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

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Abstract

This paper provides novel evidence on how dietary habits – a key health behavior – are transmitted across generations, exploiting unique grocery transaction data linked with administrative records. We document strong intergenerational persistence in dietary habits, exceeding that of income, and consider several channels that might explain this pattern. Specifically, we find that socioeconomic status and geography account for only a small share of the transmission. Combined with the absence of a dietary response following a parent's unexpected lifestyle-related death, these findings underscore the importance of early-life influences and habit formation.

Keywords: health behaviors, inequality, intergenerational mobility, diet.
JEL-codes: D12, I12, J62.

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1 Introduction

Parents shape many aspects of their children's lives, from education and career choices to broader measures of well-being. While much of the economics literature has focused on the intergenerational transmission of income and wealth, a growing body of research examines the transmission of health, recognizing its fundamental role in overall well-being (see, e.g., Mazumder, 2024). Diet is a key determinant of health, and, in light of the ongoing obesity epidemic and the rising prevalence of lifestyle-related diseases, understanding how dietary habits are passed across generations is crucial.[1]

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. Specifically, we document a strong intergenerational persistence of dietary choices that exceeds income persistence across all measures we consider, and we further investigate heterogeneities and mechanisms, showing how socioeconomic status, location, family background, and childhood habit formation shape dietary transmission. We leverage customer-linked spending by product categories from 1.7 billion shop visits between the first quarter of 2019 and the second quarter of 2021 at the largest Swiss retailer.[2,3] We enrich the consumption data with family linkages and individual socio-demographic information from the Federal Statistical Office, allowing us to observe the shopping behavior of 270,957 individuals (12% of the population of interest) and their parents. The main variable of interest and our measure of the healthiness of an individual's diet is the expenditure share of fresh fruit and vegetables relative to total food expenditures. This measure correlates strongly with recommended nutritional guidelines and key micronutrient intakes, making it a reliable criterion for healthy eating patterns.

In the first part of the paper, we document an extensive intergenerational persistence in dietary choices. We estimate a rank-rank slope of 0.250 and find that children whose parents spend one percentage point more on fruit and vegetables have, on average, a 0.247 percentage point higher spending themselves. Further, 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%). We then explore heterogeneities and show that parental influence is stronger in rural areas and among children with lower income or education levels, whereas it weakens with increasing distance between children and parents. Children from families with foreign origins also exhibit

[1] A variety of health conditions, including obesity, cardiovascular diseases, and diabetes, have been linked to inadequate diet, accounting for 18% of all North American deaths (Afshin et al., 2019).

[2] Switzerland provides an insightful case to study dietary patterns, as almost everyone has sufficient access to healthy food. It has a high density of grocery stores, the average distance to the nearest store is just 600 meters, and 80% of the population have a store within 2 kilometers (Swiss Federal Statistical Office). In comparison, the median distance to the nearest food store in the United States is 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, where, according to the World Bank, less than 0.1% do not have the financial means to follow a healthy diet. This is the case for 1.5% of households in the United States and 12% in China.

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

greater dietary mobility. Taken together, these findings highlight that higher socioeconomic status and exposure to new social or cultural environments tend to foster healthier eating and loosen intergenerational lock-in.

In the second part of the paper, we study a number of underlying mechanisms that may explain the strong intergenerational persistence of dietary choices. Such mechanisms include the transmission of socioeconomic status across generations, location and network effects, unobserved family backgrounds, such as genetic variations in taste and predispositions to diseases, and habit formation during childhood.

First, because highly educated and high-income individuals tend to eat healthier, we examine the extent to which the intergenerational transmission of these socioeconomic variables drives our results. Using a counterfactual analysis that shuts down the parent-to-child transmission of income and education, we find that the transmission of these variables explains only about 10% of the observed dietary persistence. This finding has important implications. Not only does it suggest that income redistribution may have a limited impact on nutritional inequality, but it also indicates that income and diet are transmitted through different mechanisms.

Second, we examine location preferences, recognizing that families in urban versus rural areas may share local food environments and store access, and that children often live in locations similar to those of their parents. Yet, we find that only 6% of the observed dietary persistence is due to children living in similar spatial environments as their parents.

Third, we analyze whether information about a predisposition to lifestyle-related diseases induces family members to change their diets. Along this line, Fadlon and Nielsen (2019) find significant changes in consumption of preventive care and other health-related behaviors in response to health shocks of a family member. Using death records for the years 2016-2021 together with grocery store data for the same period, we estimate the effect of an unexpected death of a parent from lifestyle-related diseases on the share of fruit and vegetable consumption using a staggered difference-in-differences design. While this shock might highlight shared health risks, we detect no significant effect on children's fruit and vegetable share over the two years following the event. However, consistent with Oster (2018), we find a small decline in convenience food purchases, which suggests that some individuals make an effort to avoid unhealthy food.

Another potential channel that we consider is the transmission of taste from parents to children. Parents can affect children's taste through genes (nature) as well as through epigenetics and fetal programming (nurture). To test whether the observed persistence is solely driven by nature, we focus on children of divorced parents, allowing us to observe each parent's diet separately. Due to social norms, most of these children grew up with their mothers. Hence, if the persistence were solely nature-driven, we would expect comparable maternal and paternal transmission. However, the stronger maternal influence that we find points to a non-negligible nurture channel.

Finally, we argue that childhood environment and habit formation are key drivers of our findings. The role of early-life environment in shaping health behaviors is well documented in the nutrition literature (see, e.g., Birch, 1999; Scaglioni et al., 2018). Similarly, in economics, Adamopoulou et al. (2024) show that early-life meat scarcity increases meat consumption later in life. More importantly, they find intergenerational spillovers, as individuals whose mothers experienced meat scarcity consume more meat themselves, providing further evidence of the long-term influence of early-life conditions on dietary habits across generations.

Our findings contribute to the literature on the intergenerational transmission of health behaviors. While economic research has traditionally focused on income (Chetty et al., 2014, Bratberg et al., 2017, Corak, 2020, Deutscher and Mazumder, 2020, Acciari et al., 2022, Asher et al., 2024), wealth (Charles and Hurst, 2003, Clark and Cummins, 2015, Adermon et al., 2018, Belloc et al., 2024), and education (Black et al., 2005) due to their straightforward measurability and data availability, health is a fundamental component of well-being and major driver of public expenditures. Accordingly, a growing body of literature studies the intergenerational transmission of health outcomes based on different measures, such as longevity (Black et al., 2024), self-reported health status (Halliday et al., 2020), quality-adjusted life years (Bencsik et al., 2023), or health care utilization (Andersen, 2021, Chang et al., 2024).

Our study also contributes to the broader literature on health behaviors. As lifestyle-related chronic diseases account for a growing share of morbidity, mortality, and healthcare spending, understanding the determinants of health behaviors has become increasingly relevant.[4] Prior research has examined various health-related behaviors, including sleep, physical activity, and alcohol consumption (Avery et al., 2025, Charness and Gneezy, 2009, Schilbach, 2019). At the same time, several studies document that dietary patterns remain stable even in the face of major life events or policy interventions, suggesting that habits could be an important source of this persistence.[5] Particularly, Oster (2018) shows that significant health shocks or informational interventions lead to only minor changes in eating habits.

Motivated by the importance of health behaviors, others explore the role of the family in shaping habits such as smoking (Darden and Gilleskie, 2016; Li and Gilleskie, 2021) and preventive care (Fadlon and Nielsen, 2019). A few studies have specifically explored the transmission of dietary habits across generations (Tosi and Rettaroli, 2022; Adamopoulou et al., 2024). However, challenges remain, including small sample sizes, measurement difficulties, and reliance on self-reported survey data.[6] We contribute to this literature by constructing an objective,

[4]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.

[5]This literature studies, for instance, migration (Bronnenberg et al., 2012, Atkin, 2013, 2016), family shocks (Hut, 2020, Hut and Oster, 2022), super market openings (Allcott et al., 2019a), as well as food subsidies (Hastings et al., 2021, Goldin et al., 2022, Bailey et al., 2024), food labels (Araya et al., 2022, Barahona et al., 2023), or sin taxes (Allcott et al., 2019b, Dubois et al., 2020, Dickson et al., 2023, Kiesel et al., 2023).

[6]Tosi and Rettaroli (2022) and Adamopoulou et al. (2024) use the Italian Multipurpose Survey on Households, which might be subject to under-reporting biases. While Tosi and Rettaroli (2022) attempt to mitigate this by trimming extreme values, this approach alters the underlying distribution of calorie intake. Similarly, their index measures adherence to WHO guidelines but does not differentiate between specific sources of macronutrients. In contrast, Adamopoulou et al. (2024) analyzes the frequency of meat consumption and constructs an indicator for unbalanced diets based on multiple categorical cutoffs. This approach inherently simplifies dietary complexity by imposing discrete thresholds that may not fully capture variation in diet quality.

tractable, and transparent measure of diet quality that overcomes many of these limitations. Using high-frequency grocery transaction data covering 12% of the relevant population, we capture expenditure shares on fresh fruit and vegetables, avoiding self-reported biases, arbitrary cutoffs, and subjective weighting schemes. Similarly, scanner data used for example in Oster (2018), although rich in granular purchase information, typically lack detailed socioeconomic information and family linkages. By combining grocery transaction records with administrative data, our study overcomes these limitations, allowing us to examine intergenerational transmission while controlling for socioeconomic background, location preferences, and other relevant factors.

The remainder of the paper is structured as follows. Section 2 introduces the data and presents summary statistics. Section 3 explains our measures of intergenerational mobility. Section 4 presents the results on the intergenerational transmission of diet and compares them to income mobility. In Section 5, we explore the potential mechanism behind these results, and Section 6 concludes.

2 Data

We analyze the intergenerational transmission of diet by combining (i) individual transaction data from the largest Swiss retailer with (ii) administrative data from the Federal Statistical Office. Throughout this paper, we refer to *children* as adult residents for whom 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.[7] Locations are coded on a grid of 350,000 100×100–meter cells with a mean population of 25 customers. 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 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.

[7]The retailer held a market share of 32.7% in 2020. The major product groups include, among others, *fruit and vegetables*, *meat and fish*, *eggs and dairy*, and *convenience*. The household types are *small households*, *young families*, *established families*, *golden agers*, and *pensioners*.

We focus on the children's share of fresh fruit and vegetables relative to total food expenditures over the sample period. This is a suitable measure for a healthy diet because (i) fruit 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 fruit 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.[8] Furthermore, this measure provides a transparent and objective approximation of dietary quality as it does not require any weighting of different nutrients or products.

Administrative Data. We enrich this unique consumption data with administrative records 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 family linkages.[9] The residence locations are coded on the same 100×100–meter grid as in the grocery transaction data. The *Old-Age and Survivors Insurance* dataset contains annual gross labor market income for every resident for the years 2016 to 2021. We average annual household income for the years 2016–2021 to reduce biases in permanent income from transitory shocks.[10] We define adjusted household income by dividing by the square root of household size (including children). Finally, the 2010–2021 *Structural Survey* gives information on the highest completed education in a household.[11]

2.2 Sample Construction

We restrict our analysis to customers whom we can uniquely match with residents using the common variables of age and location, and further refine the match with information on house-

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

[9] Family linkages, including 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.

[10] We compute the total 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. 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 the age of 25 at the time of the survey.

hold type. The detailed steps of this procedure are provided in the Online Appendix. We then assign the transaction data to all adult residents in a household. The procedure links 337,950 children to at least one parent. We restrict the sample to 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 likely 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 average value of the father and mother weighted by their respective food expenditures. This results in a final sample of 270,957 children.[13]

2.3 Summary Statistics

Table 1 displays summary statistics for the children's monthly food expenditures and the share allocated to fruit and vegetables. The average child's household spends 399 Swiss francs per month (450 USD on July 29, 2024) and allocates 15% of this money to fruit and vegetables. To put this figure in perspective, the *National Nutrition Survey* indicates that only 12% of Swiss households reach the recommended five daily portions of fruit and vegetables. In the cumulative distribution function of our variable, this point aligns with roughly 23% of grocery spending. At the other end of the distribution, about one-third consume no more than a single portion per 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.[14]

Looking at different characteristics, we find that grocery spending is highest among individuals aged 45–54, whereas the share of expenditures allocated to fruit and vegetables ranges from 15% among younger cohorts to 17% among older ones. This gives a first indication of a potential – albeit small – life cycle in diet. Food expenditures also grow with income and education: the top income quintile spends 458 Swiss francs per month compared to 269 Swiss francs for the bottom quintile. Children living in wealthier and better-educated households also consume relatively more fruit 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 areas than in suburban or rural areas. One explanation could

[12] Because we detect minor life cycles in diet, we provide all our results conditional on age groups (see Section 3, for details).

[13] As a robustness check, we increase the size of the final dataset by employing a probabilistic matching procedure based on machine learning techniques. This approach expands the sample by 32%. Using the larger dataset leaves our findings qualitatively unchanged.

[14] This survey continuously selects 3,000 households each year, and participants take notes on their expenditure for an entire month. Note that, as we do not observe beverage expenditures, our actual coverage of food products is higher.

Table 1: Summary Statistics for Children's Expenditures

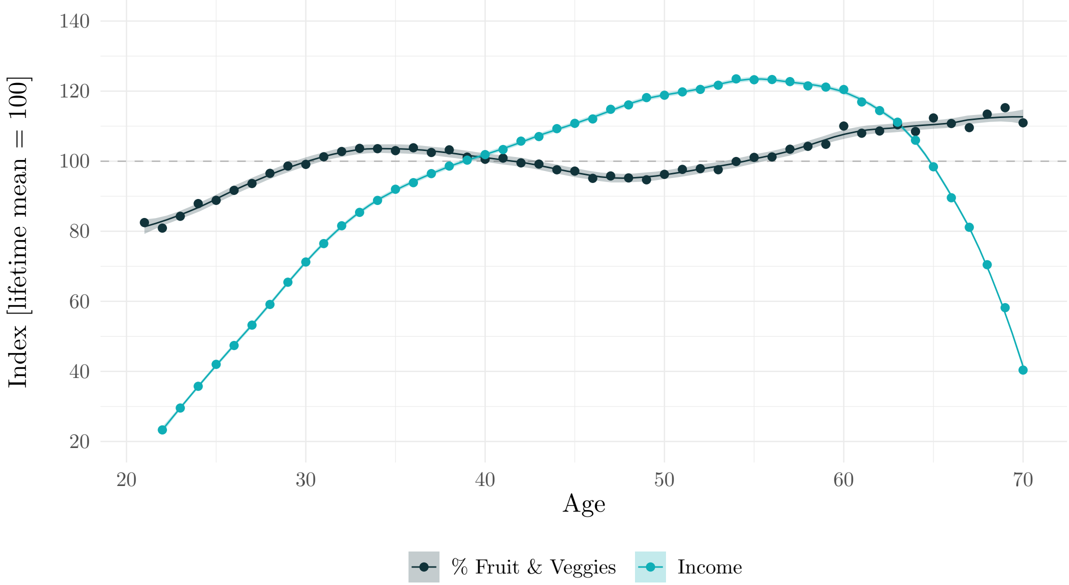
	Monthly Spending			% Fruit & Vegetable			Budget Survey	
	Mean	p50	SD	Mean	p50	SD	Spending	Share
Overall	399	323	284	0.15	0.14	0.07	616	0.65
By Age								
< 34	298	239	207	0.15	0.14	0.07	459	0.65
35–44	425	357	287	0.15	0.14	0.07	654	0.65
45–54	459	382	316	0.14	0.14	0.07	728	0.63
55–64	393	325	274	0.16	0.15	0.08	663	0.59
65+	345	286	237	0.17	0.16	0.08	616	0.56
By Household Income								
1st Quintile	269	212	191	0.14	0.13	0.08	409	0.66
2st Quintile	294	230	215	0.14	0.13	0.08	485	0.61
3st Quintile	374	305	259	0.14	0.13	0.07	604	0.62
4st Quintile	422	354	283	0.15	0.14	0.06	713	0.59
5st Quintile	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: The table presents summary statistics for the transaction records of food expenditures in our final dataset (N = 270,957). In the columns titled *Budget Survey*, we compare these figures with the average monthly grocery expenditures for food and beverages reported in the administrative Household Budget Surveys for the years 2015 to 2017 (N = 9,955). The last column shows the average monthly expenditures in our data relative to the survey. Quintiles of *Household Income* are computed using a household's average gross labor market income for the period 2016-2020. The budget survey provides summary statistics for each income quintile. All other variables reflect their values for the year 2020. *Highest Education* represents the highest level of education completed by any household member, and *Pop. Density* refers to the population density of the municipality where the individual resides.

be that households in sparsely populated areas are more likely to obtain fresh products from a farmer or own a garden. Yet, children in rural areas spend 386 Swiss francs, which is only marginally less than children in urban areas (389 Swiss francs), so we do not expect this to affect our results.

To assess the representativeness of our data, Table A1 in the Appendix presents summary statistics for the 270,957 matched children and compares them to the 2.3 million children in the population who meet the same selection criteria. The average *child* in the final dataset is 43.7 years old with a total household income of 142,370 Swiss francs. 54% of them are female and 62% are married. Further, 53% hold a tertiary degree, and 90% live in multi-person households. Regarding geographical characteristics, 77% of the children in our sample live in the German-speaking part of Switzerland, 19% in the French-speaking, and 4% in the Italian-speaking region. Comparing these figures with the population reveals larger discrepancies in household size, population density, income, and marital status. This is expected, as it is easier

Figure 1: Life Cycle in Income and Diet



Notes: The figure shows the average of two variables for each age group between 21 and 70: (i) the annual household income in the target population adjusted by the square root of household members (3.1 million observations) and (ii) the expenditure share on fruit and vegetables in the sample (270,957 observations). All values are normalized to 100 based on the lifetime average of each variable. The conditional expectation functions, together with uniform 95% confidence bands, are estimated using a local regression, with weights proportional to the size of the age groups.

to uniquely match multi-person households and individuals in less densely populated areas. Since household size is positively associated with income, and married individuals are more likely to live in multi-person households, these factors explain the observed differences in income and marital status. As shown in the table, we can correct for these discrepancies by reweighting our sample to match the population distribution of household size and population density, thereby correcting for the mechanical overrepresentation of certain household types.[15]

3 Measuring Mobility

In this paper, we rely on four standard measures of mobility that we introduce below (see Deutscher and Mazumder (2023) for an extensive discussion on these measures). We need to consider that the focus is on diet, not income, and the two outcomes potentially exhibit important differences. While at first glance, it might not be clear that higher consumption of fruit and vegetables above a certain threshold yields additional benefits (as it is for income), recall that 88% of the population falls short of the recommended intake, implying that the vast majority remains below this threshold.

In addition to these considerations, both diet and income exhibit systematic fluctuations over

[15]Reweighting the sample does not meaningfully change the intergenerational transmission results.

the life cycle, which need to be taken into account when studying intergenerational mobility. Figure 1 illustrates life-cycle patterns in diet and income by plotting average income and the share of fruit and vegetable consumption as functions of age. To ensure comparability, both variables are normalized to their respective lifetime means. While both series fluctuate over the life cycle, the variation in diet is much smaller than in income. Income more than doubles between ages 21 and 60 before declining again toward retirement. By contrast, diet follows an s-shaped pattern: young individuals tend to consume relatively few fruits and vegetables, but intake improves by about 30 percent by age 35. It then declines by roughly 10 percent until age 50, after which it increases again.[16]

Given the visible, albeit small, life cycle in diet, and since we observe children and parents at the same point in time, we estimate percentile ranks conditional on age as in Chetty et al. (2014) for the positional measures, and we control for age if the measure directly depends on the share of fruit and vegetables. Unless otherwise indicated, we compare a child's diet to the weighted average of their parents' diet, where the weights are proportional to the expenditure.

Rank-Rank Slope. Our first measure of intergenerational mobility is the rank-rank slope (RRS). Let r_{ci} denote child i's percentile rank (from 1 to 100) and let r_{pi} be the corresponding parent's variable. The percentile ranks are computed within each age category. We fit a rank-rank regression by regressing the children's percentile rank on the parents' percentile 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. 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. For instance, if each child were in the same percentile as their parents, the slope would be one.

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. Instead of taking logarithms, we use a quadratic specification, which better fits the data, as shown in the following regression model:

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

where s_{ci} and s_{pi} are, respectively, the child's and parents' fruit and vegetable share, and x_i contains the child's and parents' ages, along with their squared terms. Since we fit a polynomial

[16]For both variables, the graph shows the values of the variable at a point in time. Thus, both age and cohort effects could drive these differences. The increase later in life could also partly reflect higher survival rates among individuals with healthier diets.

regression, the slope changes over s_{pi}. We therefore report the average marginal effects (AME), which we refer to as the *intergenerational elasticity* (IGE), with a slight abuse of terminology.

Conditional Expected Rank. The conditional expected rank (CER) is the expected percentile rank of children having parents at percentile p:

$$CER(p) = \mathbb{E}[r_{ci}|r_{pi} = p]. \tag{3}$$

We focus on the CER at the 25th and 75th percentiles, denoted CER25 and CER75. The CER can be estimated parametrically (from a rank-rank regression) and nonparametrically. We opt for a middle ground and use a nonparametric local linear regression evaluated at percentile p.

Transition Matrix. Transition matrices break down the children's and parents' distribution into groups of equal size. We group children and parents conditional on age into quintiles and compute the conditional probability that a child is in bin p_j given their parents are in bin p_k:

$$TP_{j,k} = Pr(s_{ci} \in p_j|s_{pi} \in p_k). \tag{4}$$

4 Intergenerational Persistence Results

This section presents results on the persistence of dietary habits across generations. Table 2 reports coefficients and standard errors computed 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. Panel (a) of Table 2 shows an estimated rank-rank slope of 0.250, indicating that a 10-percentile increase in the parental dietary rank is associated with a 2.5-percentile increase in the child's rank. To put this into perspective, it would take approximately 3.16 generations to close the gap between two families at the 10th and 90th percentiles.[17]

To show that conditioning the percentile ranks on age deals with the life-cycle fluctuations, we compare the results using conditional and unconditional percentile ranks, allowing the intercept and the slope to change over the life cycle by saturating the model in children's age. While Figure 2a shows that the rank-rank slope is almost identical across both specifications, Figure 2b reveals that the intercept largely depends on the specification of the percentile ranks, and when using unconditional percentile ranks, the intercept captures the life cycle observed in Figure 1.

[17] 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 $N = \frac{log(1/\Delta_{10,90})}{log(\beta)}$.

Table 2: Main Mobility Measures

	(a) Rank-Rank Reg.		(b) IGE	(c) CER		(d) Transition Prob.		
	Intercept	Slope	AME	25	75	Q1Q1	Q1Q5	Q5Q5
Diet	37.75	0.250	0.247	44.97	56.07	31.26	11.47	31.89
	(0.09)	(0.002)	(0.002)	(0.68)	(0.66)	(0.17)	(0.13)	(0.17)
Income	43.17	0.145	0.113	47.48	53.98	26.43	14.14	28.60
	(0.13)	(0.003)	(0.002)	(0.78)	(0.83)	(0.22)	(0.19)	(0.21)

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 for diet gives the average marginal effect for a quadratic specification and the IGE for income 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.

This observation suggests that conditional percentile 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 remarkably sizable well into later life.[18]

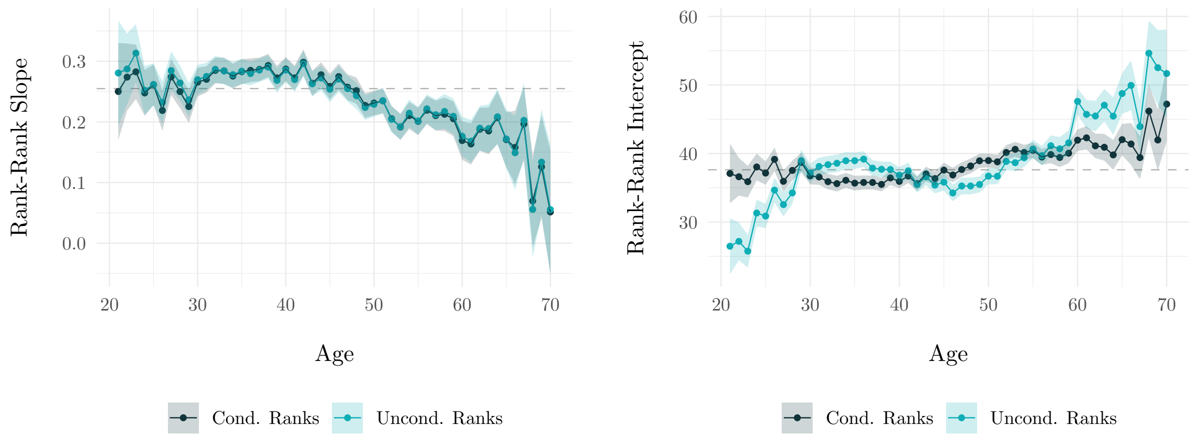
Intergenerational Elasticity. Panel (b) of Table 2 reports the estimated average marginal effect. A one percentage point increase in parents' fruit and vegetable consumption is, on average, associated with a 0.247 percentage point increase in their children's consumption. Although not shown in the table, the slope declines at higher levels of parental consumption, indicating diminishing returns. This pattern suggests that targeted policy interventions aimed at families with particularly poor diets may yield greater improvements in children's nutritional behavior.

Conditional Expected Ranks. Panel (c) in Table 2 presents the estimated conditional expected rank. Children whose parents are at the 25th percentile of fruit and vegetable consumption reach, on average, the 45th percentile in their own generation. In contrast, those with parents at the 75th percentile are expected to reach the 56th percentile. These results point to substantial intergenerational persistence in diet, yet also reveal meaningful reversion to the mean.

Transition Matrix. Figure 3 shows the estimated transition matrix with the corresponding confidence intervals. We include selected key results of the transition matrix in Table 2 panel d). Without intergenerational persistence of diet across generations, we would observe 20% of children in each cell. The estimated transition probabilities reveal a strong persistence in diet

[18] Estimates for older age groups are noisier due to smaller sample sizes. Note that, as before, both age and cohort effects could explain these differences.

Figure 2: Rank-Rank Slope: Life Cycle



(a) Rank-Rank Slope

(b) Rank-Rank Intercept

Notes: Figure 2a shows the rank-rank slope by age group. The grey line is estimated using percentile 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 is estimated using unconditional percentile ranks. Figure 2b shows the intercepts from the respective regressions. The dashed lines show the average rank-rank slope and intercept reported in Table 2. 95% confidence intervals are computed using bootstrapped standard errors (1,000 replications).

between generations, as children are most likely to be in the same quintile as their parents. Focusing on the tails of the parents' distribution, we find that 31.3% of children whose parents purchase the fewest fruit and vegetables also fall at the bottom of the distribution (corresponding to a Q1Q1 transition), while only 11.5% move up to the top (Q1Q5). If, on the other hand, an individual's parents are in the top 20% fruit 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.

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 deal with life-cycle variation in income, we follow 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). We generate a new data set for children between 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. Further, we average income over the years 2016-2021 to smooth out transitory fluctuations. We estimate the same measures for intergenerational income mobility that we use for diet, again conditioning on age, and present the results in Table 2. We estimate a rank-rank slope of 0.145 and an intergenerational elasticity

Figure 3: Transition Matrix

Child's Produce Consumption Quintile \ Parents' Produce Consumption Quintile	1	2	3	4	5
5	11.5 % [11.2, 11.7]	15.0 % [14.7, 15.3]	18.4 % [18.1, 18.7]	23.2 % [22.9, 23.5]	31.9 % [31.6, 32.2]
4	15.0 % [14.7, 15.3]	18.3 % [18.0, 18.6]	20.6 % [20.3, 20.9]	22.4 % [22.1, 22.7]	23.8 % [23.5, 24.1]
3	18.8 % [18.5, 19.1]	20.5 % [20.2, 20.8]	21.4 % [21.1, 21.8]	20.8 % [20.5, 21.1]	18.4 % [18.1, 18.7]
2	23.5 % [23.1, 23.8]	22.9 % [22.6, 23.2]	20.7 % [20.4, 21.0]	18.4 % [18.1, 18.7]	14.5 % [14.3, 14.8]
1	31.3 % [30.9, 31.6]	23.3 % [23.0, 23.6]	19.0 % [18.6, 19.3]	15.2 % [14.9, 15.5]	11.4 % [11.1, 11.6]

Notes: The figure shows the transition probabilities for children's diet conditional on their parents' diet (Equation 4). We analyze transitions between quintiles of the distribution and calculate the quintiles on age groups within the respective subsample of children and parents. 95% confidence intervals in parentheses are estimated using 1,000 bootstrap replications.

of 0.113.[19] The conditional expected ranks at the 25th and 75th percentile are 47.48 and 53.98. 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.[20] Comparing our estimated mobility measures between diet and income in Table 2, we find that intergenerational transmission is consistently stronger for dietary behavior across all metrics. Figure 4 underscores this difference graphically: the slope of the rank-rank regression for diet (darker line) is substantially steeper than for income (lighter line), with the dots representing the average child percentile rank at each parental percentile rank.

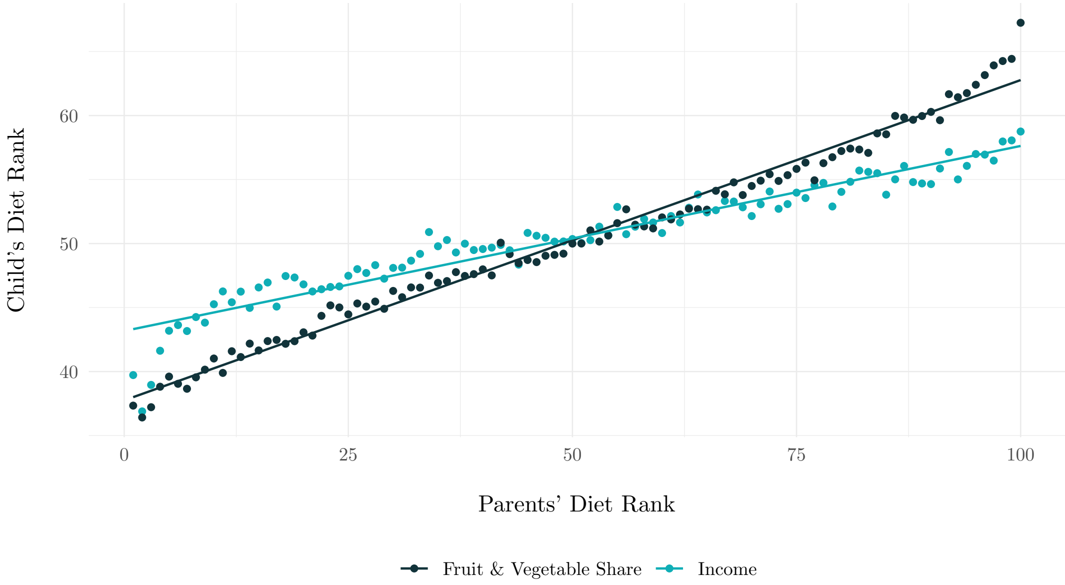
Such pronounced persistence in dietary choices – an important health behavior – may help explain broader intergenerational persistence in health status. At the same time, this strong relationship suggests that the development of dietary habits during childhood could be a persistent channel through which parents influence their children, potentially to a greater extent than their influence on economic outcomes. It is worth noting that income is particularly mobile in Switzerland, so the persistence of diet relative to income may differ in other countries.[21]

[19] We estimate the intergenerational elasticity using a classical log-log specification, however, including also a quadratic term.

[20] Different sample selection procedures and income definitions lead to comparable findings. 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.

[21] Previous studies report rank-rank income slopes of 0.34 for the U.S. (Chetty et al., 2014), 0.24 for Canada (Corak, 2020), 0.22 for Sweden and Norway (Bratberg et al., 2017), 0.25 for Italy (Acciari et al., 2022), and 0.21 for Australia (Deutscher and Mazumder, 2020).

Figure 4: RRS of Diet and Income



Notes: The figure shows the estimation results for the rank-rank regression in Equation (1) for diet and income. The dots represent estimates of the conditional expectation of children's ranks at each parental percentile.

4.3 Other Dietary Measures

To complement our main analysis based on fruit and vegetable consumption, we extend our investigation to additional dietary dimensions. These include expenditure shares on meat and fish, eggs and dairy, and convenience food (i.e., ready-made or processed items requiring minimal preparation) as well as binary indicators for being vegetarian, a heavy meat consumer, or a high user of convenience food. While these categories are less directly interpretable in terms of healthfulness, given their broader nutritional profiles, they offer a richer view of intergenerational dietary transmission. The results, reported in the Online Appendix, reveal substantial persistence across all categories. Although the strength of transmission for these additional measures is somewhat lower than for fruit and vegetables, it still exceeds that of income, underscoring the deep-rooted nature of dietary behaviors across generations. We focus on fruit and vegetable consumption in the main analysis because it reflects a homogeneous and widely endorsed component of a healthy diet, in contrast to the more heterogeneous nature of other food categories.

4.4 Heterogeneities

Heterogeneities in the persistence of dietary choices across socioeconomic dimensions may allow some individuals to adopt healthier diets while leaving others more constrained. This section explores differences by income, education, urbanization, distance to parents, and national origin, and sets the stage for the analysis of potential mechanisms, which we examine in detail in the following section. 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 observations within each group so that the parents' distribution mirrors that of the full sample.[22]

Table 3 shows the results for the different subgroups. The second column contains the P-value of the Wald test testing for equality of the rank-rank slope across all the subgroups. 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 parental transmission of diet is unaffected by children's educational attainment. Instead, the intercept increases with education, indicating that more highly educated children consume more fruit 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, highly educated individuals may have a more profound nutritional knowledge, a better assimilation of dietary information, or higher patience.

Second, Panel (b) digs into differences between income groups.[23] As shown, the rank-rank slope and intergenerational elasticity monotonically decrease as children's income increases. For the poorest children, we find a rank–rank slope of 0.279 compared to 0.208 for the richest individuals. These differences are also statistically significant, suggesting that percentile ranks are more persistent over generations among low-income children. Figure 5 shows the rank-rank regression lines 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 only 2.5 percentage points more likely to find himself at the bottom of the distribution than at the top. For children living in suburban (rural) areas, this difference is over 20 (27) percentage points.

Panel (d) analyzes the role of the distance between children and parents. 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. This result is not surprising, as living away from one's family is often associated with moving away from one's

[22]For instance, the reweighting procedure gives equal weights to all percentiles in the rank-rank regression and the conditional expected rank. For an extensive discussion of weighting approaches in these settings, see Deutscher and Mazumder (2023).

[23]To account for the life cycle in income, we condition income quartiles on age and focus on working-age children (25-64). The results are unaffected if we use all observations.

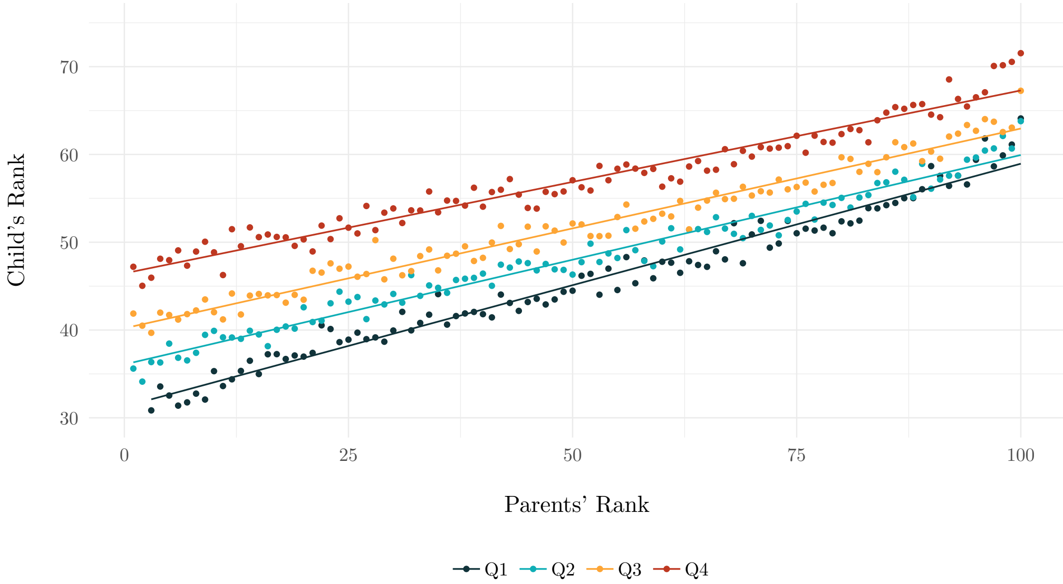
Table 3: Heterogeneities

	Rank-Rank		IGE	CER		Transition Prob.			
	RRS	P-value	AME	25	75	Q1Q5	Q1Q1	Q5Q5	N
(a) Child's Education									
Primary	0.242	0.446	0.247	39.044	49.192	7.66	43.78	24.16	7,272
	(0.012)		(0.014)	(3.745)	(4.364)	(0.68)	(1.22)	(1.18)	
Secondary	0.234		0.222	40.347	50.766	8.18	37.68	24.61	82,763
	(0.003)		(0.004)	(1.118)	(1.329)	(0.21)	(0.34)	(0.34)	
Tertiary	0.229		0.223	49.002	60.652	15.46	23.43	36.66	103,676
	(0.003)		(0.003)	(1.089)	(1.005)	(0.27)	(0.30)	(0.29)	
(b) Child's Income									
1th Quartile	0.279	0.000	0.268	39.874	51.591	8.00	40.98	28.46	64,881
	(0.004)		(0.004)	(1.271)	(1.462)	(0.22)	(0.40)	(0.40)	
2nd Quartile	0.239		0.226	42.772	52.301	9.22	32.83	27.07	64,873
	(0.004)		(0.004)	(1.279)	(1.423)	(0.26)	(0.40)	(0.39)	
3rd Quartile	0.228		0.220	46.784	55.771	12.04	27.91	31.40	64,863
	(0.004)		(0.004)	(1.362)	(1.318)	(0.28)	(0.40)	(0.41)	
4th Quartile	0.208		0.214	51.812	61.904	18.18	20.86	38.73	64,852
	(0.004)		(0.005)	(1.495)	(1.203)	(0.37)	(0.41)	(0.38)	
(c) Child's place of residence									
Rural	0.236	0.009	0.228	42.015	51.837	8.02	35.43	24.67	58,732
	(0.004)		(0.004)	(1.367)	(1.456)	(0.24)	(0.39)	(0.44)	
Suburban	0.235		0.230	43.952	55.093	10.98	31.57	29.34	157,660
	(0.002)		(0.003)	(0.870)	(0.870)	(0.17)	(0.24)	(0.24)	
Urban	0.221		0.224	53.833	62.738	20.28	22.80	41.82	54,319
	(0.004)		(0.006)	(1.581)	(1.358)	(0.46)	(0.50)	(0.40)	
(d) Distance to Parents									
1th Quartile	0.281	0.000	0.273	41.547	55.697	8.57	34.77	30.60	63,842
	(0.004)		(0.004)	(1.294)	(1.455)	(0.25)	(0.40)	(0.41)	
2nd Quartile	0.252		0.244	44.069	54.820	10.44	31.43	30.71	63,841
	(0.004)		(0.004)	(1.375)	(1.311)	(0.27)	(0.40)	(0.42)	
3rd Quartile	0.225		0.222	43.804	53.989	12.88	29.90	30.77	63,841
	(0.004)		(0.004)	(1.356)	(1.341)	(0.29)	(0.40)	(0.41)	
4th Quartile	0.202		0.204	49.483	57.584	15.34	26.68	33.52	63,841
	(0.004)		(0.005)	(1.444)	(1.309)	(0.33)	(0.39)	(0.37)	
(e) Nationality									
Swiss	0.251	0.052	0.248	45.141	56.124	11.46	31.31	31.89	267,421
	(0.002)		(0.002)	(0.709)	(0.674)	(0.13)	(0.18)	(0.17)	
Foreign	0.217		0.209	39.556	59.714	10.84	29.45	29.55	3,536
	(0.017)		(0.023)	(6.171)	(5.160)	(1.39)	(2.08)	(1.41)	

Notes: The table shows the results for different subsamples defined by education, income, residence, distance to their parents, and national origin. 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.

childhood environment. However, it is striking that children 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 habits and is consistent

Figure 5: RRS by Income Quartiles



Notes: The figure shows estimation results for the rank–rank regression in Equation (1) for the four income quartiles. The dots represent estimates of the conditional expectation of children's ranks at each parental percentile.

with previous findings on diminishing social interactions and responses to family-related shocks with increasing distance (see, e.g., Fadlon and Nielsen, 2019 and Büchel et al., 2020).

An additional analysis indicates that while shared store preferences, shopping frequency, and the degree of urbanization influence the intergenerational persistence of dietary habits, they have limited explanatory power for the distance-based heterogeneity. Dropping children who shop at the same store decreases the distance gradient only slightly. Similarly, the distance gradient remains substantial across rural, suburban, and urban subsamples – despite differences in store density. Further, we find that shopping frequency has a negligible effect on dietary composition. These findings suggest that shared grocery habits and store preferences do not fully explain the observed heterogeneity, pointing instead toward deeper behavioral mechanisms and network effects.

Finally, in Panel (e), we examine heterogeneity by nationality, using parental nationality to distinguish between children of Swiss and foreign origin. We find meaningful differences: dietary habits are more strongly transmitted in Swiss households, while those of foreign origin exhibit greater dietary mobility. This result is not surprising, as individuals with foreign origins are more likely to be exposed to peers whose backgrounds differ from those of their own families, leading to more diversified social networks. This aligns with the idea that migrants may be more likely to adapt their eating habits to new environments, leading to weaker intergenerational persistence (see Atkin, 2013, 2016).

5 Mechanisms

In the previous subsection, we documented a strong intergenerational persistence in dietary habits. At the same time, we observe substantial heterogeneity in this persistence, raising important questions about the underlying mechanisms. We now consider a number of potential channels, including the transmission of socioeconomic status across generations, location and network effects, unobserved family background (such as genetic variations in taste and predispositions to diseases), and habit formation during childhood.

5.1 Socioeconomic Status

We have shown that mobility is significantly higher among better-earning and higher-educated children, who also tend to follow healthier diets. Given the well-documented intergenerational persistence of income, a natural question arises: To what extent does the transmission of socioeconomic status drive dietary persistence? This subsection isolates and quantifies the component of intergenerational transmission in diet that cannot be attributed to the transmission of income and education. To isolate this channel, we compute counterfactual distributions in the spirit of Chernozhukov et al. (2013). More precisely, we are interested in estimating 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.[24] This counterfactual distribution is identified by combining the cumulative distribution function (cdf) with an alternative covariate distribution. Then, from this counterfactual distribution, we can easily compute a counterfactual transition matrix.

More formally, let $F_{s_c|s_p}$ 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. All the distributions outlined in the section are conditional on the age variables; however, we omit the dependency for notational ease unless needed for clarity. 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 $F_{x_c|s_p,x_p}(x_c|s_p, x_p)$ to a different distribution $F_{x'_c|s_p,x_p}(x_c|s_p, x_p)$. We denote this counterfactual distribution $F_{s_c|s_p}\langle x_c|x'_c\rangle\ (s_c|s_p)$. Starting from the cdf of the children's diet conditional on (s_p, x_p, x_c), we can attain $F_{s_c|s_p,x_p}\langle x_c|x'_c\rangle(s_c|s_p, x_p)$ by integrating the conditional cdf over the

[24] A least squares regression of children's diet on parents' 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 Table 3, 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 interpret. Instead, by estimating counterfactuals, results remain straightforward to interpret.

alternative covariate distribution:

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

where $\mathcal{X}_j$ denotes the support of the covariates x_j for $j = \{c,p\}$ conditional on the other variables. Then, integrating Equation (5) over the distribution of the parents' covariates yields the desired result:

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

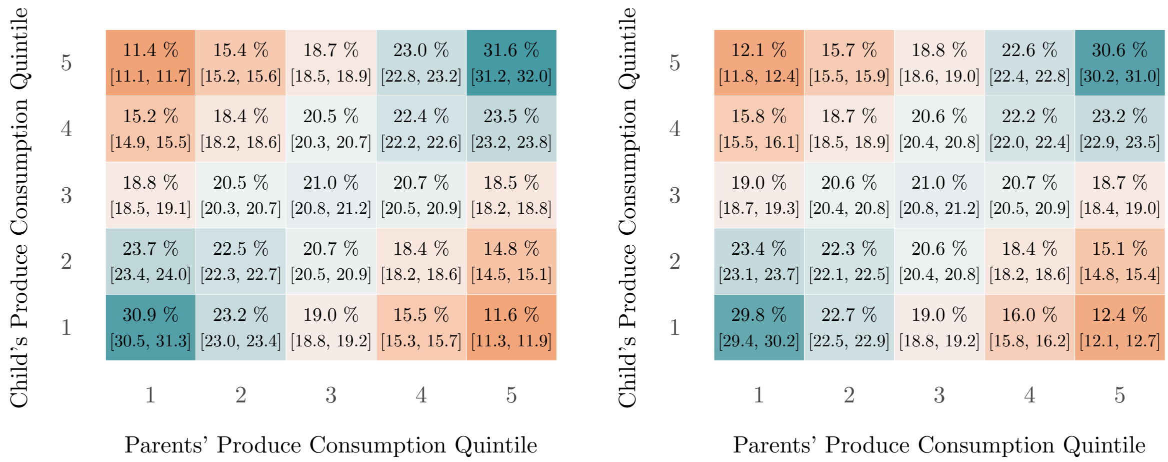
In the counterfactual scenario we consider, we close the pathway from parents' diet to children's diet that operates through the intergenerational transmission of education and income. Consequently, the counterfactual distribution of children's income and education should be independent of parental socioeconomic variables. We further assume that parents' age and diet do not affect children's characteristics. Thus, the counterfactual covariate distribution is the conditional distribution of x_c given a_c, where children's age in the conditioning set captures life-cycle changes in income as well as differences in the distribution of education across cohorts.

The estimation follows the plug-in approach. We obtain an estimate of the conditional cdf $F_{s_c|s_p,x_c,x_p}$ by inverting the estimated conditional quantile function. We estimate the conditional quantile function by fitting a flexible quantile regression model for the set of quantiles $\{0.005, 0.015, \ldots, 0.995\}$. 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 life cycle, which is discontinuous after reaching retirement age. All variables are interacted with a second-order polynomial of the parents' diet. We estimate $F_{x_c|a_c}$ using the empirical distribution function.

For this analysis, we restrict the sample to the 135,213 children for whom we observe their and their parents' education. The validity of this approach 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 6 shows the estimated transition probabilities with the corresponding bootstrap 95% confidence intervals. 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 nonparametric results for the entire sample in Figure 3. Panel (b) shows the counterfactual transition probabilities. While the transition matrix resembles that in Panel (a), mobility is statistically significantly higher, particularly at the extremes of the distribution. 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 (= 31.6 − 20.0) percentage points more likely to be in the fifth quintile than if there was no intergenerational transmission of diet. We refer to this as an excess

Figure 6: Transition Matrices: the Role of Income and Education



(a) Transition Matrix

(b) Counterfactual Transition Matrix

Notes: Figure 6a shows the transition matrix and Figure 6b shows the counterfactual transition matrix. In the counterfactual scenario, children's income and education are assigned independently from their parents' values. The results are estimated using the sample of 135,213 children for whom we observe their as well as their parents' education. 95% confidence intervals in parentheses are estimated using 1,000 bootstrap replications.

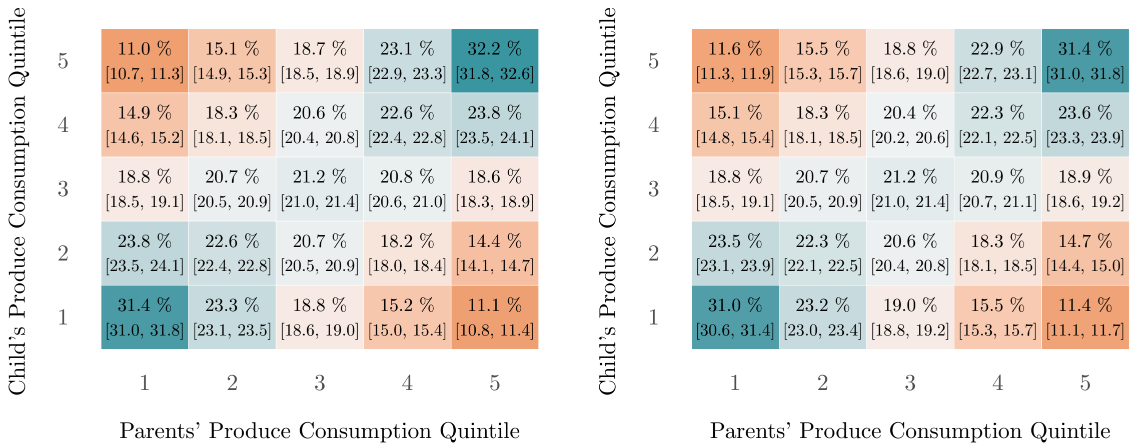
probability. In the counterfactual scenario where we close the channel going through income and education, this number declines to 10.6 ($= 30.6 - 20.0$) percentage points. This change suggests that the transmission of income and education over generations explains less than 9% of this excess probability. 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.

To summarize these transition matrices with a single number, we compute the normalized anti-diagonal trace, following Jäntti and Jenkins (2015). The normalization 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 transmission drive only 8.8% of the results.[25]

These results suggest that only a small share of the intergenerational persistence in diet can be explained by the transmission of income and education. This finding is surprising and carries important implications. Even if income and education were fully mobile across generations, strong dietary persistence would remain, implying that policies focused solely on income redistribution or financial assistance may have a limited impact on reducing nutritional inequality. This conclusion aligns with evidence showing that monetary incentives have had only modest success in promoting healthier food choices among SNAP recipients (see, for example, Verghese et al. (2019) and references therein). More broadly, the findings point to the existence of distinct

[25] Starting from the counterfactual distribution, we can compute all mobility measures, and we find that the results are consistent across the different metrics. Further, the results are robust if we drop children and parents who either have zero income or are retired.

Figure 7: Transition Matrices: the Role of Location



(a) Transition Matrix (b) Counterfactual Transition Matrix

Notes: Figure 7a shows the transition matrix and Figure 7b shows the counterfactual transition matrix. In the counterfactual scenario, children's locations are assigned independently of their parents' values. The results are estimated using the sample of 120,424 children for whom we observe both their and their parents' residence location and education. 95% confidence intervals in parentheses are estimated using 1,000 bootstrap replications.

transmission channels for diet and income. Since well-being spans multiple dimensions that are inherited through different mechanisms, focusing exclusively on income mobility provides an incomplete picture. A deeper understanding of these separate pathways is therefore essential for designing more effective policies to address disparities in overall well-being.

5.2 Current Location

Besides socioeconomic characteristics, the transmission of location preferences might partly explain our results. Yet, these variables are more difficult to measure than income or education, and more importantly, it is unclear which characteristics of a location are meaningful in determining diet. In this analysis, we use population density as a broad measure of location characteristics, which tends to persist across generations.[26] Because individuals in urban areas tend to follow healthier diets, the intergenerational transmission of location may partially contribute to the persistence of dietary habits.

To assess the contribution of location to dietary persistence, we repeat the exercise used for income and education, but now remove the intergenerational link in location, measured by degree of urbanization. Specifically, we construct a counterfactual in which an individual's probability of living in an urban, suburban, or rural area is independent of their parents' location.

We again fit a flexible quantile regression model where we interact parents' diet with dummies

[26] Children who grew up in rural (urban) areas are more likely to live in rural (urban) areas later in life. For instance, 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 whose parents live in urban areas also live in an urban area, while only 12% of them reside in a rural area.

for the degree of urbanization. Figure 7 displays the original and the counterfactual transition matrices.[27] 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.

This analysis suggests that, although location is an important determinant of diet, the intergenerational transmission of urbanization contributes little to dietary persistence. These results align with previous papers discovering limited adaptations in diets in response to changes in spatial environments (see, for example, Atkin, 2013, 2016, or Allcott et al., 2019a).

5.3 Dietary Response to Health Information Shocks

Diet is a key health behavior and may also be shaped by health-related goals. For instance, a revealed predisposition for a lifestyle-related disease could motivate family members to consciously adjust their eating behaviors. To assess the relevance of this channel, we examine how the death of a parent from a lifestyle-related disease affects their children's diet. Such events may serve as informative health shocks, especially given that individuals with a high genetic risk for heart disease nearly double their risk of stroke or heart attack, while a healthy lifestyle can cut this risk by half (Khera et al., 2016).

For this analysis, we combine grocery store data and administrative vital statistics covering the years 2016 to 2021. The vital statistics include information on all deaths, including underlying conditions. 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 that of children who face the same shock in later years. To capture an unexpected shock, we focus on deaths without preexisting conditions. We apply the estimator proposed by Callaway and Sant'Anna (2021) and present the results in an event-study plot. Figure 8 shows no change in fruit and vegetable intake for up to two years after the shock. The coefficients are small and not statistically significant, suggesting that individuals might not perceive this shock as informative about their own risk for lifestyle diseases or simply do not respond to this information.[28]

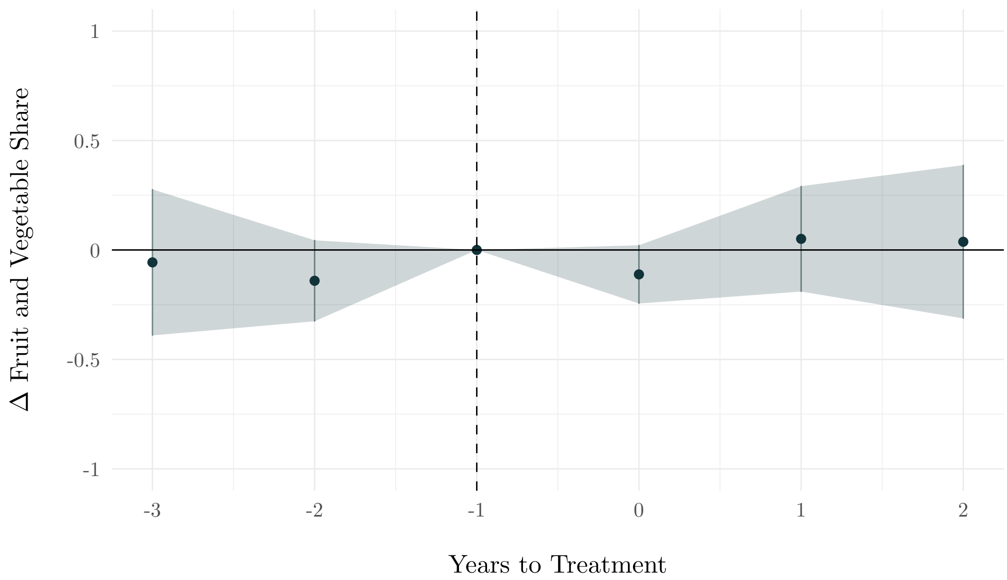
We complement this analysis by examining the impact of the shock on expenditure shares of meat and fish, convenience food, and eggs and dairy. As shown in Table 4, the estimated effects are generally close to zero. The only statistically significant effect is a small reduction in spending on convenience food: following the death of a parent, individuals reduce their expenditure share on convenience food by 0.285 percentage points (2.3%), on average.

These findings are consistent with Oster (2018) and Hut and Oster (2022), who find only minimal dietary improvements following a diabetes diagnosis, but contrast with Fadlon and Nielsen (2019), who document sizable behavioral responses to health shocks within families. In their

[27] As before, we recompute the original matrix using the same flexible model. The marginal differences in the results compared to Figure 6a are due to the slightly different samples.

[28] Although not reported in the paper, we find no meaningful heterogeneity in the effect when examining differences by the gender of the child or deceased, age at death, or children's socioeconomic characteristics.

Figure 8: Effect of the Lifestyle-Related Death of a Parent



Notes: The figure shows 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 35,073 observations, coefficients are normalized to the year before the treatment, and standard errors are clustered at the individual level.

Table 4: ATT of Lifestyle-Related Death of a Parent on Dietary Behavior

	Fruit & Veggies	Meat & Fish	Convenience	Eggs & Dairy
Avg. treatment effect	-0.008	0.177	-0.285	0.161
	(0.111)	(0.148)	(0.106)	(0.110)
Pre-treatment mean	15.8	23.5	12.4	18.1

Notes: The table shows difference-in-differences estimates of the lifestyle-related death of a parent's effect on their children's annual expenditure on different product categories using the estimator suggested by Callaway and Sant'Anna (2021). We use the *not-yet-treated* units as the comparison group, and standard errors are clustered at the individual level.

setting, two mechanisms help explain why individuals change health behaviors: such shocks provide new information about personal risk and make these risks more salient. Our null results suggest that these mechanisms may be less effective in the case of diet. One reason could be that diet – unlike actions such as taking preventive medication or undergoing screenings – involves higher daily effort, sustained self-control, and delayed rewards. That is, even when individuals receive salient signals about their health risks, adjusting dietary choices may be too costly to act upon. Still, the modest effect on convenience food may reflect some limited effort to avoid unhealthy options, as observed in Oster (2018).

One limitation of our analysis is that we consider only information shocks, and other events, such as diagnoses, 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, Hut and Oster (2022) find only minimal and non-lasting effects of such diagnoses.

5.4 Taste

It is well understood that our taste influences dietary choices. Our families affect our taste both genetically (nature) and through environmentally mediated biological processes such as epigenetics and fetal programming (nurture). These two channels provide explanations of how persistence in taste might drive our results.

A child's genotype, determined at conception and fixed throughout life, influences how sensory signals, such as those from taste receptors, are perceived and processed. Variations in taste and olfactory receptor genes shape individual sensitivities and preferences for certain flavors and foods shaping dietary preferences and intake.[29] At the same time, genes do not act in isolation; they interact with environmental factors. For example, a child's genetically influenced taste preferences may be reinforced by parental dietary choices. Fetal programming suggests that maternal diet during pregnancy can have lasting effects on a child's metabolic health and dietary preferences. For instance, suboptimal maternal nutrition can lead to physiological adaptations in the fetus, potentially increasing the risk of specific eating behaviors or metabolic disorders later in life (see, e.g., Barker, 1990; Almond and Currie, 2011). Similarly, epigenetic mechanisms (i.e., environmentally induced changes in gene expression) are not only a key biological pathway through which fetal programming can occur, but may also provide an additional biological channel for dietary persistence across generations. These modifications can influence taste sensitivity, metabolic efficiency, or predispositions toward specific foods.

Evidence supports the relevance of these pathways, showing that food intake, even during pregnancy and breastfeeding, can influence a child's taste preferences. For example, reducing sodium and sugar consumption sharpens the perception of saltiness and sweetness (Wise et al., 2016). Similarly, infants show greater initial acceptance of fruit and vegetables when their mothers consume them regularly during pregnancy (Mennella et al., 2001; Forestell, 2024) and breastfeeding (Forestell and Mennella, 2007).

To assess the importance of genetic variations in taste, we analyze matrilineal and patrilineal 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.[30] Hence, if the dietary transmission were only due to the genotype-driven difference in tastes (nature), we should see no difference in the transmission of diet between their mother and their father. In contrast, a stronger link to the mother's diet

[29] Evidence is particularly rich for genetic influences on the perception of bitter (Mennella et al., 2005, Gervis et al., 2023), sweet (Mennella et al., 2005, Mennella et al., 2016, Søberg et al., 2017), and alcohol (Allen et al., 2014), as well as for associations with the consumption of specific foods such as fruit, cheese, fish, and tea (Cole et al., 2020).

[30] We focus on divorced parents who did not remarry to avoid possible contamination due to a new partner. According to the *Federal Statistical Office*, around 80% of children under 14 with separated parents lived with their mother in the year 2000. Although this share has evolved over time, more recent data from the *Federal Department of Home Affairs* (2022) confirm that children continue to spend the majority of nights with their mother far more often than with their father.

Table 5: Average Marginal Effect 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)
Fruit & Vegetable Share Mother	0.220	0.255	0.229			
	(0.018)	(0.014)	(0.014)			
Fruit & Vegetable Share Father				0.159	0.138	0.154
				(0.024)	(0.025)	(0.025)
Observations	3,149	5,203	4,913	1,273	1,254	1,523

Notes: The table shows the average marginal effect of mothers' and fathers' diets separately for the subsample of children with divorced parents who never remarried. We estimate separate regressions of the child's fruit and vegetable share on each parent's share and its square. Further, we control for the parents' and child's age as well as their squares. Standard errors are computed using 1,000 bootstrap replications.

indicates that the nurture channel is non-negligible.[31] The results in Table 5 show that the intergenerational link between children and their mothers is substantially stronger than with their fathers. This relationship changes only slightly with the child's age at the time of divorce.

Taken together, the findings from the literature and our empirical results suggest that parents influence children's dietary preferences not only through genetic transmission but also through a range of environmental and behavioral channels.

5.5 Habits

In the previous subsections, we showed that socioeconomic variables have only limited explanatory power for the intergenerational transmission of diet, indicating that the mechanisms by which diet and socioeconomic status are passed across generations may differ fundamentally. At the same time, Figure 2 shows substantial dietary persistence later in life, and we observe minimal (if any) changes in diet following a news shock about disease predisposition. Taken together, with the much stronger matrilineal resemblance among children of divorcees, these findings point to habits as a central driver. This would imply that diet, like other health-related behaviors such as smoking, exercise, and sleep, is shaped by habits that may take root early in childhood and are influenced by parents.

These habits likely reflect a wide range of *nurture-based* components, including environmentally mediated biological processes (see Section 5.4), diet-related knowledge, and skills that parents pass on to their children. This is consistent with longstanding evidence from the psychology and nutrition literature showing that the family plays a central role in shaping children's food preferences (e.g., Birch, 1999; Scaglioni et al., 2018). Building on these results, Atkin (2013)

[31] There is no inherent genetic reason for dietary transmission to be stronger from mothers than fathers, given that taste receptor genes are not located on the X or Y chromosomes (Bachmanov and Beauchamp, 2007).

provides a habit formation model to explain how local food cultures emerge and persist over time. Similarly, Fadlon and Nielsen (2019) highlight the importance of the family in shaping health behaviors. Recent evidence by Adamopoulou et al. (2024) further supports the behavioral channel, showing that parents' eating patterns significantly shape their children's dietary choices. These findings resonate with our own and underscore the importance of viewing diet as a learned behavior shaped by early and repeated exposure.

While parental diet is likely a major determinant of a child's *habit stock*, many other factors, including childhood networks and location, may also play a role (see, for example, Story et al. (2008) for an overview). Understanding the determinants of this habit stock and distinguishing them from genetic influences is crucial for informing effective policy. If habits are formed early and remain stable over time, interventions targeting children and their environments may yield larger effects than those aimed solely at adults.

Unfortunately, we do not observe habits directly. Instead, we observe realized food purchases, which we interpret as the outcome of an underlying and unobserved habit stock. In the Online Appendix, we introduce a simple framework on habit formation (see, for example, Campbell and Cochrane (1999), Fuhrer (2000), and Carroll et al. (2000) for some early work on habit formation models). We model the persistence of diet between generations as the result of a habit stock built during childhood and adjusting over a lifetime. The results of the model point to the slow alteration of habits as an important driver of our results.

6 Conclusion

While most research on intergenerational mobility has focused on outcomes such as income and education, this paper turns to an important but often overlooked health behavior: diet. As a key determinant of health, it may serve as a crucial channel through which health and well-being are transmitted across generations. At the same time, the detrimental consequences of poor diets impose a significant social and economic burden. This paper sheds light on the intergenerational transmission of dietary habits by combining unique supermarket transaction data with administrative records that include family linkages. We provide novel evidence that family background is a strong predictor of long-run eating patterns, suggesting that the diet consumed at one's parents' dinner table plays a lasting role in shaping nutritional preferences throughout our lives.

Our results show that the intergenerational transmission of diet varies across observable covariates. Higher-educated and better-earning children generally eat better, independent of their parents. While the transmission mechanism (in terms of the rank-rank slope) does not vary by 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 distancing oneself from the childhood environment may help break unhealthy patterns.

We explore potential drivers of dietary persistence, including the intergenerational transmission of income and education, as well as family background. 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 of diet. A similar exercise for location preferences reveals that they explain around 6% of the persistence. Further, we find that the unexpected death of a parent due to a lifestyle-related disease does not affect diet, suggesting that changing their diet may be too costly for individuals, even when faced with information about health risks. 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 factors likely influence eating habits, our results point to a substantial direct effect of childhood diet and suggest that habit formation is a key mechanism – implying not only that the apple does 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 policy. Recognizing the strong influence of family on dietary choices can help guide more targeted interventions aimed at fostering healthier eating habits. By identifying the origins of unhealthy eating patterns and understanding how they are transmitted across generations, policymakers and healthcare professionals can design strategies to address the growing burden of diet-related diseases more effectively. Our results suggest that lump-sum transfers or SNAP benefits are unlikely to shift entrenched dietary behaviors. Instead, interventions that directly target children's diets, while habits are still forming, may prove more effective and cost-efficient. Examples include healthy school lunch programs, nutritional education, and informational campaigns in schools and medical settings. Future work should focus on assessing the effectiveness of such interventions.

Finally, this paper shows that even in a high-income country with relatively uniform access to healthy food and a dense grocery-retail network, diet is highly persistent across generations. Building on this baseline, researchers should test how variation in economic disparities and access to healthy food shape the intergenerational transmission of diet.

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A Data: Additional Summary Statistics

Table A1: Summary Statistics for Children

	Final Sample (N = 270,957)			Population (N = 2,276,806)	
Panel a)	Mean	Wt. Mean	SD	Mean	SD
Age	43.72	43.85	10.69	43.70	11.70
Age Father	71.87	71.79	9.66	71.05	10.35
Age Mother	71.03	71.21	10.35	70.85	11.36
HH Income	142.37	131.53	137.04	129.68	109.09
HH Income Adjusted	83.25	83.01	87.01	81.60	64.88
Panel b)	Share	Wt. Share	N	Share	N
Gender			270,957		2,276,806
Female	0.539	0.545	146,148	0.508	1,155,646
Male	0.461	0.455	124,809	0.492	1,121,160
Marriage			270,957		2,276,806
Married	0.623	0.517	168,776	0.503	1,145,736
Not Married	0.377	0.483	102,181	0.497	1,131,070
Highest Education			193,711		1,554,739
Tertiary	0.535	0.502	103,676	0.500	777,901
Secondary	0.427	0.451	82,763	0.446	694,110
Primary	0.038	0.048	7,272	0.053	82,728
Language Region			270,711		2,274,341
German	0.769	0.806	208,283	0.723	1,644,202
French	0.191	0.170	51,643	0.220	500,133
Italian	0.040	0.025	10,785	0.057	130,006
Pop. Density			270,711		2,274,341
Rural	0.217	0.216	58,732	0.216	490,681
Suburban	0.582	0.522	157,660	0.522	1,186,301
Urban	0.201	0.263	54,319	0.263	597,359
Household Size			270,957		2,276,806
1	0.102	0.210	27,715	0.210	478,435
2	0.269	0.332	72,900	0.332	754,928
3-4	0.511	0.372	138,377	0.372	846,201
5+	0.118	0.087	31,965	0.087	197,242

Notes: This table presents summary statistics for the children in the final dataset alongside summary statistics for the relevant population. Columns 1 and 3 report the mean and standard deviation (SD) for the final sample, while Columns 4 and 5 present the corresponding values for the population. Column 2 shows the results after reweighting the sample to match the population distribution of household size and population density. *HH Income Total* represents a household's average annual gross labor market income for the period 2016–2020, measured in 1,000 CHF. *HH Income Adjusted* is income adjusted by the square root of household size. All other variables reflect their values for the year 2020. *Highest Education* indicates the highest level of education completed by any household member, and *Pop. Density* refers to the municipality's population density.

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

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1 Additional Results – Other Dietary Measures

In this section, we examine the intergenerational transmission of different components of the grocery basket, alongside three indicators of dietary preferences. Specifically, we focus on the shares of meat and fish, eggs and dairy, and reliance on convenience foods. In addition, we investigate the persistence of certain dietary types: being a vegetarian, a meat lover, or a convenience-oriented shopper. We define the latter two categories as belonging to the top quartile of consumption within their respective groups.

Table 1 presents the intergenerational transmission results for these outcome variables. Panel (a) reveals strong intergenerational persistence across all dietary measures, though the magnitudes are somewhat smaller than those observed for fruits and vegetables. Nonetheless, all effects exceed those found for income. In particular, meat consumption shows a rank-rank slope of 0.192, indicating a substantial parental influence on their children's meat-purchasing behavior. Convenience food purchases exhibit slightly lower persistence, with a rank-rank slope of 0.179.

Transition probabilities provide additional support for these patterns. Children from low-meat-consuming households (Q1) have a 29.8% probability of remaining in the lowest meat consumption quartile, while those from high-meat-consuming households (Q5) have a 28.5% probability of staying at the top, underscoring the persistence of dietary habits. Convenience food follows a similar pattern.

For the binary outcomes in Panel (b), we only estimate average marginal effects using logistic regressions. Across all outcomes, the effects are close to 0.10. For instance, if a parent is vegetarian, the probability that their child is also vegetarian increases by approximately 10

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Table 1: Main Mobility Measures: Other Dietary Dimensions

	(a) Rank-Rank Reg.		(b) IGE	(c) CER		(d) Transition Prob.		
	Intercept	Slope	AME	25	75	Q1Q1	Q1Q5	Q5Q5
Panel a)								
Share Meat & Fish	40.671	0.192	0.195	46.534	54.937	29.808	13.645	28.461
	(0.097)	(0.002)	(0.002)	(0.688)	(0.652)	(0.168)	(0.136)	(0.171)
Share Convenience	41.330	0.179	0.177	46.621	53.862	28.824	14.019	27.738
	(0.093)	(0.002)	(0.002)	(0.699)	(0.678)	(0.165)	(0.140)	(0.169)
Share Dairy & Eggs	42.540	0.155	0.139	47.701	54.064	26.640	14.661	27.166
	(0.096)	(0.002)	(0.002)	(0.664)	(0.616)	(0.165)	(0.139)	(0.166)
Panel b)								
Vegetarian			0.105					
			(0.006)					
Meat Lovers			0.105					
			(0.002)					
Lazy			0.101					
			(0.002)					

Notes: The results are estimated using 270,957 observations. The IGE gives the average marginal effect for a quadratic specification. Standard errors are computed using 1,000 bootstrap replications.

percentage points.

It is important to highlight the key differences between these additional measures and the ones considered in the paper. First, fruit and vegetables form a homogeneous category in terms of health benefits: they are unprocessed, widely acknowledged as a cornerstone of a healthy diet, and increased consumption is generally beneficial for almost everyone.

By contrast, categories such as meat and fish encompass a wide range of products, from highly processed and red meats to fresh fish and chicken—items that fall under different classifications in dietary guidelines. As a result, these categories provide a noisier measure that does not capture a specific component of dietary choices, making interpretation involved.

2 Data – Matching Procedure

This section describes how we match the *customers* in the grocery transaction data with the *residents* in the administrative data. We begin by selecting 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*.[1] We take some additional steps to isolate the unique matches between *residents* and *customers*, proceeding as follows:

1. First, we exclude pairs where the customer's shopping behavior does not fit the resident's locations of residence, since these residents are unlikely to be the actual holders of the

[1]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).

linked loyalty card. To this end, 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.

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 before they moved out.[2]

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

[2] Excluding them entirely leaves our estimates unchanged.

3 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 addiction (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:

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

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

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

where c^* denotes the optimal (healthy) intake of fruit 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:

$$\frac{\partial g(c_t - c^\star)}{\partial c} = \begin{cases} > 0, & if\ c_t < c^* \\ = 0, & if\ c_t = c^* \\ < 0, & if\ c_t > c^*, \end{cases} \tag{3}$$

and

$$\frac{\partial h(c_t - h_t)}{\partial c} = \begin{cases} > 0, & if\ c_t < h_t \\ = 0, & if\ c_t = h_t \\ < 0, & if\ c_t > h_t. \end{cases} \tag{4}$$

The two terms in Equation (2) 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:

$$u(c_t, h_t) = -(c_t - c^*)^2 - \rho(c_t - h_t)^2, \tag{5}$$

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:

$$c_t(h_t) = wc^* + (1 - w)h_t, \tag{6}$$

where the weight w is a function of the parameters (ϕ, β, ρ). Section 3.2 provides a detailed derivation of the solution 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.

3.1 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 $c^* = 0.23$. We set the latter equal to the 88th percentile of the distribution of c_t, as the national nutrition survey indicates that only 12% of households meet the recommended intake of fruits and vegetables. If we knew initial habits h_1, we could directly estimate $(1-w)$ in Equation (6). Since we do not directly observe habits, we proxy them with parents' diet denoted $\tilde{h}_1$, introducing a measurement error, and 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 (1) and the policy function for consumption in Equation (6):

$$h_t = h_1 \left(1 - w\phi\right)^{t-1} + c^* w\phi \sum_{j=0}^{t-2} \left(1 - w\phi\right)^j \tag{7}$$

$$c_t = h_1(1-w)\left(1 - w\phi\right)^{t-1} + c^* \left[(1-w)w\phi \sum_{j=0}^{t-2} \left(1 - w\phi\right)^j + w \right]. \tag{8}$$

A regression of c_t on $\tilde{h}_1$ interacted with age dummies identifies $\xi \cdot (1-w)\left(1-w\phi\right)^{t-1}$ for all 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 $\xi \cdot (1-w)\left(1-w\phi\right)^{t-1}$ on the coefficients by fitting a linear model in t on the logarithm of the first step slope coefficients.[3] The resulting point estimate is

$$(1 - \hat{w}\hat{\phi}) = 0.988. \tag{10}$$

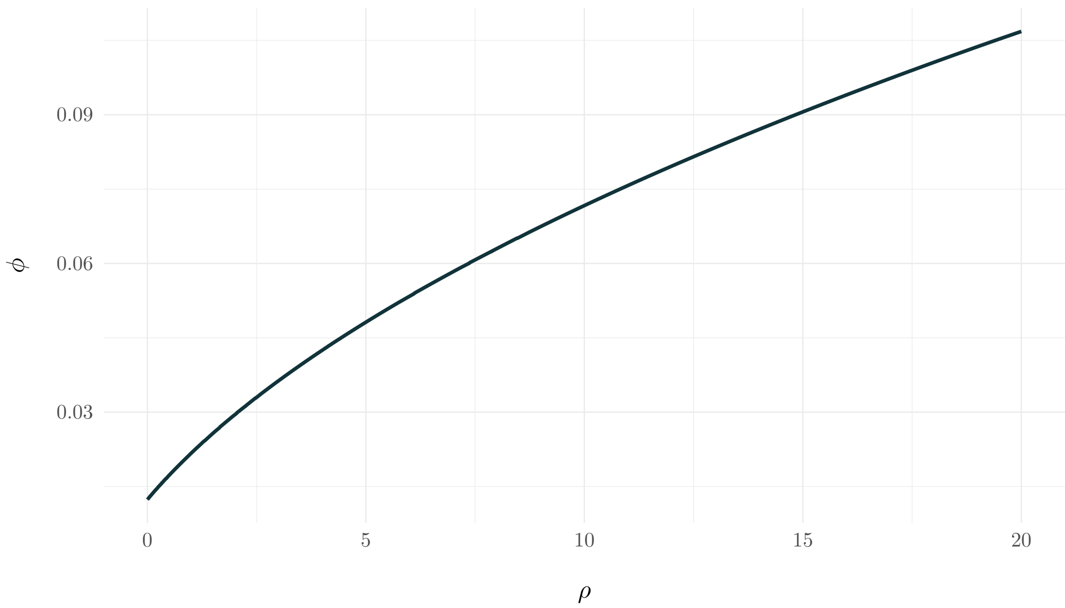
This expression does not separately identify ϕ and ρ because different values of the parameters are consistent with these results. As an example, consider an individual with $\rho = 1$ and $\phi = 0.021$, satisfying Equation (10). This individual gives a weight of $w = 0.57$ to healthy eating. Yet, the values $\rho = 2$ and $\phi = 0.028$ also satisfy Equation (10) and are, thus, observationally equivalent. This second individual values following a healthy diet less, and she assigns a lower weight to healthy eating ($w = 0.42$). However, she alters her habits faster. Hence, both of these individuals face the identical habit stock in the following periods, as the smaller deviation in

[3]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:

$$\frac{Cov(c_{t+1}, \tilde{h}_1)}{Cov(c_t, \tilde{h}_1)} = (1 - w\phi), \ \forall t > 2, \tag{9}$$

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.

Figure 1: 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 (10).

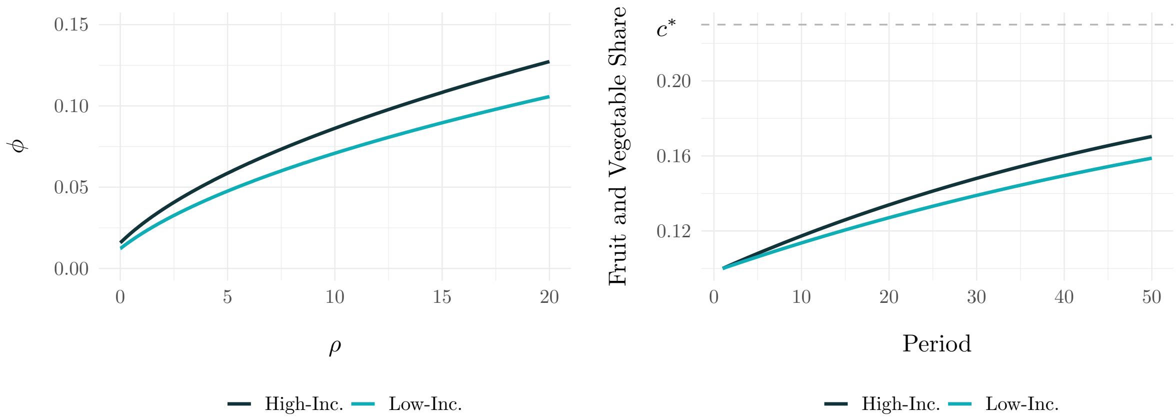
consumption is coupled with more flexible habits such that Equation (10) holds.

Figure 1 pictures the continuum of compatible values for ϕ and ρ that satisfy Equation (10). 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 have to be more amenable (higher ϕ). However, what is striking is that even for extremely high values of ρ, our model still implies sticky habits (for example, even a value of $\rho = 20$, implies $\phi = 0.105$). Hence, this provides evidence for the important role of habit formation and gives an explanation as to why most individuals do not meet the dietary recommendations.[4]

Reconciling the model with the empirical heterogeneities we estimate in the paper, we estimate our model for rich and poor individuals 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 2a 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 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

[4]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 2: Income Heterogeneities in the Model



(a) Habit Persistence Parameters

(b) Evolution of the Habit Stocks

Notes: Figure 2a 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 2b 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^*.

habit trajectories. To give an illustration, Figure 2b 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 fruit 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.

3.2 Derivations

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

$$\begin{aligned} V_t(h_t) &= \max_{c_t} -(c_t - c^*)^2 - \rho\,(c_t - h_t)^2 + \beta V_{t+1}(h_{t+1}) \qquad \text{s.t. } h_{t+1} = h_t + \phi(c_t - h_t) \\ &= \max_{c_t} -\left(\frac{h_{t+1}}{\phi} - \frac{h_t}{\phi} + h_t - c^*\right)^2 - \rho\left(\frac{h_{t+1}}{\phi} - \frac{h_t}{\phi} + h_t - h_t\right)^2 + \beta V_{t+1}(h_{t+1}) \end{aligned} \tag{11}$$

with the resulting optimality conditions:

$$0 = -\frac{2}{\phi}(c_t - c^*) - \frac{2\rho}{\phi}(c_t - h_t) + \beta V'_{t+1}(h_{t+1}), \tag{12}$$

$$V'_t(h_t) = -\frac{2(\phi - 1)}{\phi}(c_t - c^*) - \frac{-2\rho}{\phi}(c_t - h_t). \tag{13}$$

Shifting the second FOC one period ahead and combining it with Equation (12) gives the following Euler equation:

$$(c_t - c^*) + \rho(c_t - h_t) = \beta(1 - \phi)(c_{t+1} - c^*) + \beta\rho(c_{t+1} - h_{t+1}). \tag{14}$$

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

$$c_t(h_t) = wc^* + (1-w)h_t. \tag{15}$$

Inserting the guess into the Euler equation yields

$$[wc^* + (1-w)h_t](1+\rho+\beta\rho\phi) =$$
$$c^*[1-\beta(1-\phi)] + h_t\,[\rho - \beta\rho(1-\phi)] + [c^*(w+\phi w - \phi w^2) + h_t(1-w-\phi w+\phi w^2)](\beta(1-\phi)+\beta\rho).$$

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

$$\begin{aligned}
0 = {} & \phi\beta(1-\phi)w^2 + \phi\beta\rho w^2 + (1+\rho+\beta\rho\phi-\beta(1-\phi)-\beta\rho-\phi\beta(1-\phi)-\phi\beta\rho)w \\
& -1+\beta(1-\phi) \qquad (16)\\
0 = {} & \phi\beta(1-\phi)w^2 + \phi\beta\rho w^2 + (1+\rho+\beta\rho\phi-\beta(1-\phi)-\beta\rho-\phi\beta(1-\phi)-\phi\beta\rho)w \\
& +\rho-\beta\rho(1-\phi)+\beta(1-\phi)+\beta\rho-1-\rho-\beta\rho\phi, \qquad (17)
\end{aligned}$$

which both simplify to:

$$0 = (\phi\beta(1-\phi)+\phi\beta\rho)w^2 + (1+\rho-\beta-\beta\rho+\beta\phi^2)w - 1 + \beta(1-\phi). \tag{18}$$

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

$$w = \frac{-\phi^2\beta + (1+\rho)(\beta-1) + \sqrt{-4\phi\beta(-1+\beta-\phi\beta)(1-\phi+\rho) + (-\phi^2\beta+(1+\rho)(\beta-1))^2}}{2\phi\beta(1-\phi+\rho)}. \tag{19}$$

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

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