.35)	(0.29)	(0.40)	(0.39)	
4th Quartile	0.202		0.226	0.208	0.187	49.48	57.58	15.34	26.68	33.52	63,841
	(0.004)		(0.006)	(0.005)	(0.004)	(1.48)	(1.32)	(0.34)	(0.40)	(0.39)	

Notes: The table shows the results for different sub-samples 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 parentheses are computed using 1,000 replications. The number of observations in each subgroup is shown in the last column.

To correct for a possible mechanical result that children belonging to an unhealthy group have a higher chance of surpassing their parents, we use percentile ranks based on the entire sample but reweight the observations in each group such that the parents' distribution imitates the one in the entire sample.[28]

Table 3 shows the rank-rank slopes, conditional expected ranks, intergenerational elasticities, and selected transition probabilities for the different subgroups. The second column contains

[28] 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).

the P-value associated with a Wald test, 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 lie around 0.23 in all groups and are not statistically different from each other. This suggests that higher children's education does not impact how parents transfer their diet. Instead, Figure 7a reveals that the intercept increases with education such that higher-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.

Second, Panel (b) digs into differences between income groups.[29] As 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 0.279 compared to 0.208 for individuals in the fourth quartile. These differences are also statistically significant, suggesting that percentile ranks are more persistent over generations among low-income children. Figure 7b shows the rank-rank slope and expected ranks for all four income quartiles. The differences in intercepts and slopes suggest that low-earning children are less successful at breaking unhealthy childhood habits and maintaining beneficial ones. For instance, a high-earning child with parents at the 10th percentile has the same expected rank as a low-earning child whose parents are at the 70th percentile.

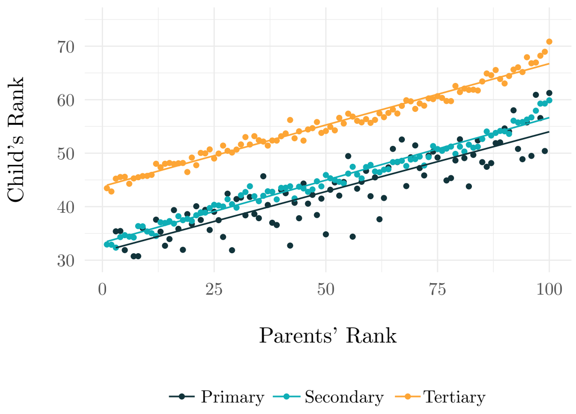
These heterogeneities are also visible across geographical characteristics. Panel (c) shows that mobility is highest in urban areas and lowest in rural areas. The transition probabilities show that children living in urban areas have an outstanding likelihood of moving up in the distribution. Strikingly, 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.

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 persistence.[30] 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 eight percentage points less likely to be trapped at the bottom if they live far away. This finding suggests that new social networks and environments might play a decisive role in breaking old

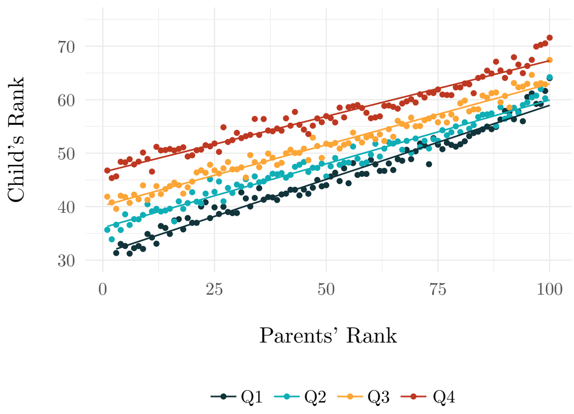
[29] To account for the lifecycle in income, we condition income quartiles on age and keep only working-age children (25-64). The results are not affected if we use all observations.

[30] 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 for the rank–rank regression in Equation (1) for different sub-populations, complementing the results in Table 3. Figure 7a displays the RRS for different education levels (primary, secondary, and tertiary) and Figure 7b for the four different income quartiles. The dots in both graphs are the expected children's ranks at each of the parents' percentiles.

habits and is consistent with previous findings on diminishing social interactions and responses to family-related shocks with increasing distance (see, e.g., 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 consider possible mechanisms driving our results. These factors influence children and their diet in many interconnected ways and could (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 preferences, 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 close 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 affects diet. Finding that the explanatory power of these factors is limited, we argue that habit formation is an important driver.

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.[31] To identify the counterfactual distribution, we combine a population's cumulative distribution function (cdf) with an alternative covariate distribution. In this subsection, we are interested in the conditional distribution of the children's diet (conditional on their parents' diet) that we would observe if their income and education were independent of their parents' socioeconomic variables. 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 the children's income and education, and let x_p contain the corresponding parental variables. The main object of interest is the counterfactual distribution of the children's diet that we would observe if we change the covariate distribution $F_{x_c|s_p,a_c,a_p,x_p}(x_c|s_p, a_c, a_p, x_p)$ 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 the 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:

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

where $\mathcal{X}_j$ denotes the support of the covariates x_j for $j = \{c, p\}$ conditional on the other

[31] 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.

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 parents' covariates yields the desired result:

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

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 the children's age in the conditioning set accounts for the lifecycle changes in income and different distributions of education 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:[32]

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

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. We estimate the conditional quantile function by fitting a flexible quantile regression model for $\tau = \{0.005, 0.015, \ldots, 0.995\}$. The regressions 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 lifecycle, which is discontinuous after reaching retirement age.[33] All variables are also interacted with a second-order polynomial of the parents' diet.

[32]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.

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

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 135,000 children for whom we observe their and 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 quantile model to further ensure a meaningful comparison.

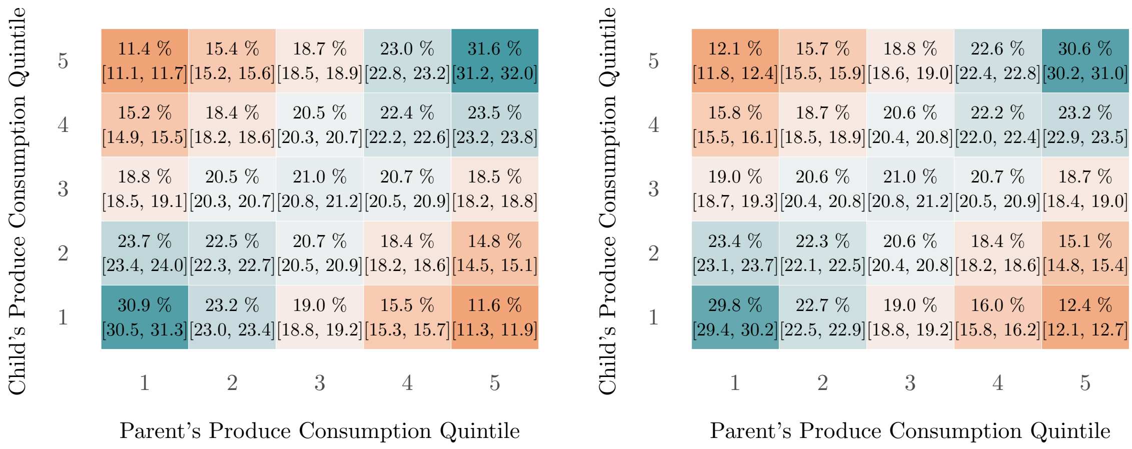
Figure 8 shows the estimated transition probabilities with the corresponding bootstrap confidence bands. Panel a) displays the transition probabilities estimated with the procedure described above; however, using the original covariates' distribution. These results are statistically indistinguishable 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, mainly 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 11.6 percentage points ($= 31.6 - 20.0$) 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 10.6 percentage points ($= 30.6 - 20.0$). This change suggests that the transmission of income and education over generations explains less than 9% 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). 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 28.4. In panel b), this statistic equals 25.9, suggesting that income and education drive only 8.8% of the intergenerational transmission of diet.[34]

Hence, these results suggest that only a small share of the intergenerational persistence of diet can be explained by the intergenerational transmission of income and education. This result

[34]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 the transmission through socioeconomic variables, the IGE at the median parental rank decreases by 9.5%.

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. The counterfactual considers the case where the children's income and education are assigned independently from their parents' values. Bootstrap confidence intervals are in parentheses. The results are estimated using the sample of 135,213 children for which we observe their as well as their parents education.

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 small effect of monetary incentives in promoting healthier food choices among SNAP recipients (see, for example, Verghese et al. (2019) and the references therein).

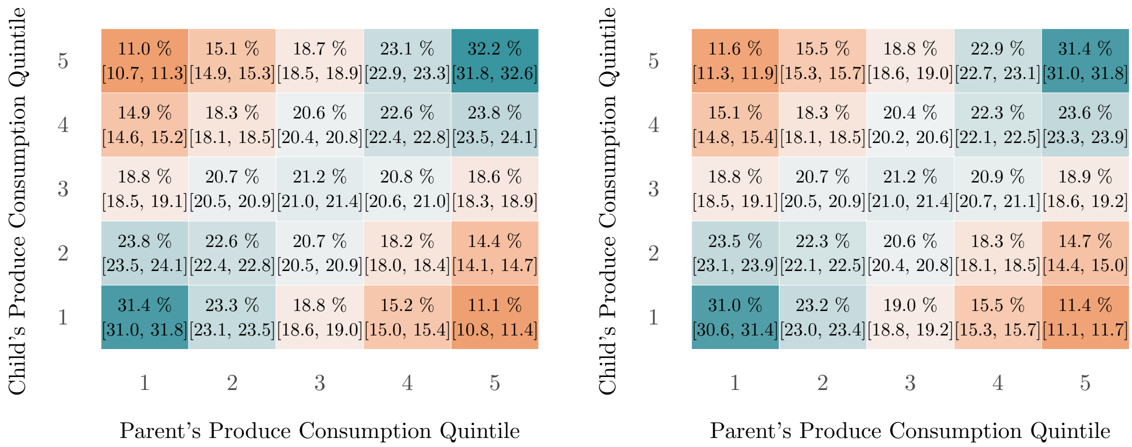
6.2 Current Location

Besides socioeconomic characteristics, also 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.[35] Hence, the transmission of location preferences may partially drive dietary persistence as people in urban areas follow a healthier diet.

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

[35] 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. Similarly, 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. The counterfactual considers the case where the children's locations are assigned independently from their parents' values. Bootstrap confidence intervals are in parentheses. The results are estimated using the sample of 120,424 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 their parents' location and other parental characteristics.

We again fit a flexible quantile regression model where we interact all variables with dummies for the degree of urbanization. Figure 9 displays the original and the counterfactual transition matrix.[36] Comparing the normalized anti-diagonal traces of the two matrices, we conclude that only 6.0% 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, the 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).

[36] As before, we recompute the original transition matrix using the same flexible model. The marginal differences in the results are likely due to different samples.

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 appreciate different foods. Second, genetic predispositions to diseases could induce 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 (Mennella et al., 2005, Gervis et al., 2023), 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). These genetic variations shape food intake, and hundreds of genes are associated with our actual consumption of fruit, cheese, fish, tea, or alcohol, potentially affecting our results (Cole et al., 2020).

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 and live alone, observing, therefore, each parent's diet separately. Due to social norms, most of these children grew up with their mothers.[37] Hence, if the dietary transmission were mostly due to the genetic transfer of tastes, we should see no difference in the transmission of diet between their mother and their father, while a stronger link to the mother's diet indicates a stronger nurture channel. The estimation results in Table 4 show that the intergenerational link between children and their divorced mothers is substantially stronger than the link with divorced fathers. This relationship changes only slightly with the child's age at the divorce. Taken together, these results suggest an important role of nurture. Yet, we are not trying to rule out that *nature* – meaning, the transmission of taste across generations – drives a share of the correlation between children's and parents' diet. Instead, the relationship between taste receptors and genes is complicated, and 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 revealed 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 individuals with a high genetic risk for heart disease almost double their risk for a stroke or heart attack, while a

[37] We choose to focus on divorced parents who did not remarry to avoid possible contamination due to a new partner. Note that we do not observe who the child lived with after the divorce. Yet, a report by the *Federal Department of Home Affairs* (2022) 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.

Table 4: Marginal IGE at the 50th percentile for children with divorced parents

	Fruit & Vegetable Share Child					
Child Age at Divorce:	≤ 10 (1)	10–18 (2)	18–25 (3)	≤ 10 (4)	10–18 (5)	18–25 (6)
Fruits & Vegetable Share Mother	0.225***	0.266***	0.238***			
	(0.019)	(0.015)	(0.016)			
Fruit & Vegetable Share Father				0.168***	0.146***	0.153***
				(0.024)	(0.026)	(0.028)
Observations	3,149	5,203	4,913	1,273	1,254	1,523

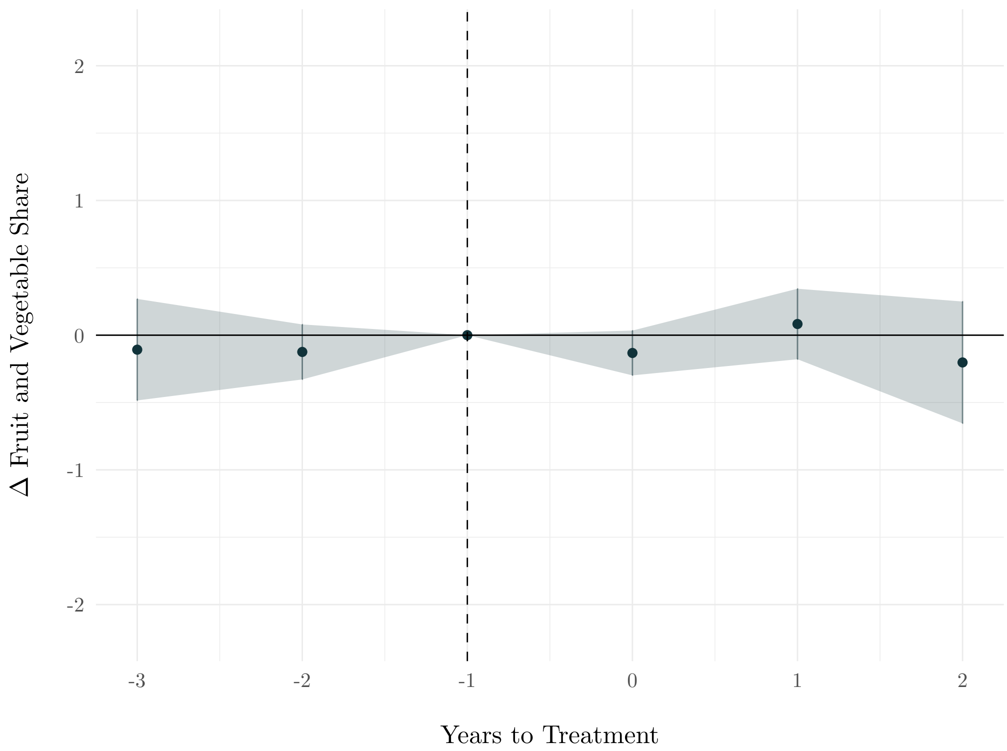
Notes: The table shows estimation results separately for divorced fathers and mothers who did not remarry and live alone. The regressions estimate the intergenerational elasticity (Equation 2), regressing the child's fruit and vegetable share on the parent's share s_{pi} and s_{pi}^2. Further, we control for the parent's and child's age as well as their squares. We report the slope coefficients at the 50th percentile of s_{pi}. Standard errors are computed using 1,000 bootstrap replications.

healthy lifestyle reduces this risk by half (Khera et al., 2016).

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. 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. Since genetic predispositions might already be known from unobserved non-fatal shocks or previous diagnoses, we alternatively focus on the deaths of individuals without any related pre-existing condition. We exclude, in this case, also deceased patients with a COVID-19 infection. This results in a data set of 22,500 observations, and the estimated coefficients remain insignificant.

One limitation 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 more substantial effect on diet as the affected person might receive or seek nutritional advice from a physician and pass the information to relatives. Nonetheless, Oster (2018) finds only minimal reductions in the caloric intake from unhealthy foods after a diabetes diagnosis, further suggesting that the predisposition to diseases is not a major channel.

Figure 10: Lifestyle-Related Death of a Parent



Notes: Difference-in-differences estimates of the lifestyle-related death of a parent's effect on their children's annual fruit and vegetable intake using the estimator suggested by Callaway and Sant'Anna (2021). We use the *not-yet-treated* units as the comparison group. The estimation uses 38,177 observations, coefficients are normalized to the year before the treatment, and standard errors are clustered at the individual level.

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, habit formation during childhood is potentially a sizable driver of our findings. These habits might capture many different *nurture* components, such as diet-related knowledge and skills that parents pass on to their children. 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).

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 (Wise et al., 2016). At the same time, infants show a higher initial acceptance of fruits and vegetables if their mother eats them regularly during pregnancy (Mennella et al., 2001, Forestell, 2024) 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, resulting in weight gain, obesity, and inflammation (May and Dus, 2021). Hence, parents shape children's taste preferences and consumption through many channels, which 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, for example, Story et al. (2008) for an overview). It is important to note that the presence of these factors does not invalidate the following 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 of diet between generations as the result of a habit stock built during childhood and adjusting over a lifetime (see, for example, Campbell and Cochrane (1999), Fuhrer (2000), and Carroll et al. (2000) 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, or handwashing (Hussam et al., 2022). Related to nutrition, 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. 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 unobserved factors outside the household, such as childhood networks, including extended family, friends, and school, 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 $c_t \in [0, 1]$ for $t = 1, 2, \ldots$, 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

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

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:

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

and

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

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, these deviations are costlier because they 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:

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

where β is the discount factor. 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 a function of the parameters (ϕ, β, ρ). Appendix C provides a detailed derivation of the solution and expression for w. The weight w given to healthy eating increases in β and ϕ and decreases in ρ. Hence, if households are forward-looking (meaning, they care about future consumption), have amenable habits, and derive significant utility from a healthy diet, then they give more weight to following a healthy diet relative to habits.

7.1 Identification and Estimation

To estimate the model, we rely on the same data we use in the rest of the paper and treat children of different ages as people in different periods of their lives. We use data on children between the ages of 30 and 60, calibrate $\beta = 0.95$, and set $c^* = 0.24$, 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 express h_t and c_t as functions of initial habits h_1 for $t \geq 2$ by iterating backwards the law of motions for habits in Equation (9) and the policy function for consumption in Equation (14):

$$h_t = h_1 (1-w\phi)^{t-1} + c^* w\phi \sum_{j=0}^{t-2} (1-w\phi)^j \tag{15}$$

$$c_t = h_1(1-w)(1-w\phi)^{t-1} + c^* \left[(1-w)w\phi \sum_{j=0}^{t-2} (1-w\phi)^j + w \right]. \tag{16}$$

A regression of c_t on $\tilde{h}_1$ interacted with age dummies identifies $\xi \cdot (1-w)(1-w\phi)^{t-1} \, \forall t$, where the term $\xi \in (0,1)$ arises from the measurement error. However, using data from different cohorts, we can identify $(1-w\phi)$ and, therefore, the path for habits. 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. Then, 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. [38] We find a point estimate of

$$(1-\hat{w}\hat{\phi}) = 0.988. \tag{18}$$

This expression does not separately identify ϕ and ρ because different values of the parameters are consistent with these results. As an example, consider an individual with $\rho = 1$ and $\phi = 0.021$, satisfying Equation (18). This individual values following her habits and a healthy diet equally, and gives a weight of $w = 0.57$ to healthy eating. Yet, the values $\rho = 2$ and $\phi = 0.028$ also satisfy Equation (18) and are, thus, observationally equivalent. While this second individual values following a healthy diet less and she assigns a lower weight to healthy eating ($w = 0.42$), she alters her habits faster. Hence, both of these individuals face the identical habit stock in the following periods, as a smaller deviation in consumption is coupled with more flexible habits such that Equation (18) holds.

Figure 11 pictures the continuum of compatible values for ϕ and ρ that satisfy Equation (18). 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). While, if individuals value a healthy diet less (higher ρ), then habits are more amenable (higher ϕ). However, what is striking is that even for extremely high values of ρ, our model still implies sticky habits, hence providing evidence for the important role of habit formation and giving an explanation as to why most individuals do not meet the dietary recommendations (for example, at $\rho = 20$, $\phi = 0.105$).[39]

Reconciling the model with the empirical heterogeneities we estimate in Section 5, we estimate our model for rich and poor households separately. Splitting the sample into income quartiles, we estimate $\hat{w}\hat{\phi} = 0.016$ for the top 25% and $\hat{w}\hat{\phi} = 0.012$ for the bottom quartile. Figure 12a shows the values of ϕ and ρ that are consistent with these results. The figure shows that as long as high-income individuals value healthy eating at least as much as low-income individuals, better-earning households face more amenable habits. If, however, low-income individuals value

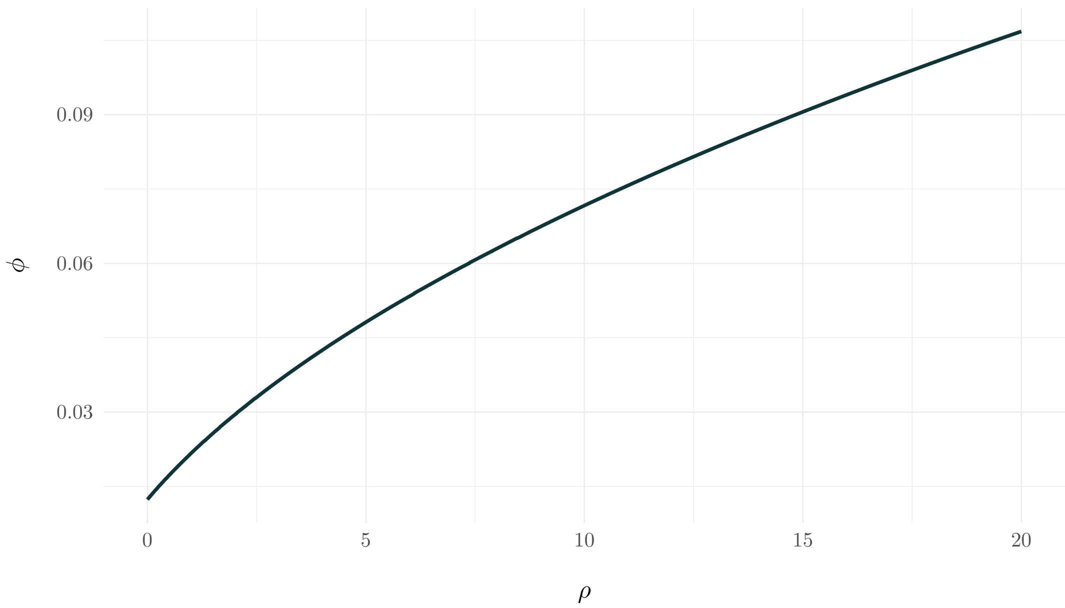
[38]One potential worry of this analysis is that the measurement error is not constant over time. More precisely, if the measurement error increases with age, it would imply that ξ is decreasing over time, consequently affecting the estimation of $log(1-w\phi)$. An alternative approach to estimate $(1-w\phi)$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

$$\frac{Cov(c_{t+1}, \tilde{h}_1)}{Cov(c_t, \tilde{h}_1)} = (1-w\phi), \;\; \forall t > 2, \tag{17}$$

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.

[39]Regarding the role of discounting, habits are less sticky if the discount rate β is low, as people have lower incentives to invest in future habits and assign more weight to following their habits.

Figure 11: Habit Persistence Parameters



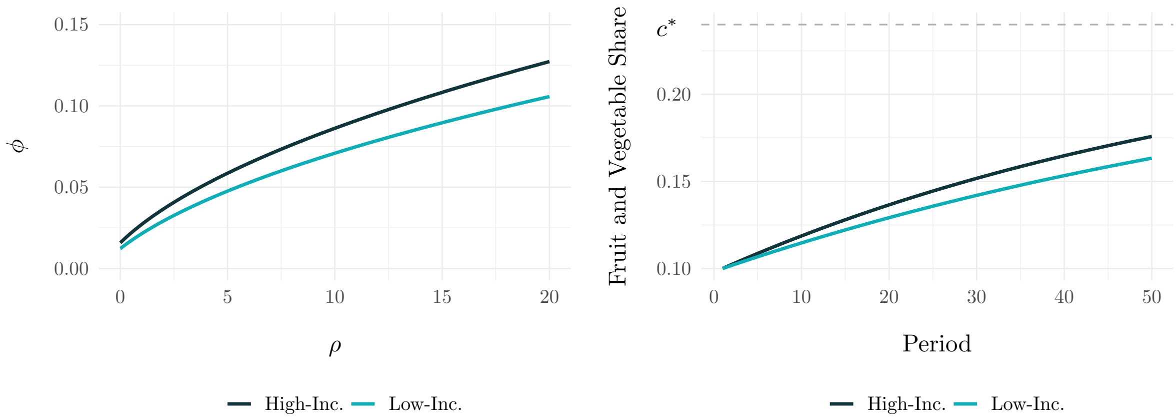
Notes: The figure shows the values of the habit persistence parameter ϕ and the relative utility weight ρ that are consistent with the result in Equation (18).

healthy eating more, it is possible that their habits adapt faster. Yet, this is unlikely to be the case as Lleras-Muney and Lichtenberg (2005) find that more educated individuals switch more easily to new drugs, suggesting their adaptation costs are lower. The difference in the estimated value of $w\phi$ for different income groups also implies that higher-income individuals have steeper habit trajectories. To give an illustration, Figure 12b shows the estimated habit trajectories of a low-income and a high-income individual, both with initial habits $h_1 = 0.10$. More affluent individuals build a habit stock that includes 1.25 percentage points more fruits and vegetables over fifty periods. All in all, these results are 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 care. Also, evidence shows that a higher socioeconomic status might reduce adaptation costs in other areas.

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 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 trans-

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. 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^*.

mission of diet varies across observable covariates. Higher-educated and better-earning children generally eat better, independent of their parents. While the transmission mechanism (in terms of the rank-rank slope) does not vary between educational levels, it grows significantly weaker as income rises. Hence, low-income individuals are particularly vulnerable to getting stuck in a cycle of unhealthy diets. Further, 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, including income, education, and family backgrounds. Isolating the part of dietary transmission going through education and income, we show that the transmission of these socioeconomic variables is responsible for only 10% of the intergenerational persistence in diet, and the transmission of location preferences explains around 6%. Further, we find that the unexpected death of a parent due to a lifestyle-related disease does not affect diet, suggesting that information about genetic predispositions is not an important determinant of diet, while there is substantial scientific evidence implying that diet affects our genes and taste perception. Similarly, the stronger persistence we observe in mother-children relationships compared to father-children relationships among children of divorcees further underscores the importance of the nurture component of intergenerational transmission. Although other unobserved variables of children likely influence eating habits throughout their lives, our results suggest that the direct effect of childhood diet is large. Thus, 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. Our results suggest that lump-sum transfers or SNAP benefits – which are not explicitly designed to improve diets – are potentially ineffective because they are unable to alter deeply anchored habits. Instead, policy interventions directly targeting the diet of young children while their habits are still forming might be more successful and cost-effective. Such policies may include, among others, healthy school lunch programs, nutritional education for children, and information campaigns at schools and doctors' offices. Future research should focus on disentangling specific mechanisms to optimally design such targeted policies. Houmark et al. (2024) presents a promising approach in this direction, using genetic data to analyze the interaction of genes and parental investments in the formation of skills.

References

Acciari, P., Polo, A., Violante, G.L., 2022. And Yet It Moves: Intergenerational Mobility in Italy. American Economic Journal: Applied Economics 14, 118–163. doi:10.1257/app.20210151.

Adermon, A., Lindahl, M., Waldenström, D., 2018. Intergenerational Wealth Mobility and the Role of Inheritance: Evidence from Multiple Generations. The Economic Journal 128, F482–F513. doi:10.1111/ecoj.12535.

Afshin et al., 2019. Health effects of dietary risks in 195 countries, 1990–2017: a systematic analysis for the Global Burden of Disease Study 2017. The Lancet 393, 1958–1972. doi:10.1016/S0140-6736(19)30041-8.

Aguilar, A., Gutierrez, E., Seira, E., 2021. The effectiveness of sin food taxes: Evidence from Mexico. Journal of Health Economics 77, 102455. doi:10.1016/j.jhealeco.2021.102455.

Allcott, H., Diamond, R., Dubé, J.P., Handbury, J., Rahkovsky, I., Schnell, M., 2019a. Food Deserts and the Causes of Nutritional Inequality. The Quarterly Journal of Economics 134, 1793–1844. doi:10/ggfq88.

Allcott, H., Gentzkow, M., Song, L., 2022. Digital Addiction. American Economic Review 112, 2424–2463. doi:10.1257/aer.20210867.

Allcott, H., Lockwood, B.B., Taubinsky, D., 2019b. Should We Tax Sugar-Sweetened Beverages? An Overview of Theory and Evidence. Journal of Economic Perspectives 33, 202–227. doi:10/gjhkhg.

Allen, A.L., McGeary, J.E., Hayes, J.E., 2014. Polymorphisms in TRPV and TAS2Rs Associate with Sensations from Sampled Ethanol. Alcoholism: Clinical and Experimental Research 38, 2550–2560. doi:10.1111/acer.12527.

Andersen, C., 2021. Intergenerational health mobility: Evidence from Danish registers. Health Economics 30, 3186–3202. doi:10.1002/hec.4433.

Araya, S., Elberg, A., Noton, C., Schwartz, D., 2022. Identifying Food Labeling Effects on Consumer Behavior. Marketing Science 41, 982–1003. doi:10.1287/mksc.2022.1356.

Asher, S., Novosad, P., Rafkin, C., 2024. Intergenerational Mobility in India: New Measures and Estimates across Time and Social Groups. American Economic Journal: Applied Economics 16, 66–98. doi:10.1257/app.20210686.

Atkin, D., 2013. Trade, Tastes, and Nutrition in India. American Economic Review 103, 1629–1663. doi:10.1257/aer.103.5.1629.

Atkin, D., 2016. The Caloric Costs of Culture: Evidence from Indian Migrants. American Economic Review 106, 1144–1181. doi:10.1257/aer.20140297.

Bailey, M.J., Hoynes, H., Rossin-Slater, M., Walker, R., 2024. Is the Social Safety Net a Long-Term Investment? Large-Scale Evidence from the Food Stamps Program. Review of Economic Studies 91, 1291–1330. doi:10.1093/restud/rdad063.

Barahona, N., Otero, C., Otero, S., 2023. Equilibrium Effects of Food Labeling Policies. Econometrica 91, 839–868. doi:10.3982/ECTA19603.

Becker, G.S., Mulligan, C.B., 1997. The Endogenous Determination of Time Preference. The Quarterly Journal of Economics 112, 729–758. doi:10.1162/003355397555334.

Belloc, M., Drago, F., Fochesato, M., Galbiati, R., 2024. Multigenerational Transmission of Wealth: Florence, 1403–1480. American Economic Journal: Applied Economics 16, 99–129. doi:10.1257/app.20220137.

Berry, J., Mehta, S., Mukherjee, P., Ruebeck, H., Shastry, G.K., 2021. Crowd-out in school-based health interventions: Evidence from India's midday meals program. Journal of Public Economics 204, 104552. doi:10.1016/j.jpubeco.2021.104552.

Birch, L.L., 1999. Development of Food Preferences. Annual Review of Nutrition 19, 41–62. doi:10.1146/annurev.nutr.19.1.41.

Black, S., Duzett, N., Lleras-Muney, A., Pope, N., Price, J., 2024. Intergenerational Transmission of Lifespan in the US. NBER Working Paper 31034. doi:10.2139/ssrn.4393374.

Black, S.E., Devereux, P.J., Salvanes, K.G., 2005. Why the Apple Doesn't Fall Far: Understanding Intergenerational Transmission of Human Capital. American Economic Review 95. doi:10.1257/0002828053828635.

Bratberg, E., Davis, J., Mazumder, B., Nybom, M., Schnitzlein, D.D., Vaage, K., 2017. A Comparison of Intergenerational Mobility Curves in Germany, Norway, Sweden, and the US. The Scandinavian Journal of Economics 119, 72–101. doi:10.1111/sjoe.12197.

Bronnenberg, B.J., Dubé, J.P.H., Gentzkow, M., 2012. The Evolution of Brand Preferences: Evidence from Consumer Migration. American Economic Review 102, 2472–2508. doi:10.1257/aer.102.6.2472.

Bruze, G., 2018. Intergenerational mobility: New evidence from consumption data. Journal of Applied Econometrics 33, 580–593. doi:10.1002/jae.2626.

Büchel, K., Ehrlich, M.V., Puga, D., Viladecans-Marsal, E., 2020. Calling from the outside: The role of networks in residential mobility. Journal of Urban Economics 119, 103277. doi:10.1016/j.jue.2020.103277.

Callaway, B., Sant'Anna, P.H., 2021. Difference-in-Differences with Multiple Time Periods. Journal of Econometrics 225, 200–230. doi:10.1016/j.jeconom.2020.12.001.

Campbell, J., Cochrane, J., 1999. By Force of Habit: A Consumption-Based Explanation of Aggregate Stock Market Behavior. Journal of Political Economy 107, 205–251. doi:10.1086/250059.

Carroll, C.D., Overland, J., Weil, D.N., 2000. Saving and Growth with Habit Formation. American Economic Review 90, 341–355. doi:10.1257/aer.90.3.341.

Chang, H., Halliday, T.J., Lin, M.J., Mazumder, B., 2024. Estimating intergenerational health transmission in Taiwan with administrative health records. Journal of Public Economics 238, 2024. doi:10.1016/j.jpubeco.2024.105194.

Charles, K., Danziger, S., Li, G., Schoeni, R., 2014. The Intergenerational Correlation of Consumption Expenditures. American Economic Review 104, 136–140. doi:10.1257/aer.104.5.136.

Charles, K., Hurst, E., 2003. The Correlation of Wealth across Generations. Journal of Political Economy 111, 1155–1182. doi:10.1086/378526.

Chernozhukov, V., Fernández-Val, I., Melly, B., 2013. Inference on Counterfactual Distributions. Econometrica 81, 2205–2268. doi:10.3982/ECTA10582.

Chetty, R., Hendren, N., 2018. The Impacts of Neighborhoods on Intergenerational Mobility II: County-Level Estimates. The Quarterly Journal of Economics 133, 1163–1228. doi:10.1093/qje/qjy006.

Chetty, R., Hendren, N., Jones, M.R., Porter, S.R., 2020. Race and Economic Opportunity in the United States: an Intergenerational Perspective. The Quarterly Journal of Economics 135, 711–783. doi:10.1093/qje/qjz042.

Chetty, R., Hendren, N., Katz, L.F., 2016. The Effects of Exposure to Better Neighborhoods on Children: New Evidence from the Moving to Opportunity Experiment. American Economic Review 106, 855–902. doi:10.1257/aer.20150572.

Chetty, R., Hendren, N., Kline, P., Saez, E., Turner, N., 2014. Is the United States Still a Land of Opportunity? Recent Trends in Intergenerational Mobility. American Economic Review 104, 141–147. doi:10.1257/aer.104.5.141.

Chetty, R., Jackson, M.O., Kuchler, T., Stroebel, J., Hendren, N., al., 2022a. Social capital I: measurement and associations with economic mobility. Nature 608, 108–121. doi:10.1038/s41586-022-04996-4.

Chetty, R., Jackson, M.O., Kuchler, T., Stroebel, J., Hendren, N., al., 2022b. Social capital II: determinants of economic connectedness. Nature 608, 122–134. doi:10.1038/s41586-022-04997-3.

Chuard, P., Grassi, V., 2020. Switzer-Land of Opportunity: Intergenerational Income Mobility in the Land of Vocational Education. Working Paper doi:10.2139/ssrn.3662560.

Clark, G., Cummins, N., 2015. Intergenerational Wealth Mobility in England, 1858-2012: Surnames and Social Mobility. The Economic Journal 125, 61–85. doi:10.1111/ecoj.12165.

Cole, J.B., Florez, J.C., Hirschhorn, J.N., 2020. Comprehensive genomic analysis of dietary habits in UK Biobank identifies hundreds of genetic associations. Nature Communications 11, 1467. doi:10.1038/s41467-020-15193-0.

Cook, P.J., Ostermann, J., Sloan, F.A., 2005. The Net Effect of an Alcohol Tax Increase on Death Rates in Middle Age. American Economic Review 95, 278–281. doi:10.1257/000282805774670419.

Corak, M., 2020. The Canadian Geography of Intergenerational Income Mobility. The Economic Journal 130, 2134–2174. doi:10.1093/ej/uez019.

Cutler, D., Deaton, A., Lleras-Muney, A., 2006. The Determinants of Mortality. Journal of Economic Perspectives 20, 97–120. doi:10.1257/jep.20.3.97.

Deutscher, N., Mazumder, B., 2020. Intergenerational mobility across Australia and the stability of regional estimates. Labour Economics 66, 101861. doi:10.1016/j.labeco.2020.101861.

Deutscher, N., Mazumder, B., 2023. Measuring Intergenerational Income Mobility: A Synthesis of Approaches. Journal of Economic Literature 61, 988–1036. doi:10.1257/jel.20211413.

Dickson, A., Gehrsitz, M., Kemp, J., 2023. Does a Spoonful of Sugar Levy Help the Calories Go Down? An Analysis of the UK Soft Drinks Industry Levy. Review of Economics and Statistics , 1–29doi:10.1162/rest_a_01345.

Dubois, P., Griffith, R., O'Connell, M., 2020. How Well Targeted Are Soda Taxes? American Economic Review 110, 3661–3704. doi:10.1257/aer.20171898.

Fadlon, I., Nielsen, T.H., 2019. Family Health Behaviors. American Economic Review 109, 3162–3191. doi:10.1257/aer.20171993.

Fernandez, R., Fogli, A., Olivetti, C., 2004. Mothers and Sons: Preference Formation and Female Labor Force Dynamics. The Quarterly Journal of Economics 119, 1249–1299. doi:10.1162/0033553042476224.

Forestell, C.A., 2024. Does Maternal Diet Influence Future Infant Taste and Odor Preferences? A Critical Analysis. Annual Review of Nutrition 44. doi:10.1146/annurev-nutr-121222-101404.

Forestell, C.A., Mennella, J.A., 2007. Early Determinants of Fruit and Vegetable Acceptance. Pediatrics 120, 1247–1254. doi:10.1542/peds.2007-0858.

Frimmel, W., Halla, M., Paetzold, J., 2019. The Intergenerational Causal Effect of Tax Evasion: Evidence from the Commuter Tax Allowance in Austria. Journal of the European Economic Association 17, 1843–1880. doi:10.1093/jeea/jvy033.

Fuhrer, J.C., 2000. Habit Formation in Consumption and Its Implications for Monetary-Policy Models. American Economic Review 90, 367–390. doi:10.1257/aer.90.3.367.

Fujiwara, T., Meng, K., Vogl, T., 2016. Habit Formation in Voting: Evidence from Rainy Elections. American Economic Journal: Applied Economics 8, 160–188. doi:10.1257/app.20140533.

Gervis, J.E., Ma, J., Chui, K.K., McKeown, N.M., Levy, D., Lichtenstein, A.H., 2023. Bitter- and Umami-Related Genes are Differentially Associated with Food Group Intakes: the Framingham Heart Study. The Journal of Nutrition 153, 483–492. doi:10.1016/j.tjnut.2022.11.005.

Goldin, J., Homonoff, T., Meckel, K., 2022. Issuance and Incidence: SNAP Benefit Cycles and Grocery Prices. American Economic Journal: Economic Policy 14, 152–178. doi:10.1257/pol.20190777.

Halliday, T.J., Mazumder, B., Wong, A., 2020. The intergenerational transmission of health in the United States: A latent variables analysis. Health Economics 29, 367–381. doi:10.1002/hec.3988.

Handbury, J., Moshary, S., 2021. School Food Policy Affects Everyone: Retail Responses to the National School Lunch Program. NBER Working Paper 29384. doi:10.2139/ssrn.3897936.

Hastings, J., Kessler, R., Shapiro, J.M., 2021. The Effect of SNAP on the Composition of Purchased Foods: Evidence and Implications. American Economic Journal: Economic Policy 13, 277–315. doi:10/gnp9t9.

Houmark, M.A., Ronda, V., Rosholm, M., 2024. The Nurture of Nature and the Nature of Nurture: How Genes and Investments Interact in the Formation of Skills. American Economic Review 114, 385–425. doi:10.1257/aer.20220456.

Hussam, R., Rabbani, A., Reggiani, G., Rigol, N., 2022. Rational Habit Formation: Experimental Evidence from Handwashing in India. American Economic Journal: Applied Economics 14, 1–41. doi:10.1257/app.20190568.

Hut, S., 2020. Determinants of Dietary Choice in the US: Evidence from Consumer Migration. Journal of Health Economics 72, 102327. doi:10/gnp9t7.

Hut, S., Oster, E., 2022. Changes in household diet: Determinants and predictability. Journal of Public Economics 208, 104620. doi:10.1016/j.jpubeco.2022.104620.

Jäntti, M., Jenkins, S.P., 2015. Income Mobility. Handbook of Income Distribution 2, 807–935. doi:10.1016/B978-0-444-59428-0.00011-4.

Khera, A.V., Emdin, C.A., Drake, I., Natarajan, P., Bick, A.G., Cook, N.R., Chasman, D.I., Baber, U., Mehran, R., Rader, D.J., Fuster, V., Boerwinkle, E., Melander, O., Orho-Melander, M., Ridker, P.M., Kathiresan, S., 2016. Genetic Risk, Adherence to a Healthy Lifestyle, and Coronary Disease. New England Journal of Medicine 375, 2349–2358. doi:10.1056/NEJMoa1605086.

Kluser, F., 2024. Cross-Border Shopping: Evidence from Household Transaction Records. CRED Research Paper 42.

Kluser, F., Seidel, T., von Ehrlich, M., 2024. Spatial Frictions in Retail Consumption. CRED Research Paper 40.

Lleras-Muney, Lichtenberg, 2005. Are the More Educated More Likely to Use New Drugs? Annals of Economics and Statistics 79/80, 671–69. doi:10.2307/20777592.

May, C.E., Dus, M., 2021. Confection Confusion: Interplay Between Diet, Taste, and Nutrition. Trends in Endocrinology & Metabolism 32, 95–105. doi:10.1016/j.tem.2020.11.011.

Mennella, J.A., Bobowski, N.K., Reed, D.R., 2016. The development of sweet taste: From biology to hedonics. Reviews in Endocrine and Metabolic Disorders 17, 171–178. doi:10.1007/s11154-016-9360-5.

Mennella, J.A., Jagnow, C.P., Beauchamp, G.K., 2001. Prenatal and Postnatal Flavor Learning by Human Infants. Pediatrics 107, e88–e88. doi:10.1542/peds.107.6.e88.

Mennella, J.A., Pepino, M.Y., Reed, D.R., 2005. Genetic and Environmental Determinants of Bitter Perception and Sweet Preferences. Pediatrics 115, e216–e222. doi:10.1542/peds.2004-1582.

Oster, E., 2018. Diabetes and Diet: Purchasing Behavior Change in Response to Health Information. American Economic Journal: Applied Economics 10, 308–348. doi:10.1257/app.20160232.

Rothstein, J., 2019. Inequality of Educational Opportunity? Schools as Mediators of the Intergenerational Transmission of Income. Journal of Labor Economics 37, 85–123. doi:10.1086/700888.

Scaglioni, S., De Cosmi, V., Ciappolino, V., Parazzini, F., Brambilla, P., Agostoni, C., 2018. Factors Influencing Children's Eating Behaviours. Nutrients 10. doi:10.3390/nu10060706.

Springmann, M., Sacks, G., Ananthapavan, J., Scarborough, P., 2018. Carbon pricing of food in Australia: an analysis of the health, environmental and public finance impacts. Australian and New Zealand Journal of Public Health 42, 523–529. doi:10.1111/1753-6405.12830.

Story, M., Kaphingst, K.M., Robinson-O'Brien, R., Glanz, K., 2008. Creating Healthy Food and Eating Environments: Policy and Environmental Approaches. Annual Review of Public Health 29, 253–272. doi:10.1146/annurev.publhealth.29.020907.090926.

Søberg, S., Sandholt, C.H., Jespersen, N.Z., Toft, U., Madsen, A.L., Von Holstein-Rathlou, S., Grevengoed, T.J., Christensen, K.B., Bredie, W.L., Potthoff, M.J., Solomon, T.P., Scheele, C., Linneberg, A., Jørgensen, T., Pedersen, O., Hansen, T., Gillum, M.P., Grarup, N., 2017. FGF21 Is a Sugar-Induced Hormone Associated with Sweet Intake and Preference in Humans. Cell Metabolism 25, 1045–1053.e6. doi:10.1016/j.cmet.2017.04.009.

Verghese, A., Raber, M., Sharma, S., 2019. Interventions targeting diet quality of Supplemental Nutrition Assistance Program (SNAP) participants: A scoping review. Preventive Medicine 119, 77–86. doi:10.1016/j.ypmed.2018.12.006.

Waldkirch, A., Ng, S., Cox, D., 2004. Intergenerational Linkages in Consumption Behavior. The Journal of Human Resources 39, 355. doi:10.2307/3559018.

Wise, P.M., Nattress, L., Flammer, L.J., Beauchamp, G.K., 2016. Reduced dietary intake of simple sugars alters perceived sweet taste intensity but not perceived pleasantness. The American Journal of Clinical Nutrition 103, 50–60. doi:10.3945/ajcn.115.112300.

A Data: Matching Procedure

This section describes how we match the *customers* in the grocery transaction data with the *residents* in the administrative data. To begin with, we select all combinations of residents and customers with the same location grid cells and age. This generates 4.5 million matches between customers and residents, and we refer to them as *pairs*.[40] We take some additional steps to isolate the unique matches between *residents* and *customers*, proceeding as follows.

1. First, we want to exclude pairs where the customer's shopping behavior does not fit the resident's past locations of residence, as these residents are likely not the owners of the loyalty card they link to. So, we calculate the median annual road distance traveled between a resident's home location and the stores visited by the customer (weighted by trip expenditures). Then, we exclude customer-resident pairs with median shopping trips exceeding 20 kilometers in any year. This step excludes 191,000 pairs.
2. Customers can register in the loyalty program as a family if they have at least one child younger than 25. Hence, we delete all pairs where the customer is registered as a family and the resident does not fulfill this criterion. This excludes 355,000 pairs.
3. Then, we select all customers that link to exactly one household (multiple residents can live in this household). This gives 1,585,204 unique customer-resident matches.
4. Although households can own multiple loyalty cards, the minimum age to register is 18. Hence, we exclude pairs with more customers than adult residents, eliminating 77,935 pairs.
5. We recover some additional unique matches by identifying consumers who have moved recently without notifying the retailer. To this end, we check whether these movers uniquely match a resident at their old location. This procedure identifies 47,571 additional unique pairs.
6. Removing the customers and residents matched in the previous step, we find an additional 3,845 unique matches at current locations. Steps (1) to (6) result in 1.55 million customers uniquely linked to a resident, accounting for 73% of active customers and 21% of Swiss adult residents.
7. For households owning multiple loyalty cards, we then aggregate expenditures within the household before calculating the relative fruit and vegetable share over the sample period at the household level.
8. 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, as these children may contaminate our measure of diet for their parents in the periods

[40]Note that some customers do not match any resident, which is most likely because their addresses in the grocery data are outdated. This is the case for 380,000 of the 2.8 million customers (13.5%), of which 260,000 are active customers (spending more than 50 Swiss francs monthly over our sample period).

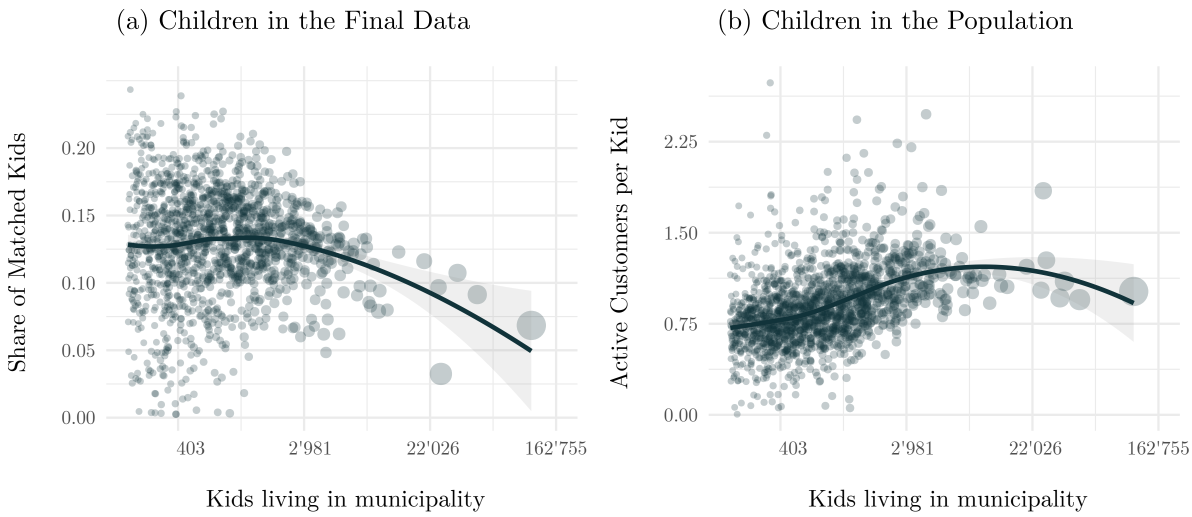
before they moved out.[41]

9. We assign the aggregated transaction data to all adult residents in the household. This provides grocery expenditures for 2,248,059 million residents living in 1.17 million different households.

10. Finally, we select the 337,950 children for whom we observe at least one of their parents in the final data set.

B Data: Additional Figures and Tables

Figure A1: Match Rate



Notes: The figure illustrates the representativeness of the retailer's loyalty program. Figure A1a shows the share of matched children as a function of the number of children living in a municipality. Figure A1b shows the number of active customers in the full customer data as a function of the number of children living in this municipality. Each dot represents a municipality, while the size is proportional to its population. The solid line is estimated by a local regression.

[41] Excluding them entirely leaves our estimates unchanged.

Table A1: Summary Statistics for Children

	Final Sample		Population	
Panel a)	Mean	SD	Mean	SD
Age	43.72	10.69	43.70	11.70
Age Father	71.87	9.66	71.05	10.35
Age Mother	71.03	10.35	70.85	11.36
HH Income Total	142.37	137.04	129.68	109.09
HH Income Adjusted	83.25	87.01	81.60	64.88
Panel b)	Pct.	N	Pct.	N
Gender		270,957		2,276,806
Female	53.9	146,148	50.8	1,155,646
Male	46.1	124,809	49.2	1,121,160
Marriage		270,957		2,276,806
Married	62.3	168,776	50.3	1,145,736
Not Married	37.7	102,181	49.7	1,131,070
Highest Education		193,711		1,554,739
Tertiary	53.5	103,676	50.0	777,901
Secondary	42.7	82,763	44.6	694,110
Primary	3.8	7,272	5.3	82,728
Language Region		270,711		2,274,341
German	76.9	208,283	72.3	1,644,202
French	19.1	51,643	22.0	500,133
Italian	4.0	10,785	5.7	130,006
Pop. Density		270,711		2,274,341
Rural	21.7	58,732	21.6	490,681
Suburban	58.2	157,660	52.2	1,186,301
Urban	20.1	54,319	26.3	597,359
Household Size		270,957		2,276,806
1	10.2	27,715	21.0	478,435
2	26.9	72,900	33.2	754,928
3-4	51.1	138,377	37.2	846,201
5+	11.8	31,965	8.7	197,242
Observations		270,957		2,276,806

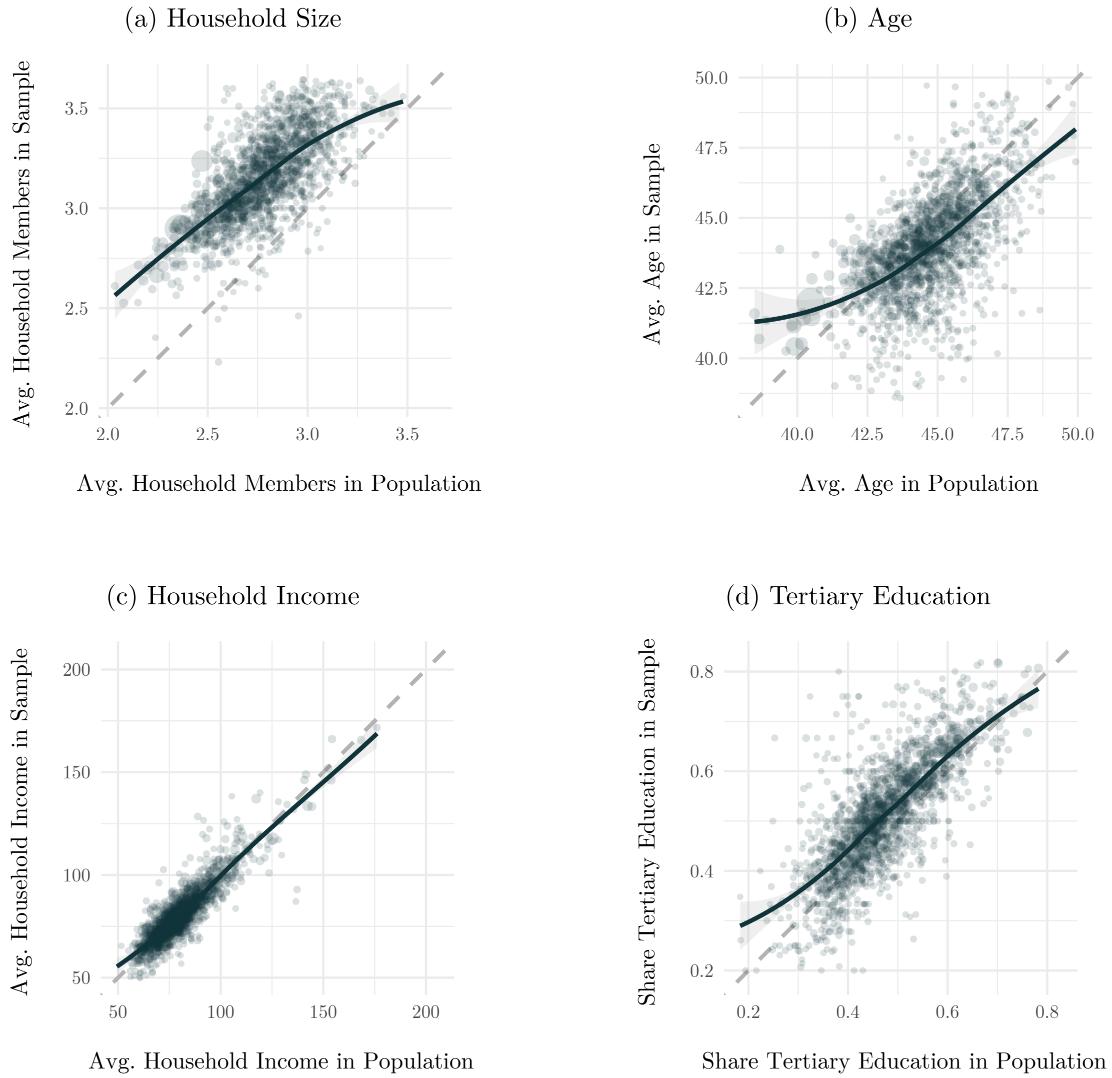
Notes: This table shows summary statistics for the households in the final data. *HH Income Total* is a household's average gross labor market income 2016-2020 in 1,000 CHF, and *HH Income Adjusted* adjusts it by the square root of household size. *Highest Education* is the highest education completed by anyone within the household, and *Pop. Density* is the municipality's population density.

Table A2: Comparison of Mobility Measures

	(a) Rank-Rank Reg.		(b) IGE			(c) CER		(d) Transition Prob.		
	Intercept	Slope	25	50	75	25	75	Q1Q1	Q1Q5	Q5Q5
Diet	36.1	0.270	0.293	0.265	0.232	46.5	54.3	32.2	10.9	32.0
	(0.28)	(0.005)	(0.008)	(0.006)	(0.005)	(1.80)	(1.91)	(0.50)	(0.37)	(0.50)
Income	43.6	0.131	0.115	0.123	0.131	46.7	52.7	24.7	14.1	28.0
	(0.3)	(0.006)	(0.007)	(0.008)	(0.009)	(2.14)	(1.91)	(0.50)	(0.42)	(0.54)

Notes: The diet results are estimated using 32,168 observations. The income results are estimated using 29,098 observations as we restrict the sample to children between 32 and 38 and fathers between 50 and 62. The IGE uses the log of the father's income as an explanatory variable and the log of the children's income as a dependent variable. Standard errors are from 1,000 bootstrap replications.

Figure A2: Municipality Averages: Sample vs. Population



Notes: The figure illustrates the representativeness of the final data by comparing municipality averages using the final data and the administrative data. Each dot represents a municipality's average, while the dot's size is proportional to the municipality's population. The solid line is estimated using 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 children 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.

C Model: Derivations

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

$$
\begin{aligned}
V_t(h_t) &= \max_{c_t} -(c_t - c^*)^2 - \rho\,(c_t - h_t)^2 + \beta V_{t+1}(h_{t+1}) \quad \text{ s.t. } h_{t+1} = h_t + \phi(c_t - h_t) \\
&= \max_{c_t} - \left(\frac{h_{t+1}}{\phi} - \frac{h_t}{\phi} + h_t - c^*\right)^2 - \rho\left(\frac{h_{t+1}}{\phi} - \frac{h_t}{\phi} + h_t - h_t\right)^2 + \beta V_{t+1}(h_{t+1}) \qquad (19)
\end{aligned}
$$

with the resulting optimality conditions:

$$
0 = -\frac{2}{\phi}(c_t - c^*) - \frac{2\rho}{\phi}(c_t - h_t) + \beta V'_{t+1}(h_{t+1}), \qquad (20)
$$

$$
V'_t(h_t) = -\frac{2(\phi-1)}{\phi}(c_t - c^*) - \frac{-2\rho}{\phi}(c_t - h_t). \qquad (21)
$$

Shifting the second FOC one period ahead and combining it with Equation (20) gives the following Euler equation:

$$
(c_t - c^*) + \rho(c_t - h_t) = \beta(1-\phi)(c_{t+1} - c^*) + \beta\rho(c_{t+1} - h_{t+1}). \qquad (22)
$$

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 ($w \in [0,1]$):

$$
c_t(h_t) = wc^* + (1-w)h_t. \qquad (23)
$$

Inserting the guess into the Euler equation yields

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

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

$$
\begin{aligned}
0 = {} & \phi\beta(1-\phi)w^2 + \phi\beta\rho w^2 + (1 + \rho + \beta\rho\phi - \beta(1-\phi) - \beta\rho - \phi\beta(1-\phi) - \phi\beta\rho)w \\
& - 1 + \beta(1-\phi) \qquad (24) \\
0 = {} & \phi\beta(1-\phi)w^2 + \phi\beta\rho w^2 + (1 + \rho + \beta\rho\phi - \beta(1-\phi) - \beta\rho - \phi\beta(1-\phi) - \phi\beta\rho)w \\
& + \rho - \beta\rho(1-\phi) + \beta(1-\phi) + \beta\rho - 1 - \rho - \beta\rho\phi, \qquad (25)
\end{aligned}
$$

which both simplify to:

$$0 = (\phi\beta(1-\phi) + \phi\beta\rho)w^2 + (1 + \rho - \beta - \beta\rho + \beta\phi^2)w - 1 + \beta(1-\phi). \tag{26}$$

Solving this equation, we find that for any calibration, there is a single root satisfying the requirement $w \in [0, 1]$:

$$w = \frac{-\phi^2\beta + (1+\rho)(\beta-1) + \sqrt{-4\phi\beta(-1+\beta-\phi\beta)(1-\phi+\rho) + (-\phi^2\beta + (1+\rho)(\beta-1))^2}}{2\phi\beta(1-\phi+\rho)}. \tag{27}$$

Under this value of w, the Euler equation and the resource constraint hold, justifying our initial guess.