Income Shocks and Demand for Sustainable Products

Abstract

As investor and consumer demand for sustainability grows, firms are increasingly incorporating sustainable products into their portfolios. We examine whether firms with a larger share of sustainable products are more exposed to household income shocks. Using scanner data on food purchases from 2004 to 2019, we find that reductions in household income significantly decrease spending on organic food, especially among high-income households. The effect is driven by high-income consumers' lower price sensitivity and stronger preference for organic products, regardless of price. Our findings suggest that firms offering sustainable products may be more susceptible to income shocks, highlighting potential trade-offs in pursuing sustainable strategies.

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1. Introduction

There is an ongoing debate about the role of corporations in adopting Environmental, Social, and Governance (ESG) policies (Hart and Zingales, 2017; Edmans, 2023). A widely held view is that firms can "do well by doing good," meaning that corporate investments in ESG activities can enhance profitability and maximize shareholder value. Despite a growing body of research on this topic, the mechanisms by which ESG activities influence corporate performance and value creation remain insufficiently understood.[1]

As demand for sustainability intensifies from key corporate stakeholders—including governments, investors, employees, and consumers—firms are increasingly reevaluating their strategic options. These strategies often involve aligning ESG objectives with business performance and consumer preferences, emphasizing long-term value creation while responding to regulatory pressures and market dynamics. Approaches include adopting green technologies, implementing sustainable sourcing practices, and differentiating products through sustainability certifications (e.g., organic or fair-trade). As more firms adopt sustainable strategies, it is crucial to rigorously evaluate the trade-offs and complexities involved in these strategic decisions.

One prominent response has been the expansion of firm portfolios to include sustainable or ESG products. Sustainable products are designed and produced with the goal of minimizing environmental harm, enhancing societal well-being, and adopting ethical and transparent business practices. Examples of such products include "organic," "cage-free," "plant-based," "eco-friendly," "plastic-free," and "fair trade" items. These products are often priced at a premium due to their perceived higher value and alignment with consumer values on sustainability (e.g., De Pelsmacker, Driesen, and Rayp, 2005; Lin, Smith, and Huang, 2008; Hainmueller, Hiscox, and Sequeira, 2015). This paper examines whether adopting ESG products could potentially increase a firm's exposure to macroeconomic risk. Specifically, we explore the possibility that, in response

[1] See Gillan, Koch, and Starks (2021) for a literature review and Starks's (2023) Presidential Address to the American Finance Association.

to a negative income shock, consumers may reduce their expenditures on ESG products to a greater extent than on non-ESG alternatives, thereby amplifying the firm's vulnerability to such shocks.

To address this research question, we use the comprehensive NielsenIQ scanner data, which covers the period from 2004 to 2019 and provides detailed information on grocery purchases made by a panel of U.S. consumers. The primary focus of our analysis is on purchases of "organic" products, as this ESG label is the most prevalent within our data. According to the Organic Trade Association (2024), the environmental impact of the food industry is an important factor motivating consumers to choose organic products.[2] We start by documenting a rise in the consumption of organic products among households in the United States. The share of organic products in total food product purchases increased from 0.7% in 2004 to more than 4% in 2019.

A key advantage of our data is the availability of yearly income observations for each household. This feature is critical for identifying the causal impact of demand shocks on ESG purchases, as it enables us to control for unobserved consumer characteristics that remain constant over time. A purely cross-sectional approach to estimating income elasticities could introduce significant bias into our results (Dubé, Hitsch, and Rossi, 2018). Although the income data in the NielsenIQ panel is self-reported, existing literature suggests that it is unbiased and yields results comparable to those obtained using administrative income data (Brancatelli et al., 2022).

Next, we compare the income elasticity of demand between organic goods and conventional products using a panel dataset of households from 2004 to 2019. Our findings indicate that household income is positively associated with organic food expenditure in cross-sectional analysis when controlling for year-fixed effects. Additionally, when we focus solely on within-household variation by incorporating both year and household fixed effects, we observe that household income continues to have a positive and statistically significant impact on organic food spending. These results underscore the robustness of the relationship between income and organic

[2] The report indicates that consumers associate organic products with health (32%), the absence of harmful substances (31%), and sustainability (27%), setting them apart from less beneficial labels. These perceptions significantly distinguish organic products from other labels that are not viewed as similarly beneficial. The report is available at: https://ota.com/market-analysis/consumer-perception-usda-organic-and-competing-label-claims-report

food expenditure across both cross-sectional and longitudinal analyses.

The effects are economically significant. Analyzing within-household variation, we estimate that a 25% reduction in household income results in a 1.6% decline in spending on organic products, nearly double the corresponding 0.9% decline observed for conventional products. In line with this result, we also find a 1% decrease from its mean in the organic share of total purchases following a 25% decline in household income. While small in magnitude, this effect is precisely estimated. Consistent with these shifts in purchasing behavior, we find that negative income shocks reduce the growth rate of organic expenditures by twice as much as they do for non-organic products. These results are consistent with the hypothesis that firms with more ESG products in their portfolio are more exposed to macroeconomic risks.

The share of organic foods has increased across all household income groups, with the most substantial growth observed among higher-income households. More importantly, our average effects mask heterogeneous effects: the sensitivity to income shocks is more pronounced among higher-income consumers. Specifically, our findings indicate that an income shock shifting a household from the high-income tertile to the low-income tertile leads to a 9.6% reduction in spending on organic products, compared to a smaller 4.2% reduction in conventional products. Additionally, the organic product share declines by 8% when a household transitions from the high to the low-income tertile. These findings imply that firms offering ESG products are particularly susceptible to macroeconomic shocks disproportionately impacting higher-income households, such as those witnessed during the dot-com bubble.

The effect of household income on the consumption of organic goods operates at both intensive and extensive margins. Our findings show that an increase in household income leads to higher spending on organic food among households that already purchase these products and a rise in the proportion of households that consume organic food. In addition, we find that the effect of household income on organic food spending is pervasive across different types of food categories, including dry grocery, fresh produce, dairy, frozen foods, deli, packaged meat, and alcoholic beverages.

We also present results using alternative ESG labels beyond organic to assess whether our findings can be generalized across various ESG categories. The decision to purchase organic food is often motivated by environmental concerns, such as reduced energy use in organic farming and minimized exposure to harmful synthetic pesticides and fertilizers for farm workers, consumers, and the broader environment. However, it is also linked to consumers' pursuit of healthier dietary habits. This raises a potential alternative interpretation of our results, as consumers may opt for organic products more due to health concerns rather than ESG or sustainability motivations. To address this, we use alternative specifications of the dependent variable for two product categories: Fresh Eggs and Dairy Milk Refrigerated. For Fresh Eggs, we account for animal welfare claims, identifying products labeled with keywords like "Cage-free," "Free roam," "Free range," and "Pasture-raised." For Dairy Milk, we focus on sustainable packaging, defining it as products packaged in carton containers instead of plastic or glass. We find that the effect of household income remains positive and significant when we focus on sustainability dimensions such as animal welfare claims and sustainable packaging, which are less likely to be driven by health-related concerns.

In summary, the results indicate that both organic and conventional food spending are influenced by changes in household income, with the demand for organic food being particularly sensitive to income fluctuations, especially among higher-income households. Furthermore, the findings suggest that our baseline results capture consumers' preference for products marketed as environmentally and socially responsible. Specifically, the preference for sustainable products grows as household income increases.

One important concern with our estimates is the potential endogeneity of household income. In our regressions, we control for several household characteristics and year and household fixed effects. Thus, unobserved household time-invariant characteristics cannot explain our within-household estimates. However, there may be unobserved time-varying factors that are correlated with both income and organic spending. For example, an individual may change jobs, resulting in both an income increase and a shift in food habits due to supply-side factors, such as greater access to organic stores or lower organic prices, or due to peer effects in the new workplace. Additionally, there could be a reverse causality concern, as higher consumption of organic goods, which are associated with well-being, may lead to increased income through improved health or productivity.

To further mitigate concerns regarding the endogeneity of income, we employ two additional empirical strategies. First, we exploit changes in employment and marital status (e.g., divorce, widowhood, and singlehood), which are strongly correlated with household income levels. The key identifying assumption in this approach is that changes in employment or marital status occur independently of the timing of purchase decisions. This strategy focuses exclusively on within-household variation to estimate the impact of household income on organic food expenditure. Our findings indicate that the allocation of household income toward organic food decreases in response to unemployment, divorce, widowhood, and single-marital status.

As a second identification strategy, we leverage the Economic Stimulus Act of 2008, enacted by the U.S. government in response to the recession that began in December 2007. A central component of this Act was a $100 billion Economic Stimulus Payment (ESP) program to boost consumer demand. We exploit the exogenous change in household spending triggered by the receipt of these payments, utilizing the natural experiment provided by the structure of the tax cut (Parker et al., 2013; Broda and Parker, 2014). The ESPs varied across households regarding amount, disbursement method, and timing. Crucially, within each disbursement method, the timing of payment receipt was determined by the last two digits of the recipient's Social Security number (SSN), which are effectively randomly assigned. We exploit this random variation in the timing of receipt to estimate the causal effect of these payments on household organic food expenditure. Specifically, we compare the spending patterns of households that received the payments during a given period to those of households that received the payments in other periods. Our analysis indicates that households significantly increased the share of their expenditure on organic products during the three-month period following the receipt of the payments.

Finally, we investigate the mechanisms through which household income influences the likelihood of purchasing organic products. Specifically, we aim to determine whether higher-income individuals allocate a larger share of their spending to organic products compared to lower-income individuals, either due to their lower price elasticity—given the generally higher cost of organic products—or as a result of non-price preferences. We construct a structural demand model to disentangle the impact of product attributes (such as prices) from other preferences similar to Dubois, Griffith, and Nevo (2014) and Allcott et al. (2019). The decomposition of our preference estimates builds on work measuring the determinants of health behaviors (Furnée, Groot, and van den Brink, 2008; Cutler and Lleras-Muney, 2010; Andretti et al., 2024). To address this question, we combine our household panel data with store-level data, which provides weekly prices for each available product, and estimate a demand model. The model is estimated separately for six product categories (Eggs, Milk, Salad, Soup, Tea, and Tortilla Chips), selected based on their importance in the average consumer basket and the availability of organic options.

In all categories, we find that higher-income consumers exhibit lower price sensitivity than lower-income consumers. However, this difference in price sensitivity does not fully account for the variation in organic purchases. Even after controlling for prices, higher-income individuals display a stronger preference for organic products. Using model simulations, we estimate how high-income individuals would behave if they had the same price sensitivity as low-income individuals. The price channel explains between 9% and 48% of the gap in organic purchases between high- and low-income households, depending on the product category. Thus, non-price preferences account for more than half of the difference in organic product purchases between these two groups. One possible explanation for the importance of non-price preferences is that organic products behave more like luxury goods compared to conventional products, as reflected in their higher income demand elasticity. Alternatively, consumers may disproportionately reduce their organic purchases in response to income shocks due to a perception that organic products are more expensive than they actually are (Haws, Reczek, and Sample, 2017).

Our paper contributes to several strands of the literature. First, we provide new insights into household consumption behavior in response to changes in income. Mian and Sufi (2011, 2014) and Mian, Rao, and Sufi (2013) show that local house price movements significantly impact consumption, while Stroebel and Vavra (2019) establish a causal link between local retail prices and house prices. Aguiar, Hurst, and Karabarbounis (2013) show that shopping time increases during recessions, while Krueger and Mueller (2010) and Nevo and Wong (2019) document rising shopping intensity during the Great Recession. Dubé, Hitsch, and Rossi (2018) observe declines in spending on generic goods during economic downturns. Based on scanner data, Brancatelli et al. (2022) show rising demand for cheaper private-label goods with falling income.

Second, our paper contributes to the literature on why the wealthy and poor eat differently in the U.S. We build on studies of the impact of proximity to supercenters (Courtemanche and Carden, 2011; Courtemanche et al., 2019) and fast-food outlets (Anderson and Matsa, 2011; Currie et al., 2010), as well as case studies on grocery store entry (Wrigley, Warm, and Margetts, 2003; Weatherspoon et al., 2012). Allcott et al. (2019) add a nutritional aspect to migration studies that explore brand preferences (Bronnenberg, Dubé, and Gentzkow, 2012), caloric costs of culture (Atkin, 2016), urban sprawl's impact on obesity (Eid et al., 2008), and geographic variations in health (Finkelstein, Gentzkow, and Williams, 2016, 2021; Molitor, 2018). Allcott et al. (2019) show that nutritional inequality across income levels is driven by demand, not availability or price, and our results suggest that preferences similarly explain differences in demand for sustainable products, rather than price or supply factors.

Third, our paper contributes to the growing literature on how various stakeholder groups influence firms' ESG practices, including institutional investors (Dyck et al., 2019; Azar et al., 2021; Gantchev, Giannetti, and Li, 2022; Heath et al., 2023), banks (Houston and Shan, 2022), governments (Brown, Martinsson, and Thomann, 2022), corporate customers (Dai, Liang, and Ng, 2021; Schiller, 2018), and end-consumers (e.g., Servaes and Tamayo, 2013; Houston et al., 2022; Meier et al., 2023; Duan, Li, and Michaely, 2024). ESG efforts affect firm value through two main channels: the discount rate, where shareholders adjust their required returns based on ESG performance (Heinkel, Kraus, and Zechner, 2001; Hong and Kacperczyk, 2009; Krüger, 2015; Albuquerque, Koskinen, and Zhang, 2019; Pástor, Stambaugh, and Taylor, 2022; Pedersen, Fitzgibbons, and Pomorski, 2021), and the cash flow channel, where ESG practices influence customer demand (Servaes and Tamayo, 2013; Dai, Liang, and Ng, 2021), employee productivity (Edmans, 2011), and wages (Krüger, Metzger, and Wu, 2022).[3]

Finally, our study relates to recent research showing that investors are willing to pay a premium for sustainable investments. Baker, Egan, and Sarkar (2022) find that ESG funds are more expensive than traditional mutual funds. Experimental and survey-based studies also show a positive willingness to pay for socially responsible investments (Bauer, Ruof, and Smeets, 2021; Humphrey et al., 2021; Heeb et al., 2023). Surveys indicate that retail investors often expect lower returns from sustainable investments than traditional assets (Riedl and Smeets, 2017; Giglio et al., 2023). Andersen et al. (2024) suggest that wealthier investors are more likely to allocate to sustainable investments, viewing them as a luxury good.

2. Sample and Data

This section describes the data used in our baseline analysis.

2.1. Sample

We draw data from the NielsenIQ Homescan Consumer Panel (NielsenIQ HCP) provided by Kilts Center at the University of Chicago Booth School of Business. These data track the grocery purchases of a large panel of U.S. households (about 60,000 per year) between 2004 and 2019. Participating households receive a universal product code (UPC) scanner, which they use to scan all their grocery purchases.

In the first week of each year, NielsenIQ surveys panelists' demographics that closest correspond to the demographics of the later months (October-December) of the prior year. We draw data on consumer demographics, such as household income bracket, household composition and size, average age of the household heads, marital status, unemployment status, and children's

[3] An alternative view suggests that ESG activities might arise from agency issues, leading to lower profitability (Masulis and Reza, 2015). Moreover, the response of stakeholders may change over time, depending on the overall level of trust in firms, markets, and institutions (Lins, Servaes, and Tamayo, 2017).

age.[4]

For each shopping trip, NielsenIQ collects detailed information on each purchased product, including its barcode (UPC), quantity purchased, price paid, product label, and store code. The data also encompass product attributes, such as brand, organic certification, type of container/package, and other attributes advertised in the product label, such as "cage-free" or "pasture-raised" eggs.

Our baseline sample includes all annual purchases of food for consumption at home (product departments: alcoholic beverages, dairy, deli, dry grocery, fresh produce, frozen foods, and packaged meat) from 2004 to 2019. The data include 194,525 households (134,784 excluding singletons when including household fixed effects) and 917,508 household-year observations.[5]

To understand whether consumers prefer organic products, we estimate a consumer demand model in Section 5, sourcing prices of all products available at each store the consumer visits from the scanner data NielsenIQ Retail Measurement Services (NielsenIQ RMS) also provided by Kilts Center. The NielsenIQ RMS collects data on sales, quantities, and prices for all distinct products (UPCs) sold weekly in participant retail stores. Even though NielsenIQ RMS covers more than 50% of the total grocery and drug sales in the United States, consumers in the NielsenIQ HCP may visit stores not included in the NielsenIQ RMS.

We focus on six product modules between 2015 and 2019: canned soup, dry seasoning, eggs, fresh carrots, fresh salad mix, liquid tea, refrigerated milk, and tortilla chips. For each product module, we create three distinct classifications—non-organic national brand, organic national brand, and private label—and compute the average price every week for each store. Finally, the demand model sample is obtained by merging these data with the NielsenIQ HCP.

[4] NielsenIQ believes panelists are reporting their "annualized" estimated income as of the time of the survey and not referring to previous year tax returns. Accordingly, in 2011, Nielsen changed the instructions in the survey for income mentioning "annualized" income instead of previous calendar year.
[5] We exclude "magnet" products that do not use standard UPC codes and are typically sold by weight – items such as fruits, vegetables, meats, an in-store baked goods.

2.2. Organic and conventional food variables

The main outcome variables used in the analysis—*Organic spending*, *Organic share* or *Organic dummy*—rely on the definition of organic food. A product is defined as organic if its label, as recorded in NielsenIQ's data, either displays a USDA organic seal or bears a non-USDA organic claim. Organic is a label that indicates that a food or agricultural product has been produced according to the organic certification standards, which require operations to use practices that cycle resources, conserve biodiversity, and preserve ecological balance.

We compare *Organic spending*, which is the dollar amount spent by a household in a year on organic food for consumption, with *Conventional spending*, i.e. the dollar amount spent by a household on non-organic food in a year. Much of our empirical analysis focuses on organic-certified spending shares to measure organic food-at-home demand. Specifically, we calculate the organic spending share for each household-year using the ratio of spending on organic food to the total spending for home food consumption. This metric reflects the extent to which households fulfill their consumption needs with organic (sustainable) products rather than conventional (non-sustainable) alternatives.

The results presented in Table 1 show that the market share of organic food experienced a substantial increase over the sample period, with the mean organic share rising from 0.72% in 2004 to 4.18% in 2019. This trend suggests a growing importance of the organic product market, potentially driven by increased consumer preference for organic options, expanded organic offerings by suppliers, or a combination of these factors. Organic shares also exhibit much heterogeneity across broad product categories. For example, in the last year of our sample, organic shares ranged from a high of 12.8% in fresh produce and 6.2% in deli items to lows of 0.5% in alcoholic beverages and 2.3% in packaged meats (see Table IA.1 in the Internet Appendix).

2.3. Household income

The main independent variables used in the analysis are based on household income. Each year, NielsenIQ surveys households regarding their total annual income, which is categorized into 20 different income brackets. When the household income level is above $15,000 and below $99,999 per year, we use the income brackets exactly as they are in NielsenIQ HCP.[6] In contrast, we group the income brackets into two broader intervals for the income levels out of this range. Households earning an income below the mean two-person federal poverty level during the sample period are grouped into a single income interval with annual income below $15,000. On the top end of the income distribution, we created an income bracket for households earning an annual income above $100,000.

In linear specifications, we use the income midpoint of each bracket. To compute the income midpoint for the *Above $100,000* bracket, we relied on data between 2006 and 2009 when NielsenIQ included higher income brackets and identified a reasonable upper limit for this bracket. Since more than two-thirds of households had an income below $149,999 during the 2006-2009 period, we defined the upper limit of this bracket to be $149,999.[7]

We also split the household-year sample into approximate tertiles of income: *Low household income* is a dummy variable that includes all households with income below $39,999; *Mid household income* variable includes households with income between $40,000 to $69,999; and *High household income* includes households with income above $70,000.

As alternative measures to household income, we also use changes in marital status from married to divorced or widowed, as well as changes in unemployment status. As it's not possible to separate voluntary (e.g. retirees, housewives, etc.) from involuntary unemployment from NielsenIQ's data, we define *Unemployed* as a dummy variable that takes the value one if at least one household head is unemployed in year *t* but gets back to being employed again, after year *t*.

2.4. Other variables

To control for determinants of consumption of organic food we use several control variables.

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[6] The income brackets are: $15,000-$19,999; $20,000-$24,999; $25,000-$29,999; $30,000-$34,999; $35,000-$39,999; $40,000-$44,999; $45,000-$49,999; $50,000-$59,999; $60,000-$69,999; $70,000-$99,999.

[7] We also verified that, during the sample period, three quarters of the IRS returns, in the bins above $100K, are in the range of $100,000-$200,000.

Household size is the number of individuals living in the household. *Household average ag*e is the average age of the heads of the household. *Children* is a dummy that takes the value of one if the household has children aged 6 or less, and zero otherwise.

2.5. Summary statistics

Table 2 shows the descriptive statistics of our baseline sample. The sample mean income midpoint is $60,871 for a mean household size of about 2.4 individuals. The mean age of household heads is 56.2 years old, and about 7% of households have children aged six or less. The mean household-year spending is $60 for organic food and $2,520 for conventional food. The mean organic share is 2.23%.

3. Results

This section presents our baseline findings on the relationship between household income and organic food consumption. We then assess the robustness of these results using alternative specifications. Lastly, we address the concern that consumer preferences for organic food may primarily reflect health considerations rather than sustainability considerations.

3.1. Household income elasticity of organic products

We begin our analysis by examining the income elasticity of organic food products and comparing it with that of conventional food products. Table 3 presents the results of estimating Poisson household-level regressions of either organic spending or conventional spending on household income[8].

In columns (1), (2), (4), and (5), *Household income* is the logarithm of the income midpoint associated with each household's income bracket. Columns (1) and (4) present the results of a specification that pools across all households and includes year-fixed effects that control for variables that are constant across households but vary over time, exploring cross-sectional

[8] Organic and conventional spending are in dollars.

variation in household income. The coefficient on household income in both specifications is positive and statistically significant. The estimates show that a 25% decrease in household income leads to a 14% ($e^{0.52338\times\ln(1-0.25)}$ - 1) and 3% ($e^{0.10697\times\ln(1-0.25)}$ - 1) decrease in organic and conventional food spending, respectively. The results indicate that the sensitivity of organic spending to income is almost five times larger than the elasticity of conventional spending.

In columns (2) and (5), we also include household fixed effects to control for unobserved time-invariant household-specific variables. Including household fixed effects is important for interpreting the estimate as the household income elasticity of organic and conventional products spending, as it captures the within-household changes in income rather than differences in income across households. As a result, the within-household estimates of the household income coefficient are substantially lower than those estimated in columns (1) and (4) using the pooled specification. Still, the coefficient on household income in both specifications is positive and statistically significant. We are interested in examining whether a shock to household income has a larger or smaller effect on organic food spending than on conventional product spending. The results in columns (2) and (5) indicate a substantially larger effect on organic food spending of a shock to household income than on conventional food spending. In particular, a 25% drop in household income has almost twice as large effect on organic products spending (-1.6%) than on conventional products spending (-0.9%).

In columns (3) and (6), the regression includes a set of dummies for each tertile of the distribution of household income (instead of the level of household income), allowing for a non-linear relationship between income and organic demand. The within-household income estimates confirm the results from columns (2) and (5). In this case, a shock to household income that moves the household from the mid to the low-income tertile leads to a 5.5% ($e^{-0.05647}$ - 1) decrease in organic spending while leading to a less than half decrease in conventional spending 2.7% ($e^{-0.02767}$ - 1). Similarly, a household income shock that moves the household from the high to the low-income tertile leads to 9.6% ($e^{-0.101}$ - 1) and 4.2% ($e^{-0.04325}$ - 1) decreases in organic and conventional spending, respectively.

Overall, the results indicate a statistically significant relationship between household income and consumer spending on both organic and conventional food for at-home consumption. Furthermore, the demand for organic food is considerably more sensitive to fluctuations in household income than the demand for conventional food.

3.2. Organic spending share and household income

The results of the previous section focus on the increase in spending on organic and conventional food products. We are also interested in the relative effect of household income on organic spending compared to the total household spending on food products. Specifically, we are interested in using the spending on both conventional and organic products as a benchmark for the changes in organic consumption. Therefore, as an alternative approach to assess the impact of household income shocks on organic spending, we analyze the effect of those shocks on each household's annual share of organic spending. This alternative also has the advantage of producing a single outcome variable that captures the relationship of interest.

Table 4 presents the results. Columns (1)-(3) use the logarithm of *Household income* as the main explanatory variable. Column (1) contains results based on a specification that pools across all households and includes year-fixed effects. The income estimate in the pooled specification implies that an income shock of -25% decreases the organic share by 9% from its sample mean (or by 0.2 percentage points).

As detailed in the previous section, we include household fixed effects to control for omitted time-invariant household-specific variables, thereby capturing the within-effect of income shocks on the organic share of expenditures in columns (2) and (3). Consistent with our findings regarding organic spending in Table 3, the inclusion of household fixed effects in columns (2) and (3) implies lower estimates of the household income effect on the organic share compared to the pooled specification in column (1).

In the most stringent specification in column (3), which also includes demographic controls, the coefficient on *Household income* implies a 1% decrease in the organic share from its mean (or

0.03 percentage points) for a 25% decrease in income. The magnitude of the impact may seem small, but it encompasses the reshuffling of consumer purchases. When household income decreases, consumers decrease overall spending, decreasing both organic and conventional product spending. To have an effect on the share, consumers must decrease organic product consumption more than conventional product consumption. If consumers decreased spending on organic and non-organic products proportionally, the effect on the organic share would be zero. Indeed, as indicated by the household income elasticity of organic spending and conventional consumption, consumers adjust organic food expenditures to a larger degree than conventional food expenditures.

The last column of Table 4 contains results using the tertiles of the distribution of household income, allowing for a non-linear relationship between income and organic demand. The estimates indicate that a negative shock in household income that transitions a household from the high to the mid (low) income tertile, implies a 0.12 (0.17) percentage points decrease in organic share, which corresponds to a decrease of the organic share from its mean of about 5% (8%). A negative shock that moves the household from the mid to the low-income tertile implies a 0.06 percentage points decrease in organic share (about 2% of the sample mean).

Figure 1 shows estimates using a finer distribution of household income, including a dummy for each of the income brackets used by NielsenIQ, except for the very low-income households that are mapped to the "Under $15,000" bracket, which is roughly the sample mean of the two-family federal poverty level. The results show that the propensity to replace the consumption of conventional products with organic products increases, in a convex way, with the household income bracket, i.e., households that reach the higher income brackets have a higher share of organic spending.

To further evaluate the impact of income on the organic share, we simulate a 25% decrease in household income, applying this reduction to the midpoint of each income bracket using the coefficients estimated in Panel B of Figure 1 with household fixed effects. On average, this income shock implies a 0.06 percentage points decrease in organic share (about 3% of the sample mean).

Considering the tertiles of the sample's income distribution, the same decrease of 25% in the income midpoints of the brackets in each tertile implies a 0.13 (0.03) percentage points decrease in organic share for the high (mid) income households, which corresponds to a decrease of the organic share, in terms of its mean, of about 6% (1%).

Overall, these results suggest that the demand for organic food is significantly more sensitive to income shocks than the demand for conventional food. As income increases, consumers are more likely to substitute conventional food with organic food options, while a decrease in income leads to the opposite effect, with consumers likely to reduce their organic food purchases in favor of conventional food alternatives.

3.3. Intensive and extensive margin

We next investigate whether the higher sensitivity of households' organic consumption to income shocks arises from households substituting organic food items with non-organic alternatives or from reducing the quantities consumed of organic foods without entirely ceasing their consumption. Specifically, we aim to determine if the observed effects on the share of organic food are primarily driven by adjustments along the extensive margin, the intensive margin, or a combination of both.

To investigate the intensive margin adjustments, we compare the income elasticity of organic demand with that of conventional demand. In Panel A of Table 5, we estimate regressions of either the logarithm of *Organic spending* in columns (1)-(3) or the logarithm of *Conventional spending* in columns (4)-(6). In columns (1) and (4), using a pooled specification, the coefficients on *Household income* imply that a 25% decrease in household income leads to about a 10.6% ($e^{0.38985\times\ln(1-0.25)}$ - 1) decrease in organic spending and about a 2.5% ($e^{0.08725\times\ln(1-0.25)}$ - 1) decrease in conventional spending. When we add household fixed effects in columns (2) and (4), the estimated coefficients on *Household income* indicate that a 25% decrease in household income leads to about a 1.9% ($e^{0.06712\times\ln(1-0.25)}$ - 1) decrease in organic spending and about a 0.8% ($e^{0.02877\times\ln(1-0.25)}$ - 1) decrease in conventional spending. Similarly to Section 3.1., the increase in organic spending is more than twice the increase in conventional spending following a positive income shock.

The results in columns (3) and (6) show that an income shock that moves the household from the mid to the low-income tertile leads to 5% ($e^{-0.05096}$ - 1) and 2.8% ($e^{-0.02823}$ - 1) decreases in organic and conventional spending, respectively. The results also show that an income shock that moves the household from the high to the low-income tertile leads to 9.9% ($e^{-0.10429}$ - 1) and 4.2% ($e^{-0.04257}$ - 1) decreases in organic and conventional spending, respectively.[9] Notice that the decrease in organic relative to conventional spending is much larger (2.4 times) for households moving from the high to low-income tertile than it is for households moving from the mid to low-income tertile (1.8 times).

We also perform the analysis at the extensive margin, using a linear probability model, replacing the dependent variable with a dummy variable (*Organic dummy*) that takes the value of one if household *i* bought organic products in year *t*, and zero otherwise. Panel B of Table 5 presents the results. Looking at the most stringent specification in column (2), a decrease in household income of 25% leads to a decrease in the probability of buying organic products of 0.29 percentage points. Furthermore, using within-household estimates and the tertiles of the distribution of household income in column (3), the estimates imply that a negative shock in household income that moves the household from the high (mid) to the low-income tertile, implies about a 1.96 (0.9) percentage points decrease in the probability of a household buying organic products in a given year. This is consistent with the fact that a lot of the consumption of organic products occurs when household income increases to a high enough level.

The results in this section show that consumer adjustments drive the higher elasticity of organic consumption to household income at both the intensive and extensive margins.

3.4. Robustness

We begin by assessing the robustness of our baseline results by conducting a similar analysis using

[9] We also assess the robustness of these results using log growth rates regressing either Δ*log*(*Organic spending*) or Δ*log*(*Conventional spending*) on Δ*log*(*Household income*). Table IA.2 of the Internet Appendix show the results that are qualitatively similar.

data for different categories of products. Following Nielsen's definition of broader product categories (product departments), we compute the organic share for each category: dry grocery, fresh produce, dairy, frozen foods, deli, packaged meat, and alcoholic beverages. Using finer categories of products is problematic in some cases as it increases the incidence of zero organic shares, but it allows us to check for the sensitivity of our baseline results to different types of products. The results presented in Table 6 suggest that our main conclusions using an aggregated analysis, except for alcoholic beverages, are not affected when using product department organic shares as a dependent variable. Specifically, excluding alcoholic beverages, a 25% decrease in household income leads to a 2% decrease, in terms of its mean, in organic share within the deli and packaged meat product categories, and to a 1% decrease, in terms of its mean, in the organic share within the remaining product categories.

To further establish the validity of our results, we employ several additional robustness checks: (1) we redefine the organic share to only include products with USDA organic certification instead of USDA or other organic certifications; (2) we restrict the sample to households with an average organic share of at least 0.5% across the years they are represented in NielsenIQ's panel; (3) we cluster the standard errors by county instead of household; (4) we apply one-lead to NielsenIQ's data on household income; (5) we estimate our baseline results using NielsenIQ's projection factors for each household; (6) we restrict the sample period to 2015-2019, the later period of the sample when the average market share of organic products is higher; and (7) we replace year fixed effects by county-year fixed effects. Table IA.3 of the Internet Appendix shows similar estimates to those in Table 4. We conclude that our baseline results are robust to these alternative specifications.

3.5. Sustainability vs. health concerns

The decision to purchase organic food is often driven by environmental concerns, including the reduced energy consumption associated with organic farming and the lower exposure of farm workers, consumers, and ecosystems (such as land and water systems) to harmful synthetic pesticides and fertilizers. Additionally, it may be linked to consumers' interest in healthier dietary habits and long-term well-being. Consequently, a potential issue with our interpretation of the results is that consumers may prefer organically certified food primarily for health concerns rather than sustainability concerns. To address this issue, we use alternative specifications of the dependent variable for two product modules: Fresh Eggs and Dairy Milk Refrigerated.

For the product categories of Fresh Eggs and Dairy Milk Refrigerated, we examine additional ESG-related claims: animal welfare and sustainable packaging, respectively. The decision to purchase these organic products is not likely to be related to health considerations. Specifically, we classify animal welfare products within the Fresh Eggs category as those that feature keywords on their labels such as "Cage-free," "Free roam," "Free range," and "Pasture-raised." In the Dairy Milk category, we define sustainable packaging products as those packaged in carton containers. While animal welfare claims are prominently advertised on product labels, the designation of sustainable packaging for dairy milk products relies on consumer preferences regarding container types (e.g., carton versus plastic or glass).

We regress the household's yearly ESG share of spending on either fresh eggs or dairy milk on the household's income. Panel A of Table 7 presents the results using *Household income* as the main explanatory variable. In column (1), we repeat our baseline specification using the share of organic spending on fresh eggs (Panel A1) or dairy milk (Panel A2) by each household. The estimates show that a decrease in income by 25% leads to a decrease of 0.08 (0.08) percentage points in the share of organic eggs (dairy milk) bought by households.

In column (2), we consider the share of eggs with animal welfare claims on the household's total spending in fresh eggs (Panel A1) or the share of sustainable packaging on the household's total spending in dairy milk (Panel A2). The estimates show that a decrease in income by 25% leads to a decrease of 0.16 (0.06) percentage points in the share of organic eggs (dairy milk) households buy.

In column (3), we consider the share of eggs (dairy milk) with ESG-related claims (organic or animal welfare/sustainable packaging) on the household's total spending on fresh eggs (Panel A1) or in dairy milk (Panel A2). The estimates show that a decrease in income by 25% leads to a decrease of 0.18 (0.07) percentage points in the share of ESG eggs (dairy milk) households buy.

In column (4), we consider the share of eggs (dairy milk) with non-organic ESG-related claims (animal welfare/sustainable packaging but not organic) on the household's total spending on fresh eggs (Panel A1) or in dairy milk (Panel A2). While the coefficient for dairy milk is not statistically significant, the estimates show that a decrease in income by 25% leads to a decrease of 0.1 percentage points in the share of non-organic ESG eggs bought by households.

The results in Panel B of Table 7 are qualitatively similar when we replace *Household income* with a set of dummies for each tertile of the distribution of household income. Noticeably, the dummy for high-income households is positive and statistically significant across all specifications, including those of the share of non-organic ESG dairy milk in column (4) of Panel B1.

Overall, the results in this section suggest that our baseline findings reflect consumer preferences for products marketed as environmentally and socially responsible, beyond purely health-related motivations. Specifically, we find that the preference for sustainable products rises with household income and is particularly pronounced among high-income households.

4. Identification Strategies

Although our baseline regressions control for all time-invariant variables that are specific to each household, there could still be residual endogeneity concerns related with measurement error and omitted variables.

First, there could be a concern about measurement errors in household income. Since household income is measured in income brackets, we only observe a change in income when households change income brackets – computed as the change in income midpoints associated with both brackets. However, it is possible that a household changes its income bracket due to a small change in income (e.g., a $1 increase in income from $24,999 to $25,000 would result in an increase of about 22% in the income midpoints associated with the income brackets). It is also possible that a household experiences a significant change in income without changing income bracket (e.g. with income changing by about 43% from $70,000 to $99,999), with that household being assigned a change of $0 in income because it remains in the same bracket ($70,000-$99.999).[10]

Second, although we use regressions with household fixed effects that account for unobserved time-invariant household heterogeneity, there is a concern about a possible bias, for example, due to household-specific time-varying omitted variables. On the one hand, the estimated results may be affected by peer effects associated with higher household income, but not by the higher income directly. For example, organic products might be seen as a way to exhibit social status by high-income individuals, or it might be that changes in income might be associated with changes in behavior, namely different dietary habits and physical activity. On the other hand, there is also the possibility that omitted variables at the product group level can bias our analysis at an aggregated level.

4.1. Changes to employment or marital status

To further address those concerns, we examine alternative variables that affect household income: unemployment of at least one household head, and marital status (i.e., divorce and widowhood). Importantly, given that we use a within-household specification, causal effects will be established through unemployment or marital status changes (e.g., from married to divorced or to widowed). We begin the analysis by testing the effect of these alternative variables on household income (relevance condition) before examining their direct effect on the organic share of spending.

Table 8 presents our estimates on the relationship between unemployment (or marital status), household income, and the organic share of spending. Column (1) shows that an unemployment spell affecting at least one household head is associated with a 10.9% ($e^{-0.11591}$ - 1) decline in household income, controlling for household size and other demographic factors. In column (2), we observe that a transition from married to either widowed or divorced is associated with a

[10] Another source of measurement error is linked to social desirability bias leading to deliberate misreporting of income in surveys. This source of measurement error might be downplayed due to NielsenIQ using anonymized household IDs.

reduction in household income by approximately 21.6% ($e^{-0.24308}$ - 1) and 22.4% ($e^{-0.25416}$ - 1), respectively.

The results in column (3) show that when at least one of the household heads involuntarily loses its job, the organic share of the household food-at-home spending decreases by about 0.05 percentage points (about 2% of the sample mean). The results in column (4) show that a change in marital status from married to widowed or divorced decreases organic share by about 0.16 or 0.09 percentage points (about 7% or 4% of the sample mean), respectively.

Columns (5) and (6) present the second-stage results of two-stage least squares (2SLS) regressions of organic share on *Household income* using either unemployment or marital status as instruments for household income, respectively. In both specifications, there is a statistically significant effect of *Household income* on the organic share, hence strengthening the causal interpretation of our baseline results. Specifically, the estimated coefficients on household income indicate that a 25% decrease in household income leads to about 0.12 or 0.18 percentage points decrease in organic share (about 5% or 8% of the sample mean), considering the results in column (5) or column (6), using unemployment or marital status as instruments for income, respectively.

4.2. Quasi-natural experiment: The 2008 tax rebates

In 2008, amid the financial crisis, the U.S. Congress enacted direct cash payments in the form of tax credits known as the 2008 tax rebates. These recovery rebates provided households with a basic credit amount ranging from \$300 to \$600, plus an additional \$300 per child. By July 2008, the average tax rebate received by American households was approximately \$900 (Broda and Parker, 2014).

Following a similar approach to Broda and Parker (2014), we identify the change in organic share caused by the receipt of a tax rebate at the household level using the fact that the law randomized the timing of the disbursement of the tax rebates. Due to administrative reasons, the IRS mailed out or deposited payments to households between the beginning of May and the end of July. The funds were not disbursed all at once, but instead, the IRS did so sequentially depending on the last digits of each taxpayer's social security number, which meant the week when each taxpayer received its rebate was, in practice, random.

We begin our analysis by regressing the weekly share of spending in organic food of households, from the week beginning on January 1, 2008 to the week ending on September 29, 2008, on two variables: *Up to 4 weeks after*, a dummy that takes the value of one if the household received the tax rebate in the first four weeks after and including the payment receipt week (that is, from week t+0 to week t+4), and 0 otherwise; and *After 5 weeks*, a dummy that takes the value of one if the household has received the tax rebate five or more weeks after the payment receipt.

The results in column (1) of Table 9 show that, on average, households increased the weekly organic share of their food expenditures by 0.05 percentage points (approximately 4% of the sample mean before the income shock) during the week of and the four weeks following the receipt of the tax rebate. However, after five weeks post-receipt of the tax rebate, the impact on the organic share, while still positive, is not statistically significant. This suggests that the effect of the tax rebate was concentrated in the initial weeks following its receipt.

In column (2), we repeat the analysis of column (1), but using a wider window of 12 weeks on or after the week of the tax rebate. The results show that, on average, households increased the weekly organic share of their food expenditures by 0.05 percentage points (approximately 4% of the sample mean prior to the income shock) during the week of and the twelve weeks after receiving the tax rebate. However, after 13 weeks post-receipt, the effect on the organic share remains positive but is not statistically significant, suggesting that the impact of the tax rebate was concentrated in the initial months following its receipt.

Overall, the results in this section show that household income has a positive causal effect on the consumption of organic products. Specifically, an increase in household income leads to an increase in the organic share of expenditures, as consumers are more likely to substitute conventional food with organic options.

5. Mechanism

In this section, we investigate why higher-income individuals purchase more organic products. Is it purely a pricing story, i.e., they can afford these (more expensive) products because they have lower price sensitivity? Or would these consumers value organic products more than low-income individuals, even if prices were the same? Understanding this mechanism can have implications for the optimal way ESG firms respond to macroeconomic shocks, for example, by adjusting prices. It also helps firms to understand if the risk associated with ESG products is like that of any other high-priced product or if something special exists for sustainable products.

We start by documenting that organic products' prices are higher (per serving). In Figure 2 we report the distribution of price per gallon for the UPCs in the refrigerated milk product category in 2019, separately for organic and conventional products. We see that, although there is some overlap, the distribution of prices for organics stochastically dominates the conventional one.

Next, we set up and estimate a structural demand model, where consumers are heterogeneous in their price sensitivity and preferences for organic products. We use the model to quantify the role of prices in explaining differences in the share of "organic" purchases between high- and low-income consumers.

5.1. Model

We follow the standard approach in IO and formalize consumer choices as a discrete problem.[11] We model demand for one product category, conditional on the timing of store visits, which we take as exogenously defined (as in Dubé, Hitsch, and Rossi, 2010, or Bronnenberg, Dubé, and Sanders, 2020). The framework is purposely simple, as we want to apply it to multiple product categories separately. This means that, for example, we do not explicitly include product characteristics irrelevant for all categories in the model.

Each consumer *i* visits store *s* and chooses which product to buy (*j*) to maximize its utility. The

[11] See, e.g. McFadden (1981), or Berry, Levinsohn, and Pakes (1995).

consumer will make the choice of $j \in (0,1,\ldots \mathrm{J})$ where $\mathrm{j} = 0$ is the no-purchase decision and $1,\ldots,\mathrm{J}$ are the different options available in this store. The utility that consumer *i* has if he decides to purchase option *j* is:

$$U_{istj} = X_j\, \beta_i - p_{jst}\alpha_i + \xi_j + \varepsilon_{istj}$$

with:

$$\beta_i = \bar{\beta} + D_i\beta$$
$$\alpha_i = \bar{\alpha} + D_i\alpha$$

where X_j is a vector of observed characteristics of option j (for example an "organic" dummy), ξ_j is a vector of unobserved characteristics (by the researcher), p_{jst} is price, D_i is a vector of demographic characteristics for individual *i*, and ε_{istj} is an idiosyncratic shock that follows the usual extreme value type I distribution. It is helpful to concentrate on all the utility terms that vary only with each option *j* – but not across individuals or with time – in term δ_j. Then we can rewrite the model as:

$$U_{istj} = \delta_j - p_{jst}\alpha_i + X_j D_i \beta + \varepsilon_{istj}$$

with

$$\delta_j = X_j\, \bar{\beta} + \xi_j$$

As usual, we need to normalize the utility of the outside option to zero, i.e., we set $U_{ist0} = \varepsilon_{isto}$. This model has an analytic solution that gives us the probability that a consumer will purchase product *j* as:

$$Pr_{ist}(j) = \frac{e^{\boldsymbol{U_{istj}}}}{\sum_k e^{\boldsymbol{U_{istk}}+1}} \tag{1}$$

5.2. Estimation

We estimate equation (1) by maximum likelihood, which allows us to recover the model primitives $(\delta_j, \bar{\beta}, \alpha, \beta)$. In the estimation routine, individuals have the following four options: no purchase, private label, organic national brand, and non-organic national brand[12]. Moreover, the core specification that we report in this table interacts *Household income* with both price and an "organic indicator." In Table IA.4 in the Internet Appendix, we report results from an alternative specification that uses income brackets as the main demographic variables, i.e. $\mathrm{D}_i^1 = \mathbb{1}_{[\text{Income}<40\text{k}]}$, $\mathrm{D}_i^2 = \mathbb{1}_{[40\text{k}<\text{Income}<70\text{k}]}$, $\mathrm{D}_i^3 = \mathbb{1}_{[70\text{k}<\text{Income}]}$.

We estimate the model separately for the following six product categories: Eggs, Milk, Salad, Soup, Tea, and Tortilla Chips. These were chosen using the following procedure: we first selected the 50 Nielsen product modules with the largest total consumer expenditure; second, we dropped those that have "remaining" in the name; finally, we selected the top 6 products in terms of share of organic purchases among the remaining modules. The first filter was chosen to guarantee that the products are well represented in the typical consumer basket, the second filter to impose some product homogeneity within the module, and the third one to provide us with a sample size of organic purchases that we can use to recover the parameters of interest. To estimate the model, we used a sample of store visits from all 50 states from 2015 to 2019, restricted to consumers in the sample for at least three years and for which we observe a minimum of 100 shopping trips. We address price endogeneity by assuming that $\xi_{jst} = \xi_j$ and using alternative-specific fixed effects.

Table 10 presents the results, which indicate, as expected, that the price coefficient is negative and significant for all six product categories. We also find that higher-income individuals tend to have lower price sensitivity, as the interactions of the price with income are always positive and statistically significant. Moreover, by interacting the *Organic* dummy variable with *Household income*, we allow the income level to affect preferences for organic products beyond the price effect.[13] Results suggest that high-income individuals value organic products more than low-income individuals, even if they were sold at the same price as conventional products.

[12] Although we could potentially be more granular and estimate the model at the brand or UPC level, this approach allows us to focus on the choices that are relevant to our paper (organic vs non-organic) and to have a parallel structure for all product categories.

[13] We cannot have an "organic" term in isolation because we include option-specific terms, which already capture that effect.

5.3. Counterfactuals

We now use the model primitives to quantify the importance of the price channel. The relevance of this channel will be larger for product categories where: (1) the price premium of organic vs conventional is higher, and (2) the difference in price sensitivity between low- and high-income individuals is also larger.

Table 11 presents the results. The top row reports the premium per serving[14] for organic products over the price of conventional products, average across all stores and weeks that we use in this sample. We see immediately that organic prices are 40%-70% higher for all 6 categories.

Then, we simulate supermarket purchases by high-income households in a fictitious world where the price channel was inactive. To implement this, we set the coefficient **"**price × income**"** to zero and then recompute the purchases of the largest income group. We find that the price channel accounts for between 9% and 48% of the different purchases between the lowest and the highest income bracket, depending on the product category. This means that the remaining preferences account for between 52% and 91% of the impact of income on the purchase of organic products.

6. Conclusion

Our study offers new insights into the link between household income and the consumption of sustainable products, particularly organic goods. Our findings indicate that household income positively affects organic food expenditure, with higher-income households showing greater sensitivity to income changes in their demand for organic products.

By examining the effects of income shocks on both the intensive and extensive margins of organic food consumption, we show that income increases boost spending among existing consumers and attract new consumers to organic products. Additionally, our analysis of alternative ESG labels, such as animal welfare and sustainable packaging, indicates that these patterns hold

[14] The exact unit varies by product module.

across various ESG categories and are not solely driven by health-related motivations.

Our study contributes to the broader literature on household consumption behavior, demonstrating that the income elasticity for organic products is significantly higher than that for conventional goods. This finding reinforces the view that sustainable products are premium goods. Additionally, our results suggest that the demand for sustainable products is primarily driven by consumer preferences rather than price or supply constraints.

Our study highlights the importance of firms carefully evaluating the trade-offs in adjusting product portfolios to include sustainable products, as these products may increase exposure to macroeconomic risks. As demand for sustainable products rises, firms should consider the financial vulnerabilities linked to targeting high-income consumers, who are particularly sensitive to economic fluctuations. Our findings suggest that firms offering sustainable products are more vulnerable to macroeconomic shocks, especially those that disproportionately impact higher-income households.

A deeper understanding of the demand for sustainable goods enables firms to make informed decisions about expanding ESG offerings, helping to balance long-term value creation with the risks associated with business cycles.

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Appendix

Table A.1
Variable Definitions

Variable	Definition
Total spending ($)	Total spending in organic and non-organic (conventional) food for consumption at home by household *i* on year *t*.
Organic spending ($)	Spending on organic food for consumption at home by household *i* on year *t*.
Conventional spending ($)	Spending on non-organic (conventional) food for consumption at home by household *i* on year *t*.
Organic dummy	Dummy that takes the value of one if household *i* bought organic food for consumption at home on year *t* and zero otherwise.
Organic share	Share (in percentage) of spending in organic food for consumption at home by household *i* on year *t*.
USDA organic share	Share (in percentage) of spending in USDA certified organic food for consumption at home by household *i* on year *t*.
Animal welfare share	Share (in percentage) of spending in animal welfare products by household *i* on year *t* where animal welfare products (within the Fresh Eggs product module) are those that include the following keywords in their labels – "Cage free", "Free roam", "Free range", and "Pasture raised".
Sustainable packaging share	Share of spending in sustainable packaging products (in percentage) by household *i* on year *t* . We define sustainable packaging products (within the Dairy Milk product module) as those that are packaged in carton containers.
ESG share	Share (in percentage) of spending in ESG products by household *i* on year *t*. We define ESG products (within the Fresh Eggs and Dairy Milk product modules) as those that are either organic or animal welfare/sustainable packaging.
ESG share (not organic)	Share (in percentage) of spending in ESG (not organic) products by household *i* on year *t* where ESG products (not organic) (within the Fresh Eggs and Dairy Milk product modules) are those that are animal welfare/sustainable packaging but that are not labeled as organic.
Household income	Annual income of the household (dollars).
Household size	Number of individuals living in the household.
Household average age	Average age of the household heads.
Children	Dummy that takes the value of one if there is a child up to 6 years old in the household and zero otherwise.
Unemployed	Dummy that takes the value of one if at least one household head is unemployed in year *t* but gets back to being employed again, after year *t* and zero otherwise.
Divorced	Dummy that takes the value of one if the marital status of the household is divorced and zero otherwise.
Widowed	Dummy that takes the value of one if the marital status of the household is widowed and zero otherwise.
Single	Dummy that takes the value of one if the marital status of the household is single and zero otherwise.
Married	Dummy that takes the value of one if the marital status of the household is married and zero otherwise.

Table 1
Evolution of Organic Share
This table shows the evolution of total spending, organic spending, and organic share over the sample period. The sample consists of Nielsen's consumer panel data tracking the yearly spending decisions of consumers on food for consumption at home in the 2004-2019 period.

Year	Number of households	Total spending ($)	Organic spending ($)	Organic share (%)			
				Average	Low income	Mid income	High income
2004	39,574	86,836,686	628,268	0.72	0.57	0.70	0.95
2005	38,858	86,687,550	723,474	0.83	0.66	0.78	1.11
2006	37,781	85,915,413	995,501	1.16	0.85	1.11	1.54
2007	63,340	151,422,956	2,029,225	1.34	0.98	1.27	1.73
2008	61,426	154,655,586	2,232,099	1.44	1.03	1.33	1.87
2009	60,495	153,915,601	2,287,549	1.49	1.03	1.34	1.96
2010	60,643	150,492,496	2,452,771	1.63	1.14	1.47	2.14
2011	62,073	161,898,983	2,860,811	1.77	1.26	1.63	2.27
2012	60,525	161,174,181	3,082,679	1.91	1.36	1.66	2.53
2013	61,083	162,231,661	3,303,259	2.04	1.41	1.85	2.66
2014	61,545	167,499,397	3,900,755	2.33	1.60	2.09	3.06
2015	61,366	166,083,070	4,521,931	2.72	1.89	2.44	3.53
2016	63,139	171,972,539	5,674,223	3.30	2.20	2.95	4.23
2017	62,818	170,945,844	6,509,120	3.81	2.58	3.38	4.78
2018	61,374	168,702,400	6,936,468	4.11	2.82	3.62	5.11
2019	61,468	166,974,791	6,975,413	4.18	2.86	3.65	5.18

Table 2
Summary Statistics
This table shows the mean, median, standard deviation, minimum, maximum, and number of observations for each variable. Variable definitions are provided in Table A.1 in the Appendix. The sample consists of Nielsen's consumer panel data tracking the yearly spending decisions of consumers on food for consumption at home in the 2004-2019 period.

	Mean	Median	Standard deviation	Minimum	Maximum	Number of observations
Total spending ($)	2580.3	2304.5	1485.5	0.5	54533. 0	917,508
Organic spending ($)	60.1	11.8	168.4	0.0	8370.7	917,508
Conventional spending ($)	2520.2	2252.4	1451.0	0.0	54236.9	917,508
Organic share (%)	2.23	0.52	5.14	0.00	100.00	917,508
USDA organic share (%)	1.73	0.36	4.13	0.00	99.09	917,508
Household income	60871.2	55000.0	35513.7	2500.0	125000.0	917,508
Household size	2.383	2.000	1.298	1.000	9.000	917,508
Household average age	56.233	56.500	13.154	18.000	118.000	917,508
Children	0.070	0.000	0.255	0.000	1.000	917,508
Unemployed	0.065	0.000	0.246	0.000	1.000	917,508
Divorced	0.150	0.000	0.357	0.000	1.000	917,508
Widowed	0.080	0.000	0.271	0.000	1.000	917,508
Single	0.144	0.000	0.351	0.000	1.000	917,508
Married	0.627	1.000	0.484	0.000	1.000	917,508

Table 3
Household Income Elasticity of Organic Demand: Poisson Regression
This table shows the results of Poisson household-level regressions of either the household's yearly organic or conventional spending in food for consumption at home on the household's income. Household's income is either the logarithm of the income midpoint associated with each household's income bracket, or a set of dummies for each tertile of the distribution of household's income. The specifications in columns (1) and (4) use standard Poisson regressions; the specifications in the other columns use conditional fixed effects poisson regressions. Variable definitions are provided in Table A.1 of the Appendix. Robust standard errors adjusted for household-level clustering are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Organic spending ($)			Conventional spending ($)		
	(1)	(2)	(3)	(4)	(5)	(6)
Household income (log)	0.52338***	0.05738***		0.10697***	0.03085***	
	(0.01220)	(0.00952)		(0.00202)	(0.00168)	
Mid household income			0.05647***			0.02767***
			(0.01064)			(0.00199)
High household income			0.10100***			0.04325***
			(0.01310)			(0.00263)
Household size	0.00350	0.01545***	0.01564***	0.14534***	0.05483***	0.05527***
	(0.00518)	(0.00469)	(0.00473)	(0.00106)	(0.00107)	(0.00107)
Household average age	-0.01001***	0.00084	0.00101	0.00282***	0.00124***	0.00130***
	(0.00050)	(0.00166)	(0.00176)	(0.00010)	(0.00031)	(0.00031)
Children	0.36636***	0.11800***	0.11735***	-0.13372***	-0.01165***	-0.01206***
	(0.01853)	(0.01596)	(0.01595)	(0.00384)	(0.00332)	(0.00332)
Household fixed effects	No	Yes	Yes	No	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	917,508	834,691	834,691	917,508	857,767	857,767

Table 4
Organic Spending Share and Household Income

This table shows the results of ordinary least squares (OLS) household-level panel regressions of the household's yearly organic share (in percentage) of spending in food for consumption at home on the household's income. Household's income is either the logarithm of the income midpoint associated with each household's income bracket, or a set of dummies for each tertile of the distribution of household's income. Regressions include the same control variables as those in Table 3 (coefficients not shown). Variable definitions are provided in Table A.1 of the Appendix. Robust standard errors adjusted for household-level clustering are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Household income (log)	0.700***	0.088***	0.095***	
	(0.017)	(0.017)	(0.017)	
Mid household income				0.055***
				(0.019)
High household income				0.171***
				(0.027)
Controls	No	No	Yes	Yes
Household fixed effects	No	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Number of observations	917,508	857,767	857,767	857,767
R-squared	0.05	0.80	0.80	0.80

Table 5
Organic Spending and Household Income: Intensive & Extensive Margin
This table shows the results of household-level regressions performed on the intensive (Panel A) and extensive margin (Panel B). The intensive margin analysis is performed in cases in which household *i* buys organic food for consumption at home both on years *t* and *t-1*. The extensive margin analysis includes all observations of the baseline sample. Panel A shows the results of household-level regressions of either the household's yearly organic or conventional spending in food for consumption at home on the household's income. Panel B shows the results of household-level regressions of the organic dummy on the household's income. Organic dummy is a binary variable that takes the value of one if household *I* bought organic food for consumption at home on year *t,* and 0 otherwise. Household's income is either the logarithm of the income midpoint associated with each household's income bracket, or a set of dummies for each tertile of the distribution of household's income. Regressions include the same control variables as those in Table 3 (coefficients not shown). Variable definitions are provided in Table A.1 of the Appendix. Robust standard errors adjusted for household-level clustering are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Intensive margin

	Organic spending (log)			Conventional spending (log)		
	(1)	(2)	(3)	(4)	(5)	(6)
Household income (log)	0.38985***	0.06712***		0.08725***	0.02877***	
	(0.00665)	(0.00617)		(0.00244)	(0.00211)	
Mid household income			0.05096***			0.02823***
			(0.00795)			(0.00260)
High household income			0.10429***			0.04257***
			(0.01018)			(0.00337)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effects	No	Yes	Yes	No	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	481,373	452,365	452,365	481,373	452,365	452,365
R-squared	0.10	0.73	0.73	0.15	0.83	0.83

Table 5 (continued)

Panel B: Extensive margin

	Organic dummy		
	(1)	(2)	(3)
Household income (log)	0.08214***	0.01012***	
	(0.00103)	(0.00141)	
Mid household income			0.00902***
			(0.00188)
High household income			0.01956***
			(0.00235)
Controls	Yes	Yes	Yes
Household fixed effects	No	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Number of observations	917,508	857,767	857,767
R-squared	0.09	0.46	0.46

Table 6
Organic Spending Share and Household Income: Product Groups
This table shows the results of ordinary least squares (OLS) household-level panel regressions of the household's yearly organic share (in percentage) of spending within each major product category of food for consumption at home on the household's income. The product categories (Nielsen's product departments) considered are dry grocery, fresh produce, dairy, frozen foods, deli, packaged meat, and alcoholic beverages. Household's income is either the logarithm of the income midpoint associated with each household's income bracket, or a set of dummies for each tertile of the distribution of household's income. All specifications include household and year fixed effects as well as all the control variables listed in Table 3. Variable definitions are provided in Table A.1 of the Appendix. The coefficients of the regressions on the variables of interest are presented in columns. All regressions were estimated using robust standard errors adjusted for household-level clustering. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Income (log)

	Dry Grocery (1)	Fresh Produce (2)	Dairy (3)	Frozen Foods (4)	Deli (5)	Packaged Meat (6)	Alcoholic Beverages (7)
Household income (log)	0.095***	0.190***	0.128***	0.056**	0.277***	0.073***	-0.017
	(0.017)	(0.043)	(0.034)	(0.025)	(0.051)	(0.024)	(0.020)
Number of observations	857,712	833,702	854,883	852,482	815,071	827,810	541,769
R-squared	0.75	0.61	0.69	0.59	0.52	0.43	0.32

Panel B: Income dummies

	Dry Grocery (1)	Fresh Produce (2)	Dairy (3)	Frozen Foods (4)	Deli (5)	Packaged Meat (6)	Alcoholic Beverages (7)
Mid income households	0.051***	0.079	0.109***	0.018	0.139**	0.086***	-0.016
	(0.019)	(0.050)	(0.037)	(0.029)	(0.058)	(0.026)	(0.024)
High income households	0.168***	0.321***	0.198***	0.090**	0.447***	0.168***	-0.022
	(0.027)	(0.069)	(0.052)	(0.040)	(0.083)	(0.037)	(0.032)
Number of observations	857,712	833,702	854,883	852,482	815,071	827,810	541,769
R-squared	0.75	0.61	0.69	0.59	0.52	0.43	0.32

Table 7
Sustainability vs. Health Concerns Mechanisms
This table shows the results of ordinary least squares (OLS) household-level panel regressions of the household's yearly ESG share (in percentage) of spending on either fresh eggs or dairy milk on the household's income. The dependent variable in the first column is the organic share of spending on fresh eggs or dairy milk. The dependent variable in the second column is the share of animal welfare claims (sustainable packaging) out of each household's spending on fresh eggs (dairy milk). The third column considers as dependent variable the share of spending using the union of all ESG related claims (organic and animal welfare or sustainable packaging). The fourth column considers as dependent variable the share of spending on fresh eggs (dairy milk) of products that have animal welfare claims or are in sustainable packages but that are not organic certified. Household's income is either the logarithm of the income midpoint associated with each household's income bracket (Panel A), or a set of dummies for each tertile of the distribution of household's income (Panel B). All specifications include household and year fixed effects as well as all the control variables listed in Table 3. Variable definitions are provided in Table A.1 of the Appendix. The coefficients of the regressions on the variables of interest are presented in columns. All regressions were estimated using robust standard errors adjusted for household-level clustering. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Income (log)

Panel A1: Fresh Eggs

	Organic share	Animal welfare share	ESG share	ESG share (not organic)
	(1)	(2)	(3)	(4)
Household income (log)	0.272***	0.543***	0.627***	0.354***
	(0.053)	(0.077)	(0.079)	(0.057)
Number of observations	798,643	798,643	798,643	798,643
R-squared	0.60	0.59	0.63	0.51

Panel A2: Dairy Milk

	Organic share	Sustainable Packaging share	ESG share	ESG share (not organic)
	(1)	(2)	(3)	(4)
Household income (log)	0.273***	0.204*	0.251**	-0.021
	(0.063)	(0.105)	(0.107)	(0.096)
Number of observations	794,790	794,790	794,790	794,790
R-squared	0.72	0.69	0.70	0.67

Table 7 (continued)

Panel B: Income dummies

Panel B1: Fresh Eggs

	Organic share	Animal welfare share	ESG share	ESG share (not organic)
	(1)	(2)	(3)	(4)
Mid income households	0.120**	0.156*	0.206**	0.085
	(0.059)	(0.087)	(0.090)	(0.068)
High income households	0.463***	0.819***	1.005***	0.542***
	(0.085)	(0.128)	(0.132)	(0.099)
Number of observations	798,643	798,643	798,643	798,643
R-squared	0.60	0.59	0.63	0.51

Panel B2: Dairy Milk

	Organic share	Sustainable Packaging share	ESG share	ESG share (not organic)
	(1)	(2)	(3)	(4)
Mid income households	0.204***	0.288**	0.331**	0.128
	(0.070)	(0.130)	(0.132)	(0.120)
High income households	0.451***	0.655***	0.750***	0.299*
	(0.104)	(0.178)	(0.182)	(0.162)
Number of observations	794,790	794,790	794,790	794,790
R-squared	0.72	0.69	0.70	0.67

Table 8
Response of Organic Spending Share to Household Income Changes
This table shows the results of household-level panel regressions of the household's yearly organic share of spending in food for consumption at home on alternative variables to household's income. Columns (1) and (2) report a first-stage ordinary least squares (OLS) regression of the logarithm of household income on the alternative variables to income used. Columns (3) and (4) report the estimates of ordinary least squares regressions (OLS) of organic share (in percentage) directly on the alternative variables used. Columns (5) and (6) present the results of two-stage least squares (2SLS) regressions of organic share on logarithm of household income using unemployment and marital status as instruments for household income. Regressions include the same control variables as those in Table 3 (coefficients not shown). Variable definitions are provided in Table A.1 of the Appendix. Robust standard errors adjusted for household-level clustering are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Income (log)		Organic share (OLS)		Organic share (2SLS)	
	(1)	(2)	(3)	(4)	(5)	(6)
Household income (log)					0.426**	0.619***
					(0.176)	(0.136)
Unemployed	-0.11591***		-0.049**			
	(0.00328)		(0.020)			
Widowed		-0.24308***		-0.156***		
		(0.00632)		(0.045)		
Divorced		-0.25416***		-0.094**		
		(0.00617)		(0.042)		
Single		-0.22082***		-0.260***		
		(0.00719)		(0.049)		
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	857,767	857,767	857,767	857,767	857,767	857,767
R-squared	0.85	0.85	0.8	0.8		

Table 9

Response of Organic Spending Share to Household Income Changes to the 2008 Economic Stimulus Payments

This table shows the results of household-level panel regressions of the household's weekly organic share (in percentage) of spending in food for consumption at home on alternative sets of dummies using periods of time around the week when each household received the tax rebate. The sample period ranges from the week beginning on January, 1, 2008 to the week ending on September, 29, 2008. "Up to 4 weeks after" is a dummy that takes the value of one if the household has already received the tax rebate up to 4 weeks after the payment week (including the contemporaneous week: from week t+0 to week t+4), and 0 otherwise. "After 5 weeks" is a dummy that takes the value of one if the household has received the tax rebate at 5 or more weeks ago. "Up to 12 weeks after" is a dummy that takes the value of one if the household has already received the tax rebate up to 12 weeks after the payment week (including the contemporaneous week: from week t+0 to week t+12), and 0 otherwise. "After 13 weeks" is a dummy that takes the value of one if the household has received the tax rebate at 13 or more weeks ago. Variable definitions are provided in Table A.1 of the Appendix. Robust standard errors adjusted for household-level clustering are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
Up to 4 weeks after	0.0522**	
	(0.0265)	
After 5 weeks	0.0373	
	(0.0382)	
Up to 12 weeks after		0.0543**
		(0.0269)
After 13 weeks		0.0716
		(0.0440)
Household fixed effects	Yes	Yes
Week fixed effects	Yes	Yes
Number of observations	773,318	773,318
R-squared	0.37	0.35

Table 10
Demand Model Estimates
This table presents the maximum likelihood estimates of the demand model described in Section 5.1. For each of the six product modules considered, we report the coefficients for "price", its interaction with household income, as well as the interaction or the organic indicator with household income. All specifications include fixed effects for each alternative (organic, non-organic, and private label). We also allow for age and the existence of kids to shift the utility of the inside options. Standard errors adjusted for store-level clustering. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

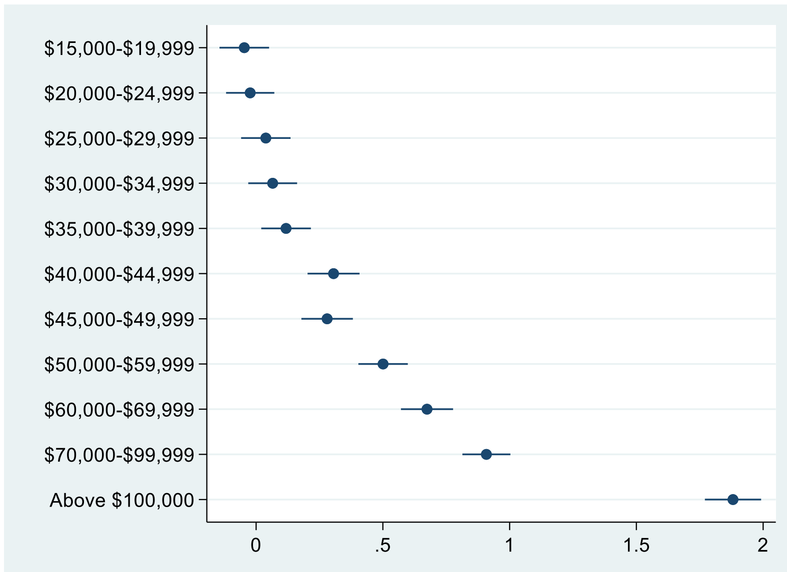
	Eggs	Milk	Salad	Soup	Tea	Tortilla
	(1)	(2)	(3)	(4)	(5)	(6)
Price	-2.789***	-27.44***	-2.355***	-9.501***	-0.970***	-5.613***
	(0.11)	(0.77)	(0.09)	(0.32)	(0.18)	(0.12)
Price × Household income	0.00684***	0.0233***	0.0124***	0.0182***	0.00620***	0.0112***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Organic × Household income	0.00808***	0.0139***	0.00320***	0.00401***	0.00400***	0.00365***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Alternative fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	28,007,211	29,055,111	24,716,381	28,882,160	28,161,885	29,111,062
Log-likelihood	-3,093,074	-4,520,517	-2,520,516	-2,410,916	-1,474,542	-1,945,153

Table 11
Mechanism: relative importance of price vs other preferences
This table leverages the estimates from the structural demand model to understand whether different price sensitivity between high- and low-income consumers is enough to explain differences in purchases of organic products. The first row reports the average difference in prices between organic and conventional products across all store visits by “high income” consumers. Below that, we present predictions from the demand model under three different scenarios: [A] Baseline, the full model; [B] Same as baseline, but forcing “high income” consumers to have the same (higher) price sensitivity as “low income” consumers; [C] Same as baseline but forcing “high income” consumers to have both the price sensitivity as well as other preferences from “low income” consumers. Finally, the last row computes the fraction of the difference between [A] and [C] that is explained by preferences other than prices.

	Eggs	Milk	Salad	Soup	Tea	Tortilla
	(1)	(2)	(3)	(4)	(5)	(6)
Organic Price Premium	69.8%	41.7%	54.5%	54.8%	39.8%	43.0%
Share of organic for “high income” consumers						
Baseline [A]	5.2%	4.8%	8.4%	8.0%	15.0%	10.7%
With "low income" price sensitivity [B]	4.5%	4.5%	6.7%	7.3%	14.3%	9.8%
With complete preferences from "low income" [C]	1.9%	1.0%	4.9%	4.9%	9.9%	6.9%
Fraction explained by non-price preferences ([B]-[C])/([A]-[C])	77.3%	90.9%	51.9%	78.0%	87.4%	76.3%

Figure 1
Organic Spending Share and Household Income Brackets
This figure shows point estimates and 95% confidence intervals for ordinary least squares (OLS) household-level panel regressions of the household's yearly organic share on a set of dummies for each household income bracket. Panel A includes year fixed effects. Panel B includes household and year fixed effects, as well as the same control variables as those in Table 3 (coefficients not shown). Variable definitions are provided in Table A.1 of the Appendix.

Panel A: Regression without household fixed effects



Panel B: Regression with household fixed effects

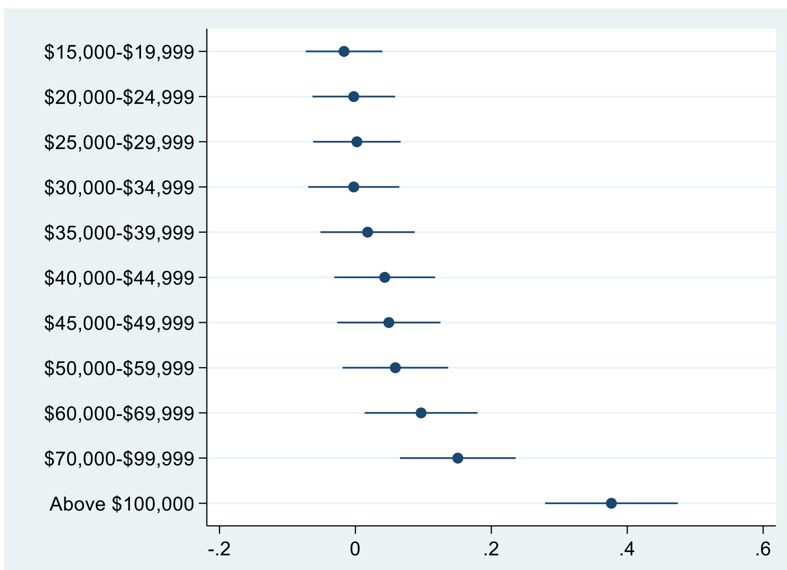
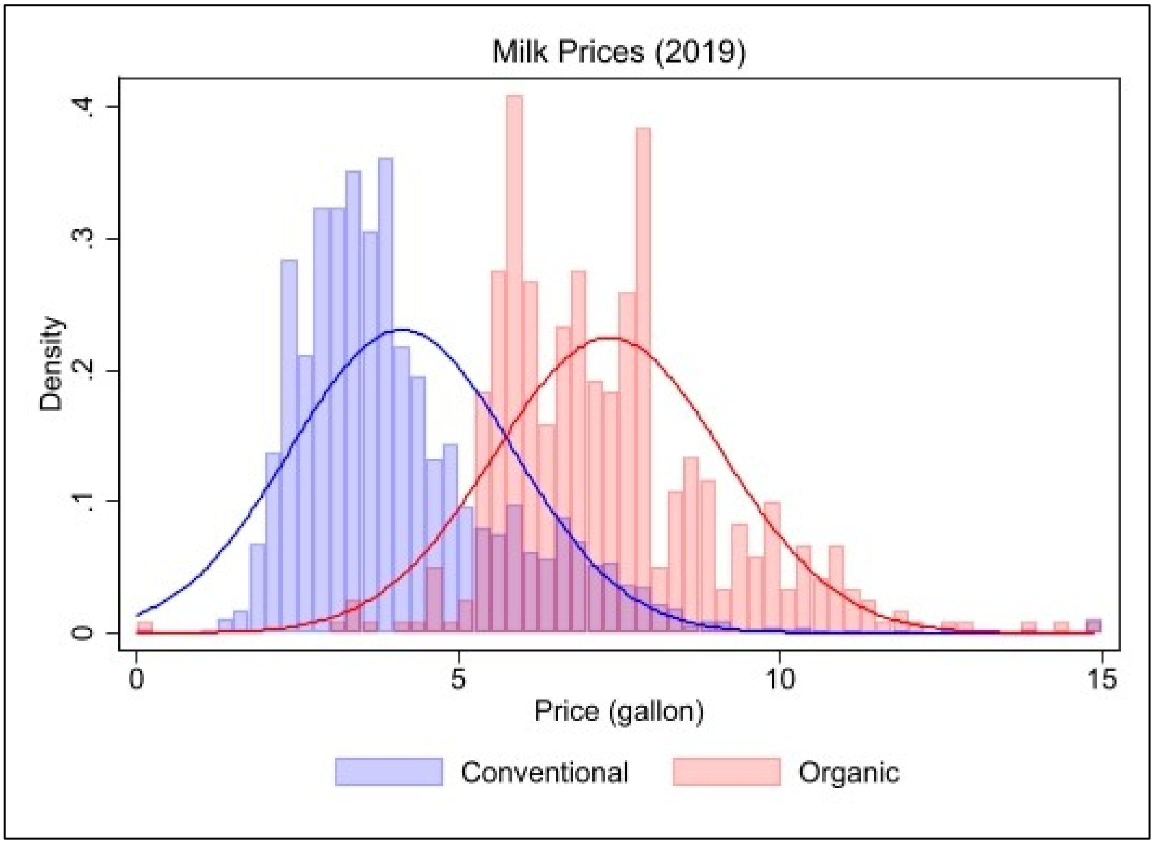


Figure 2
Price differences between organic and non-organic (Milk)
This figure plots histograms for the average price per gallon of refrigerated milk, considering 64 oz. and 128 oz. packages, paid by households across all stores in the sample, during 2019. The blue bars show the empirical distribution for the prices of non-organic (conventional) products, while the red bar show the empirical distribution for organic products. Fitted normal distributions are overlaid on top of the bars. Prices are winsorized at the top and bottom 0.1%.



Internet Appendix for

Income Shocks and Demand for Sustainable Products

Table IA.1
Evolution of Organic Share by Product Group
This table shows the evolution of organic share within each Nielsen's major product category over the sample period. The sample consists of Nielsen's consumer panel data tracking the yearly spending decisions of consumers on food for consumption at home in the 2004-2019 period.

	Alcoholic beverages	Dairy	Deli	Dry grocery	Fresh products	Frozen foods	Packaged meat
2004	0.09%	1.86%	1.83%	0.52%	1.86%	0.37%	0.23%
2005	0.08%	2.05%	2.07%	0.63%	1.93%	0.47%	0.28%
2006	0.08%	2.55%	2.61%	0.89%	3.46%	0.69%	0.35%
2007	0.11%	2.80%	2.36%	1.08%	4.21%	0.73%	0.43%
2008	0.14%	3.01%	2.53%	1.12%	4.71%	0.80%	0.46%
2009	0.18%	2.83%	2.81%	1.24%	4.86%	0.79%	0.47%
2010	0.16%	2.93%	3.30%	1.35%	5.46%	1.00%	0.49%
2011	0.15%	2.86%	3.62%	1.49%	5.78%	1.06%	0.72%
2012	0.20%	2.92%	4.11%	1.65%	6.28%	1.16%	0.66%
2013	0.21%	2.59%	4.80%	1.81%	6.79%	1.28%	0.81%
2014	0.24%	2.76%	5.56%	2.09%	7.67%	1.49%	1.07%
2015	0.35%	3.08%	5.61%	2.50%	8.55%	1.90%	1.19%
2016	0.38%	3.86%	5.78%	3.04%	9.94%	2.37%	1.55%
2017	0.42%	4.47%	5.82%	3.58%	11.29%	2.61%	1.80%
2018	0.39%	4.54%	6.16%	3.89%	12.57%	2.76%	2.23%
2019	0.48%	4.65%	6.16%	3.94%	12.75%	2.84%	2.27%

Table IA.2
Organic Spending and Household Income Growth

This table shows the results of ordinary least squares (OLS) household-level panel regressions of the household's yearly log growth rate of spending in either organic (columns 1 and 2) or conventional (columns 3 and 4) food for consumption at home on the household's income log growth rate. Regressions include the same control variables as those in Table 3 (coefficients not shown). Variable definitions are provided in Table A.1 of the Appendix. Robust standard errors adjusted for household-level clustering are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Organic spending growth		Conventional spending growth	
	(1)	(2)	(3)	(4)
Household income growth	0.01463***	0.01400***	0.00700***	0.00849***
	(0.00496)	(0.00496)	(0.00115)	(0.00115)
Controls	No	Yes	No	Yes
Household fixed effects	No	No	No	No
Year fixed effects	Yes	Yes	Yes	Yes
Number of observations	481,373	481,373	692,095	692,095
R-squared	0.01	0.01	0.01	0.01

Table IA.3
Robustness Checks

This table shows the results of ordinary least squares (OLS) household-level panel regressions of the household's yearly organic share (in percentage) of spending in food for consumption at home on the household's income. Household's income is either the logarithm of the income midpoint associated with each household's income bracket (Panel A), or a set of dummies for each tertile of the distribution of household's income (Panel B). In column (1), the dependent variable is the household's yearly USDA organic certified share of spending. In column (2) the sample is restricted to households that have a sample mean of organic share of at least 0.5%. In column (3), robust standard errors are adjusted for county clustering. In column (4), one lead of household income is considered. In column (5), regression results include Nielsen's household projection factors as sample weights. In column (6), the sample is restricted to most recent 5-year period of the sample. In column (6), year fixed effects are replaced by county-year fixed effects. Regressions include the same control variables as those in Table 3 (coefficients not shown). Variable definitions are provided in Table A.1 of the Appendix. Robust standard errors adjusted for household-level clustering are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Household income

	USDA organic share	Cut-off avg organic share	Cluster by county	Household income (t+1)	Projection factor	2015-2019	County-year fixed effects
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Household income (log)	0.074***	0.124***	0.095***	0.085***	0.085***	0.050**	0.090***
	(0.014)	(0.027)	(0.018)	(0.018)	(0.025)	(0.023)	(0.017)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	No
County-Year fixed effects	No	No	No	No	No	No	Yes
Number of observations	857,767	511,010	857,767	661,995	857,767	282,435	851,018
R-squared	0.78	0.79	0.80	0.80	0.81	0.90	0.81

Table IA.3 (continued)

Panel B: Household income dummies

	USDA organic share	Cut-off avg organic share	Cluster by county	Household income (t+1)	Projection factor	2015-2019	County-year fixed effects
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mid household income	0.053***	0.090***	0.055***	0.056***	0.035	0.056**	0.059***
	(0.016)	(0.032)	(0.020)	(0.021)	(0.031)	(0.028)	(0.019)
High household income	0.145***	0.228***	0.171***	0.139***	0.206***	0.135***	0.179***
	(0.023)	(0.042)	(0.030)	(0.029)	(0.043)	(0.039)	(0.027)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	No
County-Year fixed effects	No	No	No	No	No	No	Yes
Number of observations	857,767	511,010	857,767	661,995	857,767	282,435	851,018
R-squared	0.78	0.79	0.8	0.8	0.81	0.9	0.81

Table IA.4
Demand Model Estimates (by income bracket)
This table presents the maximum likelihood estimates of an alternative specification of the demand model described in Section 5.1. For each of the six product modules considered, we report the coefficients for "price", its interaction with dummies for mid-income and high-income households, as well as the interaction or the organic indicator with mid- and high-income household dummies. All specifications include fixed effects for each alternative (organic, non-organic, and private label). We also allow for age and the existence of kids to shift the utility of the inside options. Standard errors adjusted for store-level clustering. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Eggs	Milk	Salad	Soup	Tea	Tortilla
	(1)	(2)	(3)	(4)	(5)	(6)
Price	-2.912***	-28.74***	-1.553***	-9.956***	-0.476**	-6.573***
	(0.15)	(1.02)	(0.12)	(0.37)	(0.15)	(0.20)
Price × Mid income households	0.0201	1.233	0.0819	1.351***	0.0625	1.030***
	(0.17)	(1.18)	(0.13)	(0.50)	(0.20)	(0.23)
Price × High income households	1.414***	6.617***	0.190	3.061***	-0.147	3.151***
	(0.17)	(1.08)	(0.12)	(0.38)	(0.19)	(0.22)
Organic × Mid income households	0.166**	0.217*	0.154**	0.0649	0.125*	0.0185
	(0.08)	(0.13)	(0.07)	(0.07)	(0.07)	(0.08)
Organic × High income households	0.452***	0.915***	0.407***	0.280***	0.326***	0.104
	(0.08)	(0.11)	(0.06)	(0.07)	(0.07)	(0.08)
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Option fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	28,007,211	29,055,111	24,716,381	28,882,160	28,161,885	29,111,062
Log-likelihood	-3,091,876	-4,511,476	-2,519,751	-2,410,055	-1,473,734	-1,939,785