The Income Elasticity of Households' Greenhouse Gas Emissions: The Case of Grocery Consumption

Jenna A. M. Barrett* Bart J. Bronnenberg† Max J. Pachali‡

October 12, 2026

Abstract

Income is considered a key driver of sustainable consumption. While descriptive studies suggest strong links between income and sustainability, its causal effect on the environmental impact of food consumption remains unclear. This study estimates the income elasticity of the environmental impact of household grocery purchases, the primary source of household food choices. Using panel data that includes (1) household-level scanner data on grocery purchases in two European countries and the United States and (2) product category-level environmental impact estimates, we report that a 1% increase in income leads to negligible rises in grocery-related greenhouse gas (GHG) emissions in Germany, the Netherlands, and the United States. We test whether these small effects mask opposing impacts on quantity versus composition of shopping baskets, but find minor effects in both dimensions. Robustness checks show our findings hold across sub-samples and time horizons, and for income changes of different magnitude and persistence. Precise administrative income data for the same households and periods in the Netherlands demonstrate our findings are not driven by imprecise measurement of income. Overall, income variation has limited influence on shifts toward lower-carbon-footprint grocery consumption, which has implications for policies to reduce environmental externalities in food consumption, and for income-based targeting strategies in the retail sector.

Keywords: income elasticity, environmental impact of grocery food consumption, consumer purchase behavior, substitution effects.

*Department of Marketing, Tilburg School of Economics and Management, Warandelaan 2, 5037 AB Tilburg, The Netherlands. e-mail: a.m.barrett@tilburguniversity.edu.

†Department of Marketing, Tilburg School of Economics and Management. e-mail: bart.bronnenberg@tilburguniversity.edu.

‡Department of Marketing, Tilburg School of Economics and Management. e-mail: m.j.pachali@tilburguniversity.edu.

1 Introduction

The global food system is a major source of environmental externalities, contributing between 26% and 34% of greenhouse gas (GHG) emissions (Crippa et al., 2021; Ritchie et al., 2019) and accounting for 78% of aquatic eutrophication, 50% of habitable land use, and 70% of freshwater withdrawals (Ritchie et al., 2022). While these impacts are global in scale, they are affected by consumption decisions made at the household level (Bronnenberg et al., 2026). In particular, the retail grocery sector serves as the primary setting for these choices, providing approximately two thirds of total caloric intake in the United States (Wolfson et al., 2025) to over 80% in countries such as the Netherlands (Van Rossum et al., 2020). Because these everyday grocery decisions directly influence the externalities of food consumption, they form a natural target for policy interventions (e.g., Allcott et al., 2019; Dubois et al., 2020). Such policies require an understanding of how household income affects the environmental impact of shopping baskets through consumption quantities and diet change for several reasons.

First, understanding how income affects grocery-related GHG emissions is relevant to the design of tax policy. If higher income causally increases emissions, progressive income taxation may place a greater burden on households whose higher income generates more emissions and may reduce emissions indirectly by lowering disposable income. However, if the income elasticity is close to zero, this indirect effect on emissions will be limited, and reducing grocery-related emissions may require policies that directly target high-emission foods.

Second, measuring the income elasticity of the environmental impact of food is relevant from a business perspective. For example, to target different consumer segments and determine assortment across local markets with different income profiles (Bollinger et al., 2023), firms pursuing green policies need to know how income affects sustainable food consumption. Additionally, because our analysis covers entire shopping baskets, firms can learn how spending across product categories varies with household income. This information is essential for designing targeted marketing and promotional strategies tailored to the income distribution of a local market.

The aim of this research is to provide precise measurement of income elasticities of the environmental impact of grocery consumption. We focus on groceries as they account for the large majority of calories purchased.[1] Measuring the income elasticities of environmen-

[1] Cherchye et al. (2020) note that the grocery channel accounts for 85% of calories purchased by households. We acknowledge that income may also raise emissions through increased eating out or food-delivery. These are

tal impact of grocery consumption is challenging for theoretical and empirical reasons. To start, micro-economic theory does not predict the magnitude or direction of the elasticity of emissions from food consumption with respect to household income. Income may impact the quantity contained in, and the composition of, household shopping baskets in different, even opposite, ways (Colen et al., 2018; Muhammad et al., 2017). For instance, holding basket composition constant, more income may enable households to consume larger quantities of foods (Scholdra et al., 2022), which raises emissions. At the same time, holding quantities constant, more income may allow consumers to substitute into more expensive and more sustainable products, lowering emissions. Different food types have widely varying impact on the environment (Clark et al., 2022; Poore and Nemecek, 2018). For instance, the GHG emissions associated with producing beef for consumption are 9 times those of the same amount of chicken and 125 times those of the same amount of plant-based protein (Poore and Nemecek, 2018). Income-driven changes in basket composition therefore impact the environmental impact associated with household shopping baskets. As income can affect both quantity and composition of household consumption baskets, there is no clear theoretical prediction for the sign or size of the income elasticity of environmental impact.

Beyond the uncertainty regarding quantity and composition effects, there is no clear theoretical prior on how households adjust grocery consumption in response to different *types* of income shifts. The permanent income hypothesis (PIH) predicts that households smooth consumption over income fluctuations if they expect them to be short-lived but may change behavior in response to long-term changes in expected income. For instance, Aguiar and Hurst (2005) demonstrate that a shock to permanent income, such as unemployment, leads to a decline in food expenditure. Other papers report strong sensitivity to current income (Gicheva et al., 2010; Parker et al., 2013; Souleles, 1999). For example, Gicheva et al. (2010) find excess sensitivity of grocery expenditure to current income and argue that whereas groceries represent a relatively small share of total household expenditure, they can be adjusted more flexibly in the short term than other expenses. In addition, households may find it difficult to perfectly anticipate their long-term income trajectories, or they may simply be myopic. This too would lead to sensitivity of purchase patterns to current income (Jappelli and Pistaferri, 2010). Taken together, there is no clear theoretical prior on whether and how the environmental impact of grocery consumption is affected by shorter-term vs. longer-term income changes. Our study

unobserved in our data.

determines their role in driving sustainable grocery choices.

The literature studying the role of income on sustainable consumption faces several empirical challenges. First, a common issue in many empirical studies is their focus on the cross-sectional relationship between income and environmental impact (see Pottier, 2022, for a recent survey of this literature). This relationship is vulnerable to critiques of omitted variable bias and can be spurious, e.g., when unobserved consumer characteristics –such as education or attitudes towards the environment– are correlated with both income and food choices. Second, existing estimates of the relationship between income and environmental impact are often based on aggregated data, e.g., national or regional averages in income and consumption (e.g., Bruckner et al., 2022; Chancel, 2022; Pottier, 2022), making it difficult to control for observed and unobserved household characteristics that affect sustainable consumption. Third, existing research on income and consumption has focused on a single or a few specific food categories, some of which may be inferior goods (e.g., Cuffey et al., 2023; Gicheva et al., 2010). A final problem is that micro studies often measure income through self-reports in surveys, which can be both imprecise and error-prone (Brancatelli et al., 2022). Measuring an independent variable incorrectly, such as income in our case, can bias estimates of its effect on environmental impact, most likely attenuating them toward zero. As a result, it can be difficult to determine whether weak estimated effects between income and environmental impact reflect a genuine absence of association or arise from imprecise measurement of income. The objective of this paper is to measure the income elasticity of the environmental impact of annual grocery shopping baskets, and to overcome the empirical problems stated above by (1) studying household level purchase behavior, (2) using a detailed and comprehensive accounting system of the environmental impact of all grocery foods, and (3) validating our estimates with highly accurate measures of household income.

First, we use grocery purchase data from household panels from three markets: Germany (DE), the Netherlands (NL), and the United States (US). Germany and the United States represent major Western economies, while the Netherlands provides unique access to high-quality household income data. Together, these countries allow us to study the income elasticity of GHG emissions associated with grocery consumption in a robust and generalizable way. We obtain data from YouGov.com covering 65K German households and 19K Dutch households over the years 2011-2022. In addition, we use household scanner data from Nielsen covering

143K American households over the years 2011-2020.[2]

Second, we complement the description of barcodes in these purchase data with consensus estimates of environmental impacts like GHG emissions, land use, water use and overfertilization. These consensus estimates are so-called life-cycle estimates, capturing the environmental impact across all stages of the production- and commercialization cycle in the supply chain. These environmental impact data exist by product category, e.g., "beef and lamb," "cheese," or "coffee" (see Clark et al., 2022). We assign environmental impact to each household's annual purchases by merging these life-cycle estimates to barcodes using standardized category descriptors from Bronnenberg et al. (2026), which are obtained by mapping the Clark et al. (2022) categories into Dutch-, German-, and US scanner data.[3] Various measures of food-related environmental impact can be constructed from these data. We focus mainly on (1) the total greenhouse gas (GHG) emissions associated with a household's annual shopping basket and (2) the GHG intensity, measured as GHG emissions per 100 grams of that basket. An important advantage of these measures is that they quantify the ecological footprint of a household's annual grocery shopping across all food categories, i.e., not a subset.[4]

Third, we incorporate income data for the households represented in our consumption panel. For all three countries, we commence by tracking changes in self-reported household income over the observed time period. A unique feature of the Dutch panel is that we are able to incorporate administrative income data for the same households represented in our consumption panel. These data come directly from government tax records and cover the precise household income from labor, non-labor (e.g., from wealth), and government assistance for 78.8% of Dutch YouGov.com panelists.

To eliminate the most important concerns associated with studying cross-sectional variation in income and shopping baskets, we exploit the panel structure of the consumption and income data. Our main empirical approach is to estimate the effect of income on the environmental impact of shopping baskets using a specification that includes household fixed effects, while controlling for time trends and changes in demographics, e.g., household size. Our identifying assumption is that personal income changes are uncorrelated with unobserved changes in

[2]Since the allocation of UPCs into high-level categories changed substantially in the Nielsen data from 2021 onward, we restrict our analysis to panel years with a consistent product hierarchy.

[3]Bronnenberg et al. (2026) complement our analysis by examining how a knowledge gap acts as a barrier to sustainable consumption, whereas we focus on how household financial resources drive consumption patterns across supermarket aisles and their associated environmental impacts.

[4]Because our conclusions on GHG emissions generalize to the other types of environmental impact, we limit our discussion in the paper to this case.

preferences for sustainable foods.

We report the following findings, starting with a cross-sectional analysis as a benchmark. Using self-reported income data covering Germany, the Netherlands and the United States our cross-household estimate of the income elasticity of environmental impact is 0.26 (s.e. = 0.002) in Germany, 0.46 (s.e. = 0.004) in the Netherlands and 0.11 (s.e. = 0.001) in the United States. This implies that, for these countries, a 1% rise in income is associated with a 0.11%-0.46% increase in GHG emissions. These estimates are in line with similar estimates in the literature (see, e.g., Pottier, 2022). However, using only within-household income and consumption variation, we estimate that the income elasticity of environmental impact in terms of GHG emissions is smaller by an order of magnitude and ranges from 0.010 (s.e. = 0.003) in the United States to 0.039 (s.e. = 0.007) in the Netherlands. These estimates are remarkably comparable between the three countries studied. Next, we show that these effects are not attenuated by the use of self-reported income data. Indeed, a validation with administrative income records in the Dutch panel shows an even smaller income elasticity estimate of 0.024. Our estimation is precise and rules out income elasticities smaller than 0.012 and larger than 0.036.

We next allow for the possibility that these effects constitute sizable but oppositely signed effects on quantity versus composition of shopping baskets. We show that the income elasticity of GHG emissions can be decomposed into a purchase quantity effect and a GHG intensity (emissions per quantity) effect of the composition of the basket. Our analysis shows that both effects (quantity and intensity) are very small, rejecting the case that their effects are large and off-setting.

Our income elasticity estimates are robust to a large set of alternative specifications that allow the possibility of larger effects in subgroups or across time. For instance, we report no substantively larger effects for longer-term income changes over a period of three years, and do not find meaningful differences in the income elasticity when conditioning on specific groups, such as low-income households or households with low emissions. Across all robustness checks, we report very small effects of household income on the environmental impact and environmental intensity of grocery purchases.

We also account for the possibility that positive income shocks raise future emissions through compounding of household wealth. For the Netherlands, our analysis suggests that this indirect effect is also very small. Summed over a 20-year horizon of wealth accumulation,

we estimate that a 1% increase in income indirectly raises grocery-related GHG emissions by an additional 0.015% through wealth effects. Thus, even though this effect is incremental, the income elasticity –representing both direct and indirect effects– remains small in magnitude.

Finally, to flexibly control for price effects across grocery food aisles and to explicitly model the mechanism through which household income influences grocery consumption, we estimate a structural demand model with multi-level budget allocations. More specifically, in Appendix D, we estimate demand for emissions-intensive grocery aisles while accounting for price levels of substitutes to grocery foods like restaurants and general merchandise. The results provide further support for our conclusion that income does not meaningfully affect greenhouse gas emissions from households' grocery shopping baskets: the implied elasticities of grocery related GHG emissions with respect to income range from 0.041 (s.e. = 0.004) in Germany to 0.064 (s.e. = 0.006) in the Netherlands and confirm our main finding of economically negligible effects.

We conclude that the empirical correlation between incomes and the environmental impact from household demand in Germany, the Netherlands, and the United States is likely caused by other factors than income and discuss the implications of this finding for consumption policy and marketing practice.

The remainder of this paper is organized as follows. Section 2 discusses our data and some descriptive results. Section 3 reports on the empirical strategy and contains the main results of the paper, as well as several robustness checks and heterogeneity analyses. Section 3 also discusses the results of our structural model and economic impact. Section 4 concludes.

2 Data

2.1 Purchase Data

We use two primary data sources for purchase data. First, we use 2011-2022 YouGov (formerly GfK) consumer purchase panel data covering the grocery purchases of German and Dutch households over time. We also use 2011-2020 Nielsen consumer panel data covering grocery purchases of American households. Both data sets record individual households' purchases of fast moving consumer goods, both food and non-food, across different retailers and time periods. Panelists in both consumer panels use a home-scanning device to scan the barcodes of

each purchase made during a shopping trip.[5] For our analyses, we retain all of a household's food purchases and aggregate these over time to annual household shopping baskets. We drop observations of the first and last year of a panelist's tenure on the panel to ensure comparing full-year shopping baskets only. Combined, our panels cover over 227K unique households and approximately 116 million shopping trips.

– insert Table 1 here –

Table 1 shows the sample sizes by country and year. For instance, in a typical year the German sample contains about 23-26K households who are actively scanning throughout the year. For the Netherlands this is about 9K and for the US around 60K unique households.

Table 2 shows that YouGov panelists report a total annual average volume of 629 kilograms of grocery foods at an average value of €$1,842$ in Germany and 880 kg and €$2,535$ in the Netherlands. These purchases originate from 123 (DE) and 151 (NL) shopping trips per year on average, or $2.5-3$ shopping trips per week. These figures are consistent with those obtained from independent surveys conducted annually by Deloitte, e.g., that households make between 2 and 3 shopping trips to grocery stores a week (Deloitte, 2023). For the Nielsen households in the US, we see an average of 848 kg of grocery foods at an average value of $\$2,911$, with on average approximately 2 shopping trips per week. The data suggest panelists are diligent in scanning.

– insert Table 2 here –

2.2 Environmental Impact of Household Purchases

Measuring Environmental Impact We compute the environmental impact of panelists' annual shopping baskets using a data set developed by Clark et al. (2022). They represent each of 57,000 universal product codes (UPCs) as a collection of ingredients and measure a product's environmental impact by summing the impacts of each item in that collection. They further classify these UPCs into 63 product categories that are called "supermarket aisles." Next, they report the environmental impact in terms of greenhouse gas emissions, land use, fresh water withdrawals, and eutrophication potential for each of these 63 supermarket aisles.

[5] In the United States, we restrict our sample to Magnet households. These are panelists that also record quantities of purchases of products like fruits, vegetables and meats, that are often purchased in non-standard amounts.

Mapping UPCs into the same classification of supermarket aisles allows us to translate a household's shopping basket into greenhouse gas (GHG) emissions, as detailed in Bronnenberg et al. (2026). We also define a normalized metric, called GHG intensity, as the GHG emissions per 100 grams of a given basket.

Environmental Impact across Households Next, we report statistics on the environmental impact in terms of GHG emissions of annual shopping baskets of panelists, as well as the GHG intensity of these baskets in Table 3. In Germany, GHG emissions of annual grocery shopping baskets average $2,832$ kgCO_2eq with a standard deviation of $2,007$ kgCO_2eq, and the GHG intensity is 0.47 kgCO_2eq per 100 grams of food (SD = 0.15). In the Netherlands, GHG emissions of annual grocery shopping baskets average $3,799$kgCO_2eq with a standard deviation of $2,317$ kgCO_2eq, and the GHG intensity of a shopping basket is 0.44 kgCO_2eq per 100 grams of food with a standard deviation of 0.12. Finally, in the US the average GHG emissions are $3,778$ kgCO_2eq (SD = $2,553$) and the average GHG intensity is 0.47 kgCO_2eq per 100 grams of food (SD = 0.21).

Environmental Impact across Categories The environmental impact of shopping baskets is heavily concentrated in certain aisles (see, e.g., Clark et al., 2022). Figure 1 displays the average GHG emissions per 100 grams of supermarket aisles. Aisles that contain animal protein such as meat, dairy and cheese contribute most to environmental impact. The average environmental impact per 100 grams is the highest for the Beef and Lamb aisle at just under 8 kgCO_2eq per 100 grams, whereas the aisle (other) Meat is less than 2 kgCO_2eq per 100 grams. Cold beverages and plant-protein based products have the lowest environmental impact per 100 grams. In contrast, the environmental impact of coffee and tea per 100 grams is relatively high. Note that the dispersion in GHG emissions across aisles implies that household substitution behavior can have large effects on the sustainability of a food basket, even holding quantity constant.

– insert Figure 1 here –

2.3 Demographic Data

YouGov and Nielsen YouGov and Nielsen collect demographic data from panelists such as age, income, and household size. Table 3 displays the demographic characteristics of the

sample for Germany, the Netherlands and the United States respectively. The income definitions used vary slightly between the panels. In the YouGov panel, income refers to the labor income of the main earner. In the United States, income refers to total household income. In all three countries, income measures are collected through self-reported surveys, and income is reported in broad categories. The mean income of the main earner reported by YouGov households is €$2,443$ in Germany and €$2,389$ in the Netherlands. In the US, mean household income is $\$5,971$. These numbers are very close to national averages.[6]

– insert Table 3 here –

Administrative Data We have collected additional income data sourced from Statistics Netherlands (CBS), the central bureau of statistics in the Netherlands. Statistics Netherlands provides secured access to household-level microdata for researchers, under strict privacy regulations and anonymization.[7] In this research, we use microdata on household income and wealth and match it to the YouGov purchase data of Dutch households. The CBS data on Dutch income data are directly drawn from administrative sources such as local governments, banks, and insurers. Dutch citizens are required by law to report personal income and other tax-relevant information such as wealth or marital status (Bakker and Daas, 2012; Bakker et al., 2014). Income includes labor and non-labor income, e.g., government aid or social security. Income and wealth data are sourced directly from the Dutch Tax Administration (e.g., labor income, capital, property value), the Education Executive Agency of the Dutch Ministry of Education (e.g., student loans), the Institute for Employee Insurance (e.g., unemployment benefits). The administrative data on income and wealth is collected annually. Using these sources, Statistics Netherlands defines disposable income as gross household income (the sum of income from work of all household members, unemployment benefits, and income from wealth)[8] mi-

[6]For example, Statistics Netherlands reports that a household with a single earner on average has a net annual income of €30,700 in 2020, reflecting an average net monthly income of €2,558 (https://longreads.cbs.nl) and the median household income in the United States was approx. $5,627 per month in 2020 (https://www.census.gov). In Germany, the median net household income for couples with children was €30,714 per year (€2,560 per month), based on EU-SILC data from the Federal Statistical Office (Destatis, survey year 2025; income reference year 2024) (https://www.destatis.de).

[7]Matching administrative income and wealth data is only possible for YouGov panelists who consent to share their data with Statistics Netherlands. YouGov panelists and administrative data are matched by Statistics Netherlands, i.e., not by us, the researchers, or by YouGov. Matching is done using a combination of address data and date of birth shared by the databases of YouGov and the Central Person Registry of the Netherlands. Statistics Netherlands is able to identify a person based on the combination of these records, and provides a file which links YouGov panelist IDs to a pseudo social security number that can act as a merge field for administrative and purchase data.

[8]Income from work includes wages and salaries of employees plus the attributed pay for self-employed people and family members working in the family business. It also includes government aid and unemployment benefits.

nus the sum of alimony payments, income and health insurance premiums, and taxes on income and wealth. These data help us assess error-in-variables problems in our empirical strategy by testing whether using the regular income measures from the YouGov annual household survey produces very different estimates of the income elasticity.

In total, we observe 84,406 panelist-years with both full-year purchase data and administrative income data, reflecting 78.8% of Dutch YouGov panelists. Consenting panelists have largely similar ages, household sizes, income and GHG emissions from grocery consumption as panelists that do not consent. We further describe the differences in observable characteristics between the full sample and consenting panelists in Appendix A.

3 Income and the Environmental Impact of Grocery Baskets

3.1 Descriptive Specification

We focus on the effect of income Y_{ht}, for household h in year t, on two dependent variables: (1) the total GHG emissions, E_{ht}, associated with household h's grocery basket in year t, and (2) the GHG intensity, I_{ht}, defined as the GHG emissions per 100 grams of that basket. Our main specification measures these effects directly as income elasticities using a descriptive log-log specification with a rich set of controls. In the case of total GHG emissions, E_{ht},

$$\log(E_{ht}) = \gamma_h + \gamma_t + \eta_E \log(Y_{ht}) + \beta' x_{ht} + \epsilon_{ht}. \tag{1}$$

We include household fixed effects, γ_h, to account for time-invariant household differences in the emissions from grocery food purchasing. We also use year fixed effects, γ_t, to flexibly control for trends in emissions over time. In some specifications, we also include observed characteristics, x_{ht}, to additionally control for time-varying characteristics like household size and the amount of wealth. Furthermore, the ϵ_{ht} are stochastic terms that account for unobserved factors. The coefficient of interest is η_E which is a direct estimate of the income elasticity of GHG emissions.

Income from wealth includes the sum of the income from financial assets, income from real estate, and income from other property, minus interest paid.

3.2 Identification Strategy

Our empirical strategy relies on within-household income changes. Table 4 reports that large differences across adjacent years are not unusual for a household. Across all households and pairs of adjacent years, the 5th percentile of year-over-year income change for a household is equivalent to a $21.4-36.4\%$ drop in income, whereas, conversely, the 95th percentile represents a $40.0 - 66.7\%$ rise of income.[9] To illustrate the frequency and magnitude of changes, we provide histograms of the income variation per year in Appendix B.

– insert Table 4 here –

Our main identification assumption is that –conditional on the fixed effects and control variables– this variation in household income Y_{ht} is quasi-exogenous and orthogonal to unobserved demand factors ϵ_{ht}. Under this assumption annual household income is not influenced by factors such as changes in household food preferences that impact the greenhouse gas emissions of their shopping baskets. While we cannot formally test this assumption, we believe it is reasonable. We use several (positive and negative) income changes that, conditional on year fixed effects and controls, introduce random variation in incomes as different household segments were differently affected by these changes. This strategy aligns with similar approaches that examine the effects of income changes on private label demand based on household scanner panel data (Brancatelli et al., 2022; Dubé et al., 2018). For instance, we use residual (across households) variation from the recession in the aftermath of the financial crisis (2011-Q4 until 2013-Q3). Further, we use changes in incomes in years from industry-specific collective labor agreements. Depending on the industry households worked for, these macro shocks create random residual variation in income, even conditional on year fixed effects.

A potential concern is that the rich specification of fixed effects and control variables absorb most of the variation in household income. However, we find that, after accounting for panelist- and time-fixed effects, there is 13.6% residual variation left in income in Germany, 16.0% in the Netherlands and 11.8% in the United States.[10] We thus retain sufficient residual variation to infer the causal relationship between income changes and the emissions associated with households' shopping baskets.

[9] Because income is reported in brackets, small income changes are not observed when households remain within the same bracket, and the median annual growth rate of income is 0% in these samples. As a result, our income change measure primarily captures income changes that lead to bracket transitions. Validation with administrative income shows a median income growth rate of 2.89% in the Netherlands.

[10] A conservative estimate based on 90% winsorized income data still estimates residual variation to be a sizable 12.4%, 15.8% and 10.6% for Germany, the Netherlands and the United States respectively.

3.3 Household Level Analysis: Germany, the Netherlands and the United States

Cross-Sectional Analyses of Income and the Total Environmental Impact of Shopping Baskets Before reporting on the estimates of the log-log specification (1) above, we first report on cross-sectional analyses of the relationship between household income and total environmental impact in Columns 1-3 of Table 5. Columns 1-3 show a sizable and positive income elasticity for total environmental impact across households of $\eta_E = 0.263,\ (\text{s.e.} = 0.002)$ in Germany, of $\eta_E = 0.457,\ (\text{s.e.} = 0.004)$ in the Netherlands, and $\eta_E = 0.107,\ (\text{s.e.} = 0.001)$ in the United States, suggesting that income increases are associated with higher levels of emissions from grocery food consumption. The elasticities are largely unaffected by the inclusion of time-fixed effects (Columns 4-6). At the same time, they reduce dramatically when controlling for household characteristics (Columns 7-9). In particular, we report that including household size and social groups reduces the income elasticity to roughly a seventh of its size in Germany ($\eta_E = 0.034,\ \text{s.e.} = 0.003$) and the Netherlands ($\eta_E = 0.067,\ \text{s.e.} = 0.004$), and turns negative in the United States ($\eta_E = -0.023,\ \text{s.e.} = 0.001$). Since the cross-sectional analysis can be confounded when (unobserved) household characteristics correlate with both income and the environmental impact of grocery food consumption, we next employ a within-household analysis to derive a causal interpretation of our estimates.

– insert Table 5 here –

Within-Household Income Changes and the Total Environmental Impact of Shopping Baskets In Columns 10-12 of Table 5, we estimate the income elasticity of environmental impact controlling for panelist- and time-fixed effects and for time varying household characteristics. We report very small elasticity estimates of $\eta_E = 0.024$ with a standard error of 0.005 in Germany, $\eta_E = 0.039$ with a standard error of 0.007 in the Netherlands, and $\eta_E = 0.010$ with a standard error of 0.003 in the United States.[11] These estimates imply that increasing a household's disposable income by 1% leads to an increase in the total greenhouse gas emissions of the shopping basket by $0.010\% - 0.039\%$. At the 95% confidence level, our estimates rule out elasticities outside the interval $0.014 - 0.034$ in Germany, outside $0.025 - 0.053$ in the Netherlands, and outside $0.004 - 0.016$ in the United States. We conclude that the income elasticity of greenhouse gas emissions associated with grocery purchasing is very small. The

[11] The standard errors are all clustered at the household level.

estimates from our within-household regression specifications are more than an order of magnitude smaller than those from the cross-sectional specifications without household controls.

Cross-Sectional Analyses of Income and the Environmental Intensity of Shopping Baskets To estimate the income elasticity of GHG intensity, we replace GHG emissions, E_{ht}, in Equation (1) with GHG intensity, I_{ht}, and use the same estimation strategy to obtain an estimate of the income elasticity, η_I, with respect to the environmental intensity of shopping baskets.[12] The estimated coefficient η_I represents the percentage change in GHG intensity from a percentage change in income. We interpret this elasticity as an indicator of how income affects basket composition in terms of eco-friendliness and whether households move into more or less polluting food aisles in response to income changes, holding quantities fixed.

Table 6 reports the results. As before, Columns 1-3 report cross-sectional estimations for each country. We find a small but negative income elasticity for the GHG intensity of a shopping basket in the Netherlands. This means that higher-income households have baskets with a composition that, per unit of volume, has lower emissions. In Germany and the United States, we also find small income elasticities for the GHG intensity of a shopping basket, but with a positive sign, implying that in these countries higher-income households have, on average, higher emissions per 100 grams of purchase volume. These estimates are largely unaffected by the inclusion of time-fixed effects (Columns 4-6), and shrink further toward zero after controlling for household size and social group (Columns 7-9).

– insert Table 6 here –

Within-Household Income Changes and the Environmental Intensity of Shopping Baskets Columns 10-12 of Table 6 report the within-household estimates for the basket composition effect η_I. Once we account for persistent household differences, we find that the effects are effectively equal to 0 in all countries. The estimated elasticity in Germany is $\eta_I = 0.007\,(\text{s.e.} = 0.003)$,[13] in the Netherlands it is $\eta_I = 0.009\,(\text{s.e.} = 0.004)$, and for the United States we estimate an elasticity of $\eta_I = -0.004\,(\text{s.e.} = 0.002)$. A 1% higher income is

[12] Appendix C develops how the income elasticities of GHG emissions, η_E, and of GHG Intensity, η_I are functionally related to income elasticities of quantities, η_Q, and to each other. Specifically, one can show that the income elasticity of GHG emissions is equal to the sum of the quantity elasticity and GHG intensity elasticity, $\eta_E = \eta_Q + \eta_I$ (see also Web Appendix 1.1).

[13] This estimate means that increasing income by 1% for a German family, leads to a precise increase in the greenhouse gas intensity of only 0.007%, effectively 0.

thus associated with 0.007% higher GHG per 100 grams in Germany and 0.009% in the Netherlands, whereas it is associated with a reduction of 0.004% in the United States. In other words, the effect of income on GHG intensity of grocery shopping baskets is close to negligible.

Structural Model To complement the reduced-form results, we estimate a structural model of the income elasticity of greenhouse gas emissions from food bought in grocery stores for the three countries. In particular, we estimate a multi-stage budgeting model using the almost ideal demand system (or AIDS, see, e.g., Deaton and Muellbauer, 1980). This model adds two main benefits. First, it explicitly accounts for different mechanisms of how income affects emissions, e.g., through an expansion of budget for grocery foods or, alternatively, via substitution towards lower emission products. Second, the structural model enables us to control for the impact of (own and competitors') prices on purchase behavior. We present the model, its derivation, and full set of structural estimates in Appendix D. The structural estimates imply that a 1% income increase raises emissions by 0.041% (s.e. = 0.004) (DE), 0.064% (s.e. = 0.006) (NL), and 0.042% (s.e. = 0.004) (US). The elasticities implied by the two-stage structural demand model are very close to zero, and confirm our main result that income has an economically small effect on greenhouse gas emissions from households' grocery baskets and its causal effect is much smaller than typically reported in the literature.

Discussion While food-related GHG emissions vary significantly across households with different income levels, our analysis finds that once we account for persistent household characteristics, the causal effect of household income on the environmental impact of food purchases is very small. This pattern of results is consistent across three markets: Germany, the Netherlands and the United States.

The cross-sectional and within-household estimates differ by more than an order of magnitude, with much of the gap closing once household size is held constant, indicating that the emissions differences observed across income levels are largely attributable to correlated household attributes rather than to income itself. At the same time, the cross-sectional estimates remain informative about the heterogeneity in greenhouse gas emissions across households at different income levels. While changes in income over time may contribute to these cross-sectional differences, our within-household estimates show that the response of emissions to changes in income is small. We quantify the environmental and economic impact of these income effects in Section 3.7.

Finally, we note that our estimates are not specific to greenhouse gas as an indicator of environmental impact. We repeated our analysis using a composite index of greenhouse gas emissions, eutrophication (over-fertilization) potential, water use and land use (construction of this index follows Clark et al., 2022, exactly). We again find elasticities that are very close to 0, i.e., substantively, we find the same results for a more inclusive definition of environmental impact.

3.4 Short-Term versus Longer-Term Income Variation

Our main estimates of the income elasticity are based on all income variation, including short-run fluctuations that may be transitory and not fully reflected in consumption behavior. To examine whether the income elasticity differs for more persistent income changes, we construct three longer-term income proxies from each household's own experienced income trajectory, based on a three-year window that smooths over year-to-year variation. The first is a forward-looking measure that assumes perfect foresight and discounts actual income over the next two years ($t+1$, $t+2$) back to year t at an annual rate of 3 percent. The second is a centered measure, the average of income in the surrounding three years, $t-1$, t, and $t+1$. The third is a backward-looking measure, the average income in year t and the two preceding years. Each measure replaces current income in our baseline specification, uses panelist- and year fixed effects, controls for household size (including its leads or lags matching each income window) and social group. We display the coefficients per specification in Figure 2 and report the full analyses in Web Appendix 1.2. The income elasticity remains very small under all three longer-term measures, consistent with the estimates presented earlier. Using the forward-discounted measure, a 1% increase in permanent income is associated with a change in emissions of 0.039% (s.e. = 0.011) in Germany, 0.057% (s.e. = 0.012) in the Netherlands, and –0.012% (s.e. = 0.006) in the United States. Using the centered- and the backward-looking measure yields similar results. For emission intensity, the estimates vary little across the longer-term income measures and are not statistically distinguishable from the current-income specification, ranging from 0.007 (s.e. = 0.003) to 0.019 (s.e. = 0.005) in Germany, 0.009 (s.e. = 0.004) to 0.024 (s.e. = 0.007) in the Netherlands, and –0.010 (s.e. = 0.004) to –0.001 (s.e. = 0.004) in the United States. In sum, we do not find evidence that the emissions associated with the production of grocery baskets respond differently to more persistent income changes, at least not within the context of our data.

– insert Figure 2 here –

3.5 Heterogeneity Analyses

In this section, we provide several heterogeneity analyses for the income elasticity of environmental cost, η_E, and environmental cost intensity, η_I.

Heterogeneity across Income Levels The effect of income on the environmental impact of consumption may vary across different income levels. In particular, for higher-income households food expenditures are a smaller component of incomes than for lower-income households. We allow income elasticities to vary with income, i.e., per Engel's Law. Specifically, we classify households into low-income and high-income groups based on their income level relative to the median income (at the time of entry into the panel). We next test whether the effect of income on environmental impact differs based on the income level. Table 7 shows that –consistent with Engel's Law– lower-income households exhibit a slightly higher income elasticity of total environmental costs than their higher-income counterparts across all three countries. The elasticity is 0.043 among low-income and -0.023 among high-income households in Germany, 0.052 versus essentially zero in the Netherlands, and 0.020 versus -0.014 in the United States. From these numbers we conclude that higher-income households have significantly lower income elasticities than lower income households. However, the income elasticity for both groups is very close to 0. In addition, Table 8 shows that we find no substantive differences in the income elasticity of environmental intensity across income groups, suggesting that income variation has no meaningful effect on the composition of emissions of household grocery consumption.

Heterogeneity across Emission Levels A household that already purchases an environmentally friendly food basket may have limited scope for further emission reductions. Consequently, its response to income may be smaller than that of a household with higher baseline emissions. We test for these possibilities by dividing households using a median split on their emission level based on total GHG emissions at the year of entry into the panel and test whether the income effect on emissions is contingent on the baseline emission level. Table 7 reports no economically meaningful effects of the interaction of income changes and baseline emission level on emissions: the interaction of income with baseline emissions is 0.029 (s.e. = 0.006)

in Germany, -0.009 (s.e. = 0.008) in the Netherlands, and -0.002 (s.e. = 0.003) in the United States. To illustrate the magnitudes involved, Germany exhibits the largest interaction effect of the three countries, yet a 1% increase in income is associated with a change in emissions of 0.005% among low-baseline households and 0.033% among high-baseline households. Similarly, in the case of GHG intensity, the interactions are statistically significant but small in magnitude (Table 8). Baseline emission levels do not moderate the income-emissions relationship in any substantive way. This pattern seems to contradict the possibility that income shocks affect higher-emission households more.

Heterogeneity across Generations The income effect on environmental impact may be confounded by generation-specific developments in consumption over time. For instance, the transition from college years to joining the labor market may not only be associated with an increase in income, but also with a development in cooking preferences and changes in consumption behavior. To flexibly control for these and other generation-specific effects over time, we run a model-specification that features generation-specific[14] time-fixed effects. The specification with generation-specific time trends yields elasticities of $\eta_E = 0.022,$ (s.e. $= 0.005$), $\eta_E = 0.036,$ (s.e. $= 0.008$) and $\eta_E = 0.013,$ (s.e. $= 0.003$) in Germany, the Netherlands, and the United States respectively. These are similar in magnitude to our main income elasticity estimates.

– insert Table 7 here –

– insert Table 8 here –

3.6 Further Robustness Checks with Administrative Data

Administrative Income Data The scanner data we have used so far classify household incomes into bins, capture only income from employment of the household head (in the Netherlands and Germany), and are collected as self-reported lagged income. These traits may lead to measurement- and possibly recall error. Because accurate income dynamics are important in avoiding error-in-variables problems in our empirical strategy, we make use of the unique opportunity in the Dutch data to merge the purchase data with administrative governmental records sourced from Statistics Netherlands (CBS). Importantly, these data can be merged at the

[14]We adopt a standard definition of generations, obtained from the Pew Research Centre. See, e.g., https://www.pewresearch.org/short-reads/2019/01/17/where-millennials-end-and-generation-z-begins/.

household-year level with our purchase data for the large majority of panelists (see Appendix A). Although these administrative data are available for the Netherlands only, they allow us to validate our results using a more complete, and arguably more accurate, income measure. The administrative data allow us to detect income changes within YouGov's income bins. In addition, the rich nature of the administrative data allows us to rule out potential confounds of income, such as changes in wealth, health, employment, and working hours.

We replicate our analysis of income elasticities with respect to total GHG emissions as well as the GHG intensity using administrative income in the Netherlands. Table 9 shows the results of this specification for total emissions and Table 10 for emission intensity. Using the administrative measures of income, we report $\eta_E = 0.024,\ (\text{s.e.} = 0.006)$ and $\eta_I = 0.006,\ (\text{s.e.} = 0.003)$ respectively. These estimates are substantively similar to the estimates using the YouGov income measures (last Columns of Tables 5 and 6) and provide support that the small income elasticity estimates are not due to larger errors than in administrative data. The sample with administrative data is a subset of the sample without such data. In Web Appendices 1.2 and 1.3 we re-estimate the short- versus longer-term income measures of Section 3.4 and the heterogeneity analyses of Section 3.5 (across income levels, emission levels, and generations) using administrative rather than self-reported income. The estimates closely track those reported above throughout, and all substantive conclusions are unchanged.

Separating Effects of Income and Wealth The administrative data allows us to also control for wealth effects when studying the income elasticity of environmental costs. Consider a version of our main descriptive specification in Equation (1) where we add an effect of wealth W_{ht}.

$$\log(E_{ht}) = \gamma_h + \gamma_t + \eta_E \log(Y_{ht}) + \eta_W \log(W_{ht}) + \beta' x_{ht} + \epsilon_{ht} \tag{2}$$

Controlling for the effect of wealth, Table 9, Column 2 shows that the income elasticity for total emissions falls slightly ($\eta_E = 0.020,\ \text{s.e.} = 0.007$), but the intensity estimate does not ($\eta_I = 0.008,\ \text{s.e.} = 0.004$). The wealth elasticity is small but significant ($\eta_W = 0.006$, s.e. $= 0.002$), indicating that a 1% increase in household wealth raises emissions by 0.006%. We report a similarly small effect of wealth on GHG intensity ($\eta_W = 0.002$, s.e. $= 0.001$).

Next, we consider the case where wealth accumulates out of income over time. We postulate

the following accumulation of wealth

$$W_{ht} = (1 + r)W_{ht-1} + \delta Y_{ht-1} - D_{ht}, \tag{3}$$

where r captures the rate of return on wealth (e.g., appreciation of real estate), δ is the fraction of last year's income saved, and D_{ht} are expenses covered by capital disbursement (e.g., capital goods, renovations of real estate, etc.). This law of motion implies that if $\delta > 0$, then incomes have long-term effects on wealth and indirectly on quantities and environmental costs. In Appendix C.4, we derive that an income shock at t accumulates effects on GHG emissions over a T-year horizon that is equal to

$$\eta_{ht}^{T} = \eta_E + \eta_W \delta \sum_{\tau=1}^{T} (1 + r)^{\tau-1} \frac{Y_{ht}}{W_{ht+\tau}}$$

We can use this relation to benchmark the accumulation effect by making several reasonable assumptions. For instance, we assume a rate of return on capital $r \approx 0.06$, a savings rate $\delta \approx 0.15$, and an income-to-wealth ratio of 0.44.[15] These assumptions are optimistic about the role of income on wealth accumulation, as returns and savings rates are frequently lower and so are income to wealth ratios (Piketty and Zucman, 2014). Even in this optimistic case, the total indirect effect of an income shock over a 20-year horizon through wealth accumulation is approximately $2.43 \times \eta_W$. Using our estimate of $\hat{\eta}_W = 0.006$ for the Netherlands, a 1% increase in income raises grocery-related GHG emissions through wealth accumulation over a twenty year period by approximately $2.43 \times 0.006 = 0.015\%$. Thus, even over a long horizon, the cumulative effect remains economically small.

Changes in Health and Employment Even with household and time-fixed effects, the possibility of omitted variable bias remains. Life events such as health crises or changes in employment status may simultaneously influence income and food preferences. They could therefore also impact the environmental impact of shopping baskets. To address this concern, we make use of administrative data on the sources of household income. We remove households from the estimation sample in years in which they receive any government aid, such as

[15] For context, CBS reports that in 2024 mean disposable household income was about €60,200, while median household wealth was €135,500. See https://www.cbs.nl/en-gb/figures/detail/86272ENG

sick leave and unemployment benefits, as a source of income.[16] The coefficients in Column 3 of Tables 9 and 10 thus reflect the income elasticities for households who do not receive government aid, i.e., are unlikely to be experiencing a health crisis or other special life events. Restricting the sample in this way gives η_E = 0.019, s.e. = 0.008 and η_I = 0.007, s.e. = 0.004. These estimates are statistically equal to those reported in Table 9, Column 1.

Changes in Working Hours Related to the previous argument, changes in working hours due to life events such as illness or family expansion may also be a potential confounding factor. We argue that short-term life events such as temporary illness or family expansion that may affect income as well as consumption preferences would be reflected by a change in working hours. Therefore, we include the average total of hours worked by all employed household members in a year in our model.[17] Controlling for the number of hours spent working, we find $\eta_E = 0.020,$ s.e. $= 0.009$ and $\eta_I = 0.009,$ s.e. $= 0.004$ (Column 4) again statistically indistinguishable from Column 1.

– insert Table 9 here –

– insert Table 10 here –

Discussion

Our estimates using administrative income data for the Netherlands show that the estimated income elasticities remain of similar magnitude when using a more accurate and precise measure of income. The administrative data also allow us to disentangle income and wealth effects, demonstrating that the income elasticity estimate is robust to the inclusion of wealth. Moreover, excluding households receiving health- or employment-related government benefits and controlling for hours worked do not affect our estimates substantively or statistically. Because the merging of administrative records is, to our knowledge, unique to the Netherlands, the German and US estimates cannot be validated in the same way.

[16] Our administrative data provides insight into the type of government benefits a household is receiving. The Dutch social security system includes benefits that are available to individuals who are not able to work due to their health status. A majority of 73.20% of observations do not receive any government benefits in our sample.

[17] The administrative data includes actual hours worked, not just contract hours, along with overtime hours. We calculate household work hours as the average hours worked by all employed household members, limiting our sample to households with at least one employed member.

3.7 Quantifying the Environmental Impact

Next, for completeness, we illustrate the environmental significance of our estimated income elasticities. We do so by calculating the changes in grocery-related GHG emissions resulting from realistic annual income changes.

We illustrate environmental significance at a typical income change in Germany, and Table 11 repeats these calculations for the Netherlands and the United States. In particular, we compute the response to an average income change in each of our three countries from 2011 to 2022 (or 2011-2020 in the United States). For instance, in Germany the average income change in our data is 4.754%. The expected annual increase in grocery-related GHG emissions from this income change is then obtained by multiplying the preferred income elasticity estimate of total grocery-related GHG emissions in Germany (0.024) with the average annual percentage income increase. This yields an estimated percentage increase of $0.024 \times 4.754 = 0.114\%$.[18]

Next, the absolute change in total emissions is calculated by multiplying these percentages with the average grocery-related GHG emissions per household per country ($2,832$ kgCO_2eq, see Table 3). This amounts to $0.00114 \times 2,832 = 3.23$ kgCO_2eq per household-year in Germany. Scaling this to the German population of 40,965,000 households and valuing emissions at the current rate[19] of trading emissions in Europe of €70 per tCO_2eq, the trading price of these additional GHG emissions amounts to 9.24 million Euros. Similar calculations for the Netherlands and the United States replicate the economically small impact as described for Germany.

These magnitudes are also small relative to effects on emissions documented in the literature. Wynes et al. (2018) report mean annual reductions of 51 kgCO_2eq per person from behavioral interventions targeting meat consumption and 149 kgCO_2eq per household from interventions targeting home energy use, against an increase of 1.0-3.5 kgCO_2eqper person implied by a typical annual income change in our data.

– insert Table 11 here –

[18] Even a doubling of income implies a difference in grocery-related emissions of only 1.68% so the modest magnitudes reflect the size of the estimated elasticity rather than the size of income variation considered.

[19] See the Intercontinental Exchange tariffs, e.g., https://www.ice.com/products/197/EUA-Futures/data?marketId=6993472

4 Discussion and Conclusion

No Pure Income Effects Overall, we find that the income elasticity of environmental impact from grocery purchases is statistically significant and positive, but economically close to zero. Therefore, income changes at the household level have a negligible effect on the environmental impact of annual shopping baskets. For example, for a typical household, we find that a 1 percent change in disposable income increases the total environmental impact of its shopping basket by only 0.024, 0.039 and 0.010 percent in Germany, the Netherlands and the US respectively. The income elasticity of the environmental intensity of the shopping basket (i.e., environmental impact per quantity of food) is even smaller at 0.007, 0.009 and -0.004. This suggests that additional household income does not affect German, Dutch or American households' purchase of eco-friendly grocery baskets. Moreover, our estimates of income elasticities remain very small independently of whether income changes short- or long-term, at least over the decade-long period considered here. The same remains true when using a precise income measure, when separating income effects from wealth effects, when considering different baseline emission levels, and controlling for generation-specific time trends, health, employment status, and changes in demographics. Our findings of an economic null effect are also replicated using an AIDS-type structural demand model implemented for the three countries.

At the same time, the cross-household variation in income correlates substantially and significantly with the environmental impact of shopping baskets. This is consistent with some of the existing results in the literature (e.g., Pottier, 2022). However, using within-household income variation only, we find very different results from the literature. Income correlates cross-sectionally with other variables, e.g., education, political preferences, location, etc., some of which could shift preferences for sustainable foods. The difference between the estimates suggests the possibility that some of these other variables are omitted in cross-sectional studies. Note that even after accounting for stable differences across households, the income data have ample variation left to identify possible demand effects.

Our study extends the literature on sustainable consumption by determining the sign and size of an elasticity for which theory offers no clear prediction. As income can affect the quantity and the composition of shopping baskets in different ways, a small overall elasticity could in principle mask substantial offsetting effects on either margin, but we estimate both elasticities to be close to zero. Higher incomes thus do not lead households in rich Western countries

to shift their grocery purchases toward more sustainable food categories. Our finding of a precisely measured economic null effect in the income elasticity of environmental impact from grocery purchases has important implications for marketing practice and retailer assortments.

The Impact on Consumption Policy One of the motivations for understanding the income elasticity of environmental impact is to inform the design of taxation policies aimed at mitigating the environmental impact of food consumption. If higher income caused substantially higher grocery-related GHG emissions, progressive income taxation could place a greater burden on households whose higher income generates more emissions while also reducing emissions by lowering disposable income. Our findings indicate, however, that changes in income have only a small effect on grocery-related emissions, even when we account for the indirect effect through wealth accumulation over a 20-year horizon. Adjusting income tax rates is therefore unlikely to reduce these emissions substantially through this channel. Taxing high-emission foods, such as beef, may act more directly on food choices, although its effectiveness and distributional aspects depend on which households buy them and how they respond to higher prices.

Implications for Marketing Practice Retailers and food suppliers often differentiate product assortments based on local income levels (Bollinger et al., 2023), a strategy particularly relevant for sustainable products given their typically higher profit margins. This creates a direct economic incentive for retailers to understand how income relates to sustainable purchase decisions. In terms of income levels, our findings challenge the relevance of income as a consumer characteristic for segmentation when designing sustainable product assortments: although higher-income households have higher total grocery-related emissions, largely reflecting their larger household size, the GHG intensity of their baskets differs little.

In terms of income changes, understanding the income elasticity of environmental impact enables retailers to predict how consumer purchasing patterns may shift in response to consumer income shocks or trends. We find that overall emissions and emission intensity do not change substantially with income. Rather than assuming that higher-income consumers will automatically shift towards sustainable product categories, retailers aiming to promote sustainable consumption should consider other strategies. For instance, retailers may consider other consumer characteristics, such as environmental knowledge (Bronnenberg et al., 2026), and can aid consumers to align their sustainability preferences with their purchases through apps

or by accompanying products or recipes with environmental costs. Alternatively, retailer-level supply-side changes may promote sustainable consumption.

Conclusions This study examines the relationship between changes in household income and the environmental impact of grocery consumption in three countries –Germany, the Netherlands and the United States. Using a unique combination of household-level scanner data, administrative records on income and wealth, and detailed product-level environmental impact data, we provide novel insights into how income fluctuations influence the sustainability of grocery purchases.

We constructed a unique panel dataset that integrates households' complete shopping baskets with household income, including precise income information from Dutch tax administrations, alongside product-level data on key environmental impact indicators. Theoretically, the effect of income on the environmental impact of grocery consumption is ambiguous, as income changes can lead to shifts in either direction. Our contribution to the literature is that we provide a careful empirical analysis of the effects involved both in the aggregate as well as decomposed into grocery basket size and basket composition.

Our empirical investigation and the data sources are not without limitations. While scanner data offer systematic insights into the consumption of fast moving consumer products in the retail context, across retailers and over time (Dubois et al., 2022), they do not cover out-of-home food consumption. Although food bought by consumers in grocery stores accounts for up to 85% of their nutrition (Cherchye et al., 2020), the remaining share represents a relevant consumption channel that our data do not capture.

Further, it is important to note that we cannot rule out heterogeneity within specific product categories as our analyses focus on total basket GHG emissions and between-category shifts. However, such behavioral shifts may be less critical for overall environmental impact, as even the most "eco-friendly" versions of high-impact categories such as beef have high emissions (Eshel et al., 2025). Moreover, other consumption categories beyond the scope of our analyses (e.g. travel, electricity usage) may exhibit different income elasticities for environmental costs, especially as food typically represents a smaller component of rising incomes.

Exploring how out-of-home dining, within-category product substitution, and income-driven consumption shifts beyond food jointly shape the overall environmental cost of household consumption offers fruitful directions for future research.

References

Aguiar, M. and E. Hurst (2005). Consumption versus expenditure. *Journal of political Economy 113*(5), 919–948.

Allcott, H., B. B. Lockwood, and D. Taubinsky (2019). Should we tax sugar-sweetened beverages? an overview of theory and evidence. *Journal of Economic Perspectives 33*(3), 202–227.

Bakker, B. F. and P. J. Daas (2012). Methodological challenges of register-based research. *Statistica Neerlandica 66*(1), 2–7.

Bakker, B. F., J. Van Rooijen, and L. Van Toor (2014). The system of social statistical datasets of statistics netherlands: An integral approach to the production of register-based social statistics. *Statistical Journal of the IAOS 30*(4), 411–424.

Blundell, R. and J. M. Robin (1999, May). Estimation in large and disaggregated demand systems: an estimator for conditionally linear systems. *Journal of Applied Econometrics 14*(3), 209–232.

Bollinger, B., R. Kronthal-Sacco, and L. Zhu (2023). Sustainable product demand and profit potential. *SSRN Electronic Journal*.

Brancatelli, C., A. Fritzsche, R. Inderst, and T. Otter (2022). Measuring income and wealth effects on private-label demand with matched administrative data. *Marketing Science 41*(3), 637–656.

Bronnenberg, B. J., T. Bùi, B. Deleersnyder, L. Haerkens, G. Knox, A. van Lin, M. J. Pachali, A. Paley, R. W. Smith, and S. Stäbler (2026). Closing the knowledge gap: Understanding and reducing the environmental impact of food choices. *Journal of Marketing 90*(5), 16–34.

Bruckner, B., K. Hubacek, Y. Shan, H. Zhong, and K. Feng (2022). Impacts of poverty alleviation on national and global carbon emissions. *Nature Sustainability 5*(4), 311–320.

Chancel, L. (2022). Global carbon inequality over 1990–2019. *Nature Sustainability 5*(11), 931–938.

Cherchye, L., B. De Rock, R. Griffith, M. O' Connell, K. Smith, and F. Vermeulen (2020). A new year, a new you? within-individual variation in food purchases. *European Economic Review 127*, 103478.

Clark, M., M. Springmann, M. Rayner, P. Scarborough, J. Hill, D. Tilman, J. I. Macdiarmid, J. Fanzo, L. Bandy, and R. A. Harrington (2022). Estimating the environmental impacts of 57,000 food products. *Proceedings of the National Academy of Sciences 119*(33).

Colen, L., P. Melo, Y. Abdul-Salam, D. Roberts, S. Mary, and S. Gomez Y Paloma (2018). Income elasticities for food, calories and nutrients across africa: A meta-analysis. *Food Policy 77*, 116–132.

Crippa, M., E. Solazzo, D. Guizzardi, F. Monforti-Ferrario, F. N. Tubiello, and A. Leip (2021). Food systems are responsible for a third of global anthropogenic ghg emissions. *Nature Food 2*(3), 198–209.

Cuffey, J., L. Chenarides, W. Li, and S. Zhao (2023). Consumer spending patterns for plant-based meat alternatives. *Applied Economic Perspectives and Policy 45*(1), 63–85.

Deaton, A. and J. Muellbauer (1980). An almost ideal demand system. *The American Economic Review 70*(3), 312–326.

Deloitte (2023). Consumenten onderzoek 2023. Web report, Deloitte Retail.

Dubé, J.-P., G. J. Hitsch, and P. E. Rossi (2018). Income and wealth effects on private-label demand: Evidence from the great recession. *Marketing Science 37*(1), 22–53.

Dubois, P., R. Griffith, and M. O'Connell (2020). How well targeted are soda taxes? *American Economic Review 110*(11), 3661–3704.

Dubois, P., R. Griffith, and M. O'Connell (2022). The use of scanner data for economics research. *Annual Review of Economics 14*, 723–745.

Eshel, G., A. I. Flamholz, A. Shepon, and R. Milo (2025). Us grass-fed beef is as carbon intensive as industrial beef and $\approx$ 10-fold more intensive than common protein-dense alternatives. *Proceedings of the National Academy of Sciences 122*(12), e2404329122.

Gicheva, D., J. Hastings, and S. Villas-Boas (2010). Investigating income effects in scanner data: do gasoline prices affect grocery purchases? *American Economic Review 100*(2), 480–484.

Hausman, J., G. Leonard, and J. D. Zona (1994). Competitive analysis with differenciated products. *Annales d'Économie et de Statistique* (34), 159–180.

Jappelli, T. and L. Pistaferri (2010). The consumption response to income changes. *Annu. Rev. Econ. 2*(1), 479–506.

Muhammad, A., A. D'Souza, B. Meade, R. Micha, and D. Mozaffarian (2017). How income and food prices influence global dietary intakes by age and sex: evidence from 164 countries. *BMJ Global Health 2*(3), e000184.

Parker, J. A., N. S. Souleles, D. S. Johnson, and R. McClelland (2013). Consumer spending and the economic stimulus payments of 2008. *American economic review 103*(6), 2530–2553.

Piketty, T. and G. Zucman (2014). Capital is back: Wealth-income ratios in rich countries 1700–2010. *The Quarterly journal of economics 129*(3), 1255–1310.

Poore, J. and T. Nemecek (2018). Reducing food's environmental impacts through producers and consumers. *Science 360*(6392), 987–992.

Pottier, A. (2022). Expenditure elasticity and income elasticity of ghg emissions: A survey of literature on household carbon footprint. *Ecological Economics 192*, 107251.

Ritchie, H., P. Rosado, and M. Roser (2019). Meat and dairy production. *Our World in Data*. https://ourworldindata.org/meat-production.

Ritchie, H., P. Rosado, and M. Roser (2022). Environmental impacts of food production. *Our World in Data*. https://ourworldindata.org/environmental-impacts-of-food.

Scholdra, T. P., J. R. Wichmann, M. Eisenbeiss, and W. J. Reinartz (2022). Households under economic change: How micro-and macroeconomic conditions shape grocery shopping behavior. *Journal of Marketing 86*(4), 95–117.

Souleles, N. S. (1999). The response of household consumption to income tax refunds. *American economic review 89*(4), 947–958.

Van Rossum, C., E. Buurma-Rethans, C. Dinnissen, M. Beukers, H. Brants, and M. Ocké (2020). The diet of the dutch: Results of the dutch national food consumption survey 2012-2016.

Wolfson, J. A., A. C. Tucker, C. W. Leung, C. M. Rebholz, V. Garcia-Larsen, and E. Martinez-Steele (2025). Trends in adults' intake of un-processed/minimally processed, and ultra-processed foods at home and away from home in the united states from 2003–2018. *The Journal of Nutrition 155*(1), 280–292.

Wynes, S., K. A. Nicholas, J. Zhao, and S. D. Donner (2018). Measuring what works: quantifying greenhouse gas emission reductions of behavioural interventions to reduce driving, meat consumption, and household energy use. *Environmental Research Letters 13*(11), 113002.

Figure 1: GHG Intensity by Supermarket Aisle

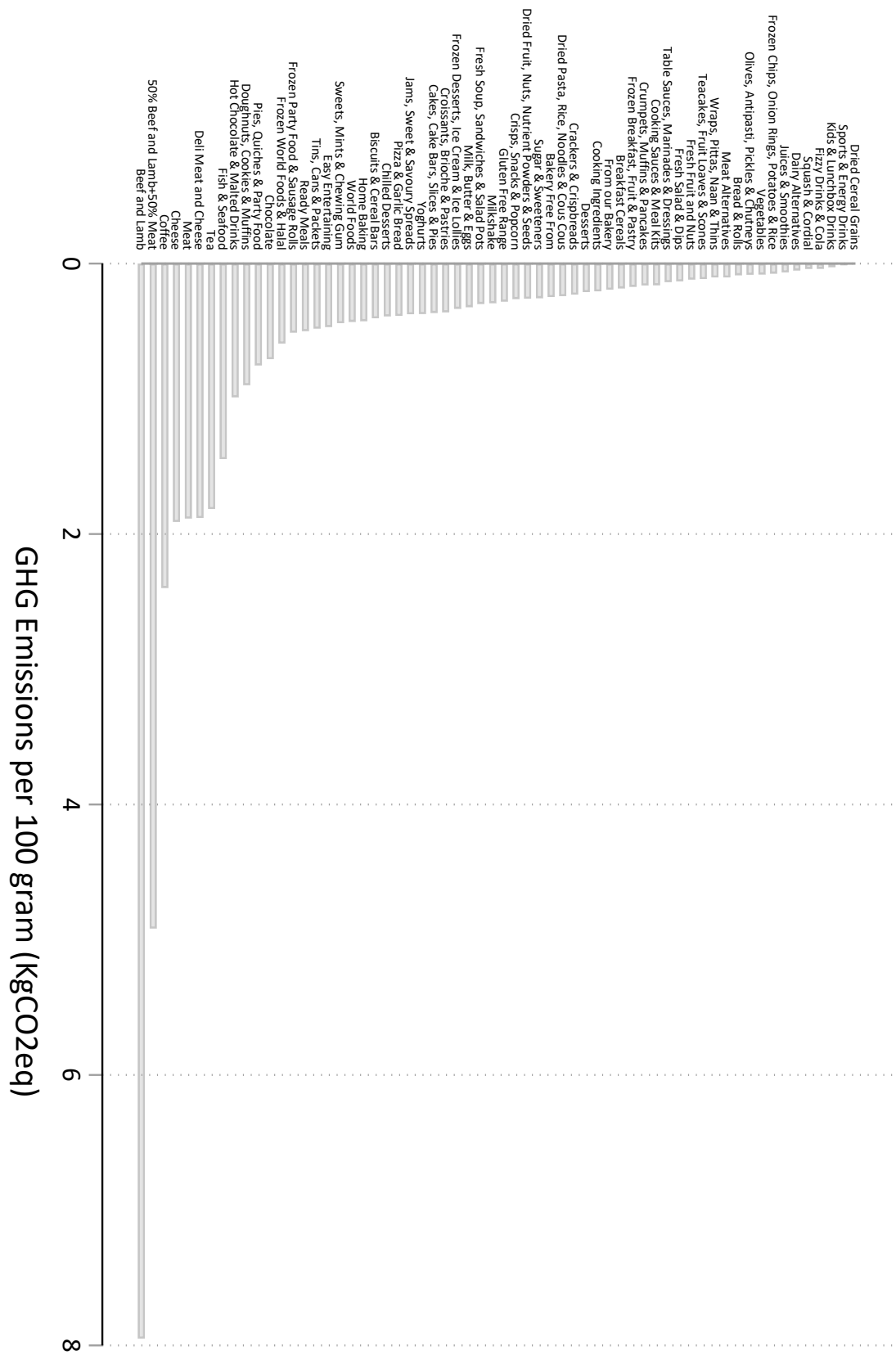
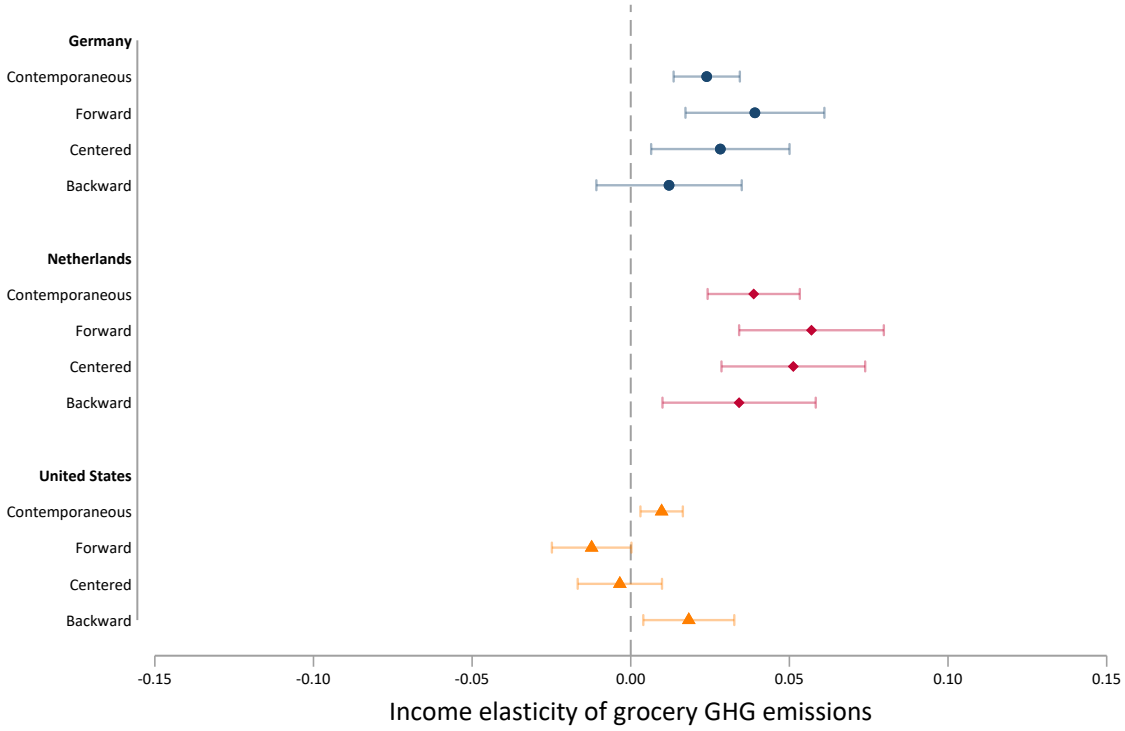


Figure 2: Coefficient Plot with Rolling Averages of Income



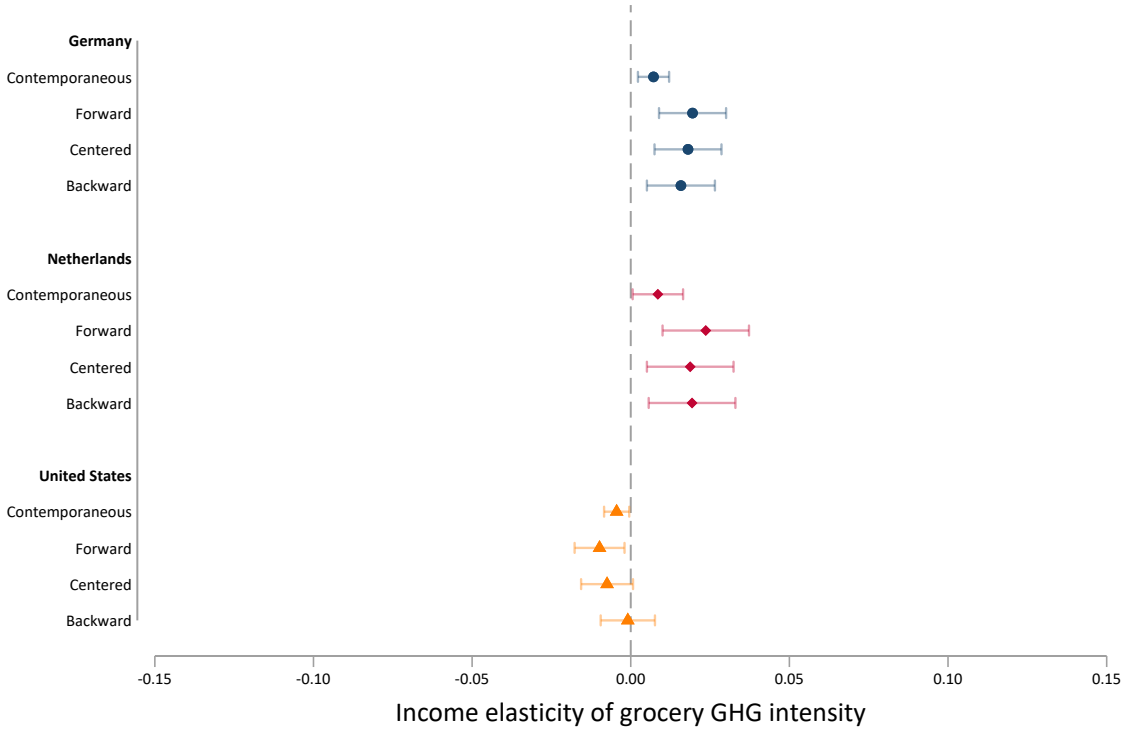


Table 1: Number of Panelists

	DE	NL	US
2011	22,917	6,125	61,831
2012	22,738	8,976	60,300
2013	23,719	9,098	60,904
2014	23,350	9,141	61,398
2015	23,199	9,192	61,227
2016	23,400	8,980	63,007
2017	23,744	8,943	62,688
2018	23,574	8,845	61,231
2019	23,353	9,669	61,316
2020	24,547	9,469	59,872
2021	26,426	9,388	0
2022	24,983	9,125	0

Note: As the allocation of UPCs into high-level categories changed substantially in the US Nielsen data from 2021 onward, we restrict our sample to panel years with a consistent product hierarchy.

Table 2: Shopping Behavior Summary Table

Characteristic	Country	Mean	SD	P25	Median	P75
Number of trips	DE	123.4	86.3	61.0	100.0	161.0
	NL	150.7	87.8	88.0	128.0	189.0
	US	106.2	66.7	61.0	90.0	133.0
Value (in €/$)	DE	1,842.2	1,136.4	1,019.8	1,588.8	2,410.5
	NL	2,535.3	1,347.4	1,521.8	2,287.5	3,278.6
	US	2,911.0	1,678.1	1,712.7	2,572.7	3,735.6
Volume (in Kg)	DE	628.7	432.3	326.8	523.7	818.1
	NL	879.8	520.7	485.5	769.6	1,153.2
	US	848.2	550.1	460.5	725.8	1,097.9

Note: All statistics are weighted using household sampling weights and computed across household years. The abbreviation P25 (P75) denotes the 25th (75th) percentile of the household-year distribution.

Table 3: Summary Statistics Panelists

Characteristic	Country	Mean	SD	P25	Median	P75
Age	DE	52.95	16.40	40.00	53.00	66.00
	NL	51.40	15.87	38.67	51.50	65.00
	US	52.63	14.42	41.00	53.00	63.00
Household Size	DE	2.01	1.09	1.00	2.00	3.00
	NL	2.15	1.19	1.00	2.00	3.00
	US	2.49	1.31	1.00	2.00	3.00
Income	DE	2,442.83	1,364.47	1,375.00	2,125.00	3,125.00
	NL	2,388.59	1,085.24	1,600.00	2,200.00	3,200.00
	US	5,970.58	4,144.99	2,291.67	4,583.33	7,083.33
Environmental Impact (KgCO2eq)	DE	2,831.85	2,007.02	1,434.40	2,341.89	3,715.54
	NL	3,798.63	2,317.19	2,013.67	3,293.53	5,137.07
	US	3,777.92	2,553.25	1,945.07	3,195.33	4,970.91
Environmental Impact Intensity	DE	0.47	0.15	0.37	0.45	0.54
	NL	0.44	0.12	0.36	0.43	0.50
	US	0.47	0.21	0.33	0.44	0.57

Note: The income variable is not directly comparable between countries. In the United States, income reflects household income, whereas Germany and The Netherlands reflect income of the main earner. The abbreviation P25 (P75) denotes the 25th (75th) percentile of the household-year distribution. Household size is top-coded at 5 (five or more members) for cross-country comparability. All statistics are weighted using household sampling weights.

Table 4: Summary of Annual Changes in Self-Reported Household Income

	P1	P5	P10	Median	P90	P95	P99
DE	-58.82%	-28.57%	-18.18%	0.00%	28.57%	42.11%	128.57%
NL	-47.06%	-21.43%	-10.00%	0.00%	20.00%	40.00%	112.50%
US	-63.33%	-36.36%	-18.18%	0.00%	29.63%	66.67%	171.43%

Note: All statistics are weighted using household sampling weights and are computed across household years. The abbreviation PX denotes the X^{th} percentile of the household-year distribution.

Table 5: The Effect of Income on Grocery-Related GHG Emissions

	Cross-sectional									Within household		
	DE	NL	US	DE	NL	US	DE	NL	US	DE	NL	US
Log income	0.263	0.457	0.107	0.298	0.475	0.099	0.034	0.067	-0.023	0.024	0.039	0.010
	(0.002)	(0.004)	(0.001)	(0.002)	(0.004)	(0.001)	(0.003)	(0.004)	(0.001)	(0.005)	(0.007)	(0.003)
Constant	5.782	4.631	7.010	5.827	4.687	6.796	7.304	7.101	7.146	7.635	7.638	7.385
	(0.019)	(0.033)	(0.012)	(0.019)	(0.033)	(0.013)	(0.020)	(0.033)	(0.013)	(0.041)	(0.057)	(0.030)
Controls							✓	✓	✓	✓	✓	✓
Time fixed effects				✓	✓	✓	✓	✓	✓	✓	✓	✓
Panelist fixed effects										✓	✓	✓
R^2	0.038	0.098	0.011	0.114	0.118	0.032	0.249	0.382	0.220	0.848	0.892	0.805
adj R^2	0.038	0.098	0.011	0.114	0.118	0.032	0.249	0.382	0.220	0.803	0.868	0.759
Observations	285,950	106,945	466,754	285,950	106,945	466,754	285,950	106,945	466,754	285,950	106,945	466,754

Note: Controls include social group and household size. Time fixed effects are at the yearly level. Standard errors are clustered at the household level in the within-household specification.

Table 6: The Effect of Income on Grocery-Related GHG Emissions per 100 gr.

	Cross-sectional									Within household		
	DE	NL	US	DE	NL	US	DE	NL	US	DE	NL	US
Log income	0.008	-0.017	0.018	0.007	-0.016	0.010	0.006	-0.009	0.005	0.007	0.009	-0.004
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.003)	(0.004)	(0.002)
Constant	-0.863	-0.726	-1.064	-0.871	-0.687	-1.289	-0.883	-0.800	-1.319	-0.886	-0.917	-1.181
	(0.008)	(0.014)	(0.007)	(0.008)	(0.015)	(0.007)	(0.010)	(0.017)	(0.008)	(0.019)	(0.031)	(0.018)
Controls							✓	✓	✓	✓	✓	✓
Time fixed effects				✓	✓	✓	✓	✓	✓	✓	✓	✓
Panelist fixed effects										✓	✓	✓
R^2	0.000	0.001	0.001	0.003	0.003	0.072	0.013	0.044	0.078	0.768	0.812	0.728
adj R^2	0.000	0.001	0.001	0.003	0.003	0.072	0.013	0.044	0.078	0.699	0.771	0.664
Observations	285,950	106,945	466,754	285,950	106,945	466,754	285,950	106,945	466,754	285,950	106,945	466,754

Note: Controls include social group and household size. Time fixed effects are at the yearly level. Standard errors are clustered at the household level in the within-household specification.

Table 7: Heterogeneity Analyses of Income on GHG Emissions

	Baseline Income Level			Baseline Emission Level			Generation Time Trends		
	DE	NL	US	DE	NL	US	DE	NL	US
Log income	0.0430	0.0517	0.0201	0.0046	0.0259	0.0055	0.0224	0.0360	0.0131
	(0.0072)	(0.0120)	(0.0046)	(0.0056)	(0.0080)	(0.0033)	(0.0053)	(0.0075)	(0.0034)
Log income * high baseline	-0.0663	-0.0536	-0.0337	0.0285	-0.0088	-0.0020			
	(0.0139)	(0.0182)	(0.0087)	(0.0056)	(0.0084)	(0.0030)			
Constant	7.4969	7.5429	7.3050	7.5108	7.6021	7.2529	7.3882	7.5107	7.3377
	(0.0538)	(0.0891)	(0.0382)	(0.0429)	(0.0605)	(0.0284)	(0.0603)	(0.0869)	(0.0470)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Panelist fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Generation x time fixed effects							✓	✓	✓
R^2	0.848	0.892	0.805	0.889	0.916	0.870	0.848	0.893	0.805
adj R^2	0.803	0.868	0.759	0.857	0.898	0.839	0.804	0.869	0.759
Observations	285,950	106,945	466,754	285,950	106,945	466,754	284,182	106,416	466,754

Note: Controls include social group and household size. Time fixed effects are at the yearly level. Standard errors are clustered at the household level. Main effects for baseline income levels, baseline emission levels and generations are included in the model but omitted from the table.

Table 8: Heterogeneity Analyses of Income on GHG Intensity

	Baseline Income Level			Baseline Emission Level			Generation Time Trends		
	DE	NL	US	DE	NL	US	DE	NL	US
Log income	0.0054	0.0043	-0.0023	-0.0001	-0.0007	-0.0228	0.0042	0.0060	-0.0021
	(0.0029)	(0.0052)	(0.0023)	(0.0025)	(0.0040)	(0.0019)	(0.0025)	(0.0041)	(0.0020)
Log income * high baseline	0.0004	0.0005	-0.0006	0.0129	0.0118	0.0322			
	(0.0003)	(0.0004)	(0.0003)	(0.0002)	(0.0003)	(0.0002)			
Constant	-0.8733	-0.8868	-1.1972	-0.8809	-0.8777	-1.0961	-0.8794	-0.9054	-1.1879
	(0.0216)	(0.0385)	(0.0201)	(0.0188)	(0.0298)	(0.0168)	(0.0280)	(0.0379)	(0.0266)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Panelist fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Generation x time fixed effects							✓	✓	✓
R^2	0.768	0.812	0.728	0.776	0.819	0.765	0.769	0.814	0.729
adj R^2	0.699	0.771	0.664	0.710	0.780	0.709	0.701	0.773	0.664
Observations	285,950	106,945	466,754	285,950	106,945	466,754	284,182	106,416	466,754

Note: Controls include social group and household size. Time fixed effects are at the yearly level. Standard errors are clustered at the household level. Main effects for baseline income levels, baseline emission levels and generations are included in the model but omitted from the table.

Table 9: Overview of Robustness Estimates of Total GHG Emissions

	(1)	(2)	(3)	(4)
Log income	0.024	0.020	0.019	0.020
	(0.006)	(0.007)	(0.008)	(0.009)
Log wealth		0.006	0.006	0.008
		(0.002)	(0.003)	(0.003)
Constant	7.684	7.650	7.658	7.699
	(0.062)	(0.071)	(0.083)	(0.091)
Controls	✓	✓	✓	✓
Time fixed effects	✓	✓	✓	✓
Panelist fixed effects	✓	✓	✓	✓
R^2	0.888	0.899	0.908	0.902
Adj R^2	0.869	0.880	0.888	0.880
Observations	84,334	72,324	54,404	48,032

Note: Controls include social group and household size. Time fixed effects are at the yearly level. Standard errors are clustered at the household level. (1) preferred specification (2) including wealth (3) health/employment changes (4) including working hours.

Table 10: Overview of Robustness Estimates of GHG Intensity

	(1)	(2)	(3)	(4)
Log income	0.006	0.008	0.007	0.009
	(0.003)	(0.004)	(0.004)	(0.004)
Log wealth		0.002	0.002	-0.001
		(0.001)	(0.001)	(0.002)
Constant	-0.919	-0.950	-0.935	-0.981
	(0.034)	(0.037)	(0.045)	(0.046)
Controls	✓	✓	✓	✓
Time fixed effects	✓	✓	✓	✓
Panelist fixed effects	✓	✓	✓	✓
R^2	0.797	0.808	0.820	0.808
Adj R^2	0.762	0.772	0.781	0.764
Observations	84,334	72,324	54,404	48,032

Note: Controls include social group and household size. Time fixed effects are at the yearly level. Standard errors are clustered at the household level. (1) preferred specification (2) including wealth (3) health/employment changes (4) including working hours.

Table 11: Quantifying the Environmental Impact of a Typical Income Change per Country

	DE	NL	US
Average Annual Income Growth (sample mean) [%]	4.754	5.182	7.976
Income Elasticity of GHG Emissions	0.024	0.039	0.010
Increase in GHG Emissions [%]	0.114	0.201	0.078
Average Household GHG Emissions (sample mean)	2,832	3,799	3,778
Households (2021) [#]	40,965,000	8,139,000	131,202,000
Total Annual GHG Increase [TCO2eq]	132,053	62,093	384,792
Equivalent Steaks per Household [#]	0.162	0.383	0.147
Cost of Emissions [€]	9,243,738	4,346,514	26,935,421

A Matching with Administrative Data

Demographics of Matched vs. Non-Matched Panelists Table S.1 displays the number of households present in the YouGov consumer panel per year, the number of households that consented to matching with administrative data, and the number of households that were successfully matched to the administrative data. As consent was requested in 2018 and 2021, the matched sample sizes are lower in earlier years. In total, we observe 84,406 panelist-years with both full-year purchase data and administrative income data.

– insert Table S.1 here –

We find only minor differences in observable characteristics between the non-matched and the matched panelists. Whereas independent sample t-tests show statistically significant differences on all characteristics, the effect sizes are small (Table S.2). For example, the matched sample is slightly older and has slightly higher income and emissions from grocery consumption than panelists that we were not able to match.

– insert Table S.2 here –

Income

Household disposable income from the CBS records is notably different from the income measures collected by YouGov through self-reported surveys, which reflects labor income of the main earner. The average disposable monthly household income among consenting YouGov panelists is €3,605, whereas Table S.2 shows that the self-reported income from labor of the main earner is €2,461 among these households in the YouGov survey.

B Income Changes

Figure S.1 displays the distribution of average year-to-year income change per household for Germany, the Netherlands and the United States, conditional on observing an income change. To give an idea, 48.5% of households in Germany, 37.3% in the Netherlands, and 30.9% in the United States experience a year-over-year income change. The figures, focusing on these income changes, demonstrate that those changes can be large and there is ample variation in household income over time.

– insert Figure S.1 here –

C Income Elasticities

C.1 Income Elasticities of Demand

Income elasticities of demand are defined as the ratio of the percentage change in quantities over the percentage change in household income. The definition of income elasticity of quantity demand Q_j for food type j is

$$\eta_{Q_j} = \frac{\partial Q_j}{\partial Y}\frac{Y}{Q_j},$$

where Y is income. Total quantity demand across all food types in a household's basket S is $Q = \sum_{j \in S} Q_j$. By writing the income elasticity for quantities of food in the basket as $\eta_Q = \frac{\partial Q}{\partial Y}\frac{Y}{Q} = \frac{\partial \sum_j Q_j}{\partial Y}\frac{Y}{Q}$, it is straightforward to show that the income elasticity is equivalent to a quantity-weighted average of the income elasticities for specific food types j,

$$\eta_Q = \sum_j \eta_{Q_j}\frac{Q_j}{Q}, \tag{S.2}$$

where the ratio $\frac{Q_j}{Q}$ is the quantity share of food type j in the household's shopping basket S.

C.2 Income Elasticities of Environmental Impact, their Relation to Elasticities of Demand

Denote the environmental impact associated with quantities Q_j by $E_j = e_j Q_j$, where e_j is the environmental intensity, e.g., GHG emissions (in $kgCO_2eq$) per quantity, of food type j . The total environmental impact of the basket purchased by a household is then (in $kgCO_2eq$) $E = \sum_{j \in S} E_j = \sum_{j \in S} e_j Q_j$. Using the same reasoning as above, the income elasticity of environmental impact E can be shown to be simply an environmental-impact weighted average of the income elasticities of quantities Q_j.

$$\eta_E = \sum_j \eta_{Q_j}\frac{E_j}{E} \tag{S.3}$$

where $\frac{E_j}{E}$ is the pollution share of good j in the shopping basket S.

C.3 Decomposition of Elasticities of Environmental Impact into Basket Quantity and Basket Composition Effects

Finally, it is sometimes useful to decompose the income elasticity of environmental impact into effects of quantities and of the environmental intensity of a shopping basket. Define the environmental intensity of a shopping basket as the environmental impact E per quantity (weight) of the basket, i.e., $I = \frac{E}{Q}$. Then, the elasticity of the environmental impact intensity of the basket with respect to household income is $\eta_I = \eta_E - \eta_Q$, and we can alternatively write this as a decomposition of the income elasticity of environmental impact into the sum of quantity and composition elasticities,

$$\eta_E = \eta_Q + \eta_I.$$

This relation can be seen as follows. Starting with $I = \frac{E}{Q}$, the definition of the elasticity η_I is

$$\eta_I = \frac{\partial \frac{E}{Q}}{\partial Y} \frac{Y}{\frac{E}{Q}}.$$

Using the product rule in differentiation and rearranging the result gives

$$\eta_I = Y \left(\frac{1}{Q} \frac{\partial E}{\partial Y} - \frac{E}{Q^2} \frac{\partial Q}{\partial Y} \right) \frac{Q}{E}.$$

Collecting terms immediately gives the result.

C.4 Total Effect of Income through Wealth Accumulation

We start with the following accumulation of wealth

$$W_{ht} = (1 + r)W_{ht-1} + \delta Y_{ht-1} - D_{ht}.$$

This law of motion implies that if $\delta \neq 0$, then income has long-term effects on wealth and indirectly on quantities and environmental costs. Iterating forward yields

$$W_{h,t+\tau} = (1 + r)^{\tau+1} W_{ht-1} + \sum_{k=0}^{\tau} (1 + r)^{\tau-k} (\delta Y_{ht+k-1} - D_{ht+k}), \tag{S.4}$$

This equation makes clear how wealth at $t + \tau$ depends on income at t. Let emissions depend on both current income and accumulated wealth:

$$\log E_{ht} = \gamma_h + \gamma_t + \eta_E \log Y_{ht} + \eta_W \log W_{ht} + \beta' X_{ht} + \varepsilon_{ht}. \tag{S.5}$$

The total effect of income at t on emissions at any $t + \tau$ can then be represented as

$$\frac{\partial \log E_{ht+\tau}}{\partial \log Y_{ht}} = \eta_E \times \mathbb{I}_{\tau=0} + \eta_W \frac{\partial \log W_{ht+\tau}}{\partial \log Y_{ht}}. \tag{S.6}$$

The first term captures the contemporaneous income effect estimated in our main analysis. The second term captures the indirect effect operating through wealth accumulation. Using Equation S.4, this can be expressed as

$$\frac{\partial \log W_{ht+\tau}}{\partial \log Y_{ht}} = (1+r)^{\tau-1} \delta \frac{Y_{ht}}{W_{ht+\tau}}$$

Summing the elasticities across all $\tau = 0, ..., T$, we get

$$\begin{aligned}
\sum_{\tau=0}^{T} \frac{\partial \log E_{ht+\tau}}{\partial \log Y_{ht}} &= \eta_E + \eta_W \sum_{\tau=1}^{T} \frac{\partial \log W_{ht+\tau}}{\partial \log Y_{ht}} \\
&= \eta_E + \eta_W \delta \sum_{\tau=1}^{T} (1+r)^{\tau-1} \frac{Y_{ht}}{W_{ht+\tau}}
\end{aligned}$$

For households with a more or less constant ratio of income to wealth, $\frac{Y_{ht}}{W_{ht+\tau}} := \rho$, using the finite geometric-series formula

$$\begin{aligned}
\sum_{\tau=0}^{T} \frac{\partial \log E_{ht+\tau}}{\partial \log Y_{ht}} &= \eta_E + \eta_W \rho \delta \sum_{\tau=1}^{T} (1+r)^{\tau-1} \\
&= \eta_E + \eta_W \rho \delta \frac{(1+r)^T - 1}{r}
\end{aligned}$$

D Structural Model

Model Setup This section develops a structural model to estimate the income elasticity of greenhouse gas emissions from food bought in grocery stores for the three countries. This structural model adds two main benefits. First, it explicitly accounts for the mechanism of how income affects emissions, e.g. expansion of budget for grocery foods, or substitution towards lower emission products. Second, the structural model enables us to more effectively control for the impact of prices of products on purchase behavior. Similar to other approaches (Dubé et al., 2018), we use an almost ideal demand system (Deaton and Muellbauer, 1980) with multi-stage budgeting across commodity groups.[20] More specifically, we assume a two-stage budgeting problem.

Households first allocate their budget across K product groups, including grocery foods, grocery non-foods, food in restaurants, general merchandise, etc. For each of these K product groups, we can construct national price indices P_t^k, for $k \in \{\text{cpg, restaurant, general merchandize, etc.}\}$ and specify household h's expenditure on CPG in year t, Y_{ht}^{cpg}, as

$$\log\left(Y_{ht}^{\text{cpg}}\right) = \rho_h + \sum_{k=1}^{K} \omega_k \log P_t^k + \delta_Y \log Y_{ht} + \upsilon_{ht}. \tag{S.7}$$

This specification follows Dubé et al. (2018) and includes income elasticities δ_Y. Furthermore, Y_{ht} represents household income in period t. ρ_h is a household fixed effect, and υ_{ht} is an error term capturing unobserved factors affecting expenditure on CPG. At the lower level, we specify expenditure share s_{hjt} for household h, aisle $j = 1, ..., A$, and year t as a function of the expenditure on CPG as

$$s_{hjt} = \alpha_{hj} + \phi_j \log\left(\frac{Y_{ht}^{\text{cpg}}}{P_t^{\text{cpg}}}\right) + \sum_{a=1}^{A} \lambda_{aj} \log P_{aht} + \epsilon_{hjt}, \tag{S.8}$$

where α_{hj} is a household-aisle fixed effect, P_t^{cpg} is a price index for CPG, P_{aht} is a price index for household h, aisle a, in year t, and ϵ_{hjt} denotes the error term. The parameter ϕ_j measures how changes in real CPG expenditure affect the expenditure share of aisle j.

[20] As in these approaches, income enters the specification log-linearly, which does not allow for income thresholds or non-monotonic responses of aisle shares.

Elasticities in Terms of Structural Model Parameters The income elasticity of quantities in aisle j is defined as $\eta_{Q_j} = \frac{\partial Q_j}{\partial Y}\frac{Y}{Q_j}$. Our derivation uses the identity $Q_j \equiv \frac{\mathcal{S}_j}{P_j}Y^{\text{cpg}}$, where $\mathcal{S}_j = \frac{P_j Q_j}{\sum_{a=1}^{A} P_a Q_a}$ and $Y^{\text{cpg}} = \sum_{a=1}^{A} P_a Q_a$ denotes expenditure in all CPG aisles. We can express the elasticities compactly using the following symbols: write $\mathcal{E}_j$ for the environmental cost share (e.g., the GHG share), $\mathcal{Q}_j$ for the quantity share, and $\mathcal{S}_j$ for the expenditure share, all of aisle j in the shopping basket of an individual household. Then, we can derive η_{Q_j}(based on the model in Equation S.7 and Equation S.8):

$$
\begin{aligned}
\eta_{Q_j} &= \frac{\partial \frac{\mathcal{S}_j}{P_j} Y^{\text{cpg}}}{\partial Y} \frac{Y}{\frac{\mathcal{S}_j}{P_j} Y^{\text{cpg}}} \\
&= \left(\frac{\partial \mathcal{S}_j}{\partial Y} Y^{\text{cpg}} + \mathcal{S}_j \frac{\partial Y^{\text{cpg}}}{\partial Y} \right) \frac{Y}{\mathcal{S}_j Y^{\text{cpg}}} \\
&= \frac{\partial \mathcal{S}_j}{\partial Y}\frac{Y}{\mathcal{S}_j} + \underbrace{\frac{\partial Y^{\text{cpg}}}{\partial Y}\frac{Y}{Y^{\text{cpg}}}}_{=\delta_Y} \\
&= \left(\frac{\phi_j}{Y^{\text{cpg}}} \frac{\partial Y^{\text{cpg}}}{\partial Y} \right) \frac{Y}{\mathcal{S}_j} + \delta_Y \\
&= \delta_Y \left(1 + \frac{\phi_j}{\mathcal{S}_j} \right)
\end{aligned}
$$

And because $\eta_Q = \sum_j \eta_{Q_j} \frac{Q_j}{Q}$ according to S.2, we get

$$
\eta_Q = \delta_Y \left(1 + \sum_j \phi_j \frac{\mathcal{Q}_j}{\mathcal{S}_j} \right).
$$

Using these income elasticities and the formula for η_E (i.e., Equation S.3), we can compute the elasticity of income from the structural parameters as

$$
\eta_E = \delta_Y \left(1 + \sum_j \phi_j \frac{\mathcal{E}_j}{\mathcal{S}_j} \right).
$$

The elasticity for GHG intensity is $\eta_I = \eta_E - \eta_Q$ which is then equal to

$$
\eta_I = \delta_Y \sum_j \phi_j \left(\frac{\mathcal{E}_j - \mathcal{Q}_j}{\mathcal{S}_j} \right).
$$

Aisle Selection Including all of the 63 food aisles is empirically infeasible given the large number of cross price elasticities, and we therefore focus on the most polluting food aisles (in-

cluding beef and lamb, dairy, fish and meat) as well as their low-environmental-impact substitutes (including meat and dairy alternatives) to understand substitution patterns between high- and low-impact foods.[21] The remaining excluded aisles are aggregated into a numeraire aisle, with emissions and prices being set to the average values of all the aisles being allocated into this numeraire group.

Price Indices Following Dubé et al. (2018), we compute household-specific price indices, P_{aht}. The construction of the price index P_{aht} starts from computing prices for aisles at the chain-year P_{ast} level and constructing a Stone price-index $\log P_{aht} = \sum_s w_{asht} \log P_{ast}$ using the budget shares w_{asht} of household h, aisle a, in year t as weights, i.e., where w_{asht} sums to 1 across chains s for all combinations of household id, aisle, and year. We restrict attention to large retail chains that together account for 75% of total volume sold. In the Netherlands and Germany, we do not account for geographical price differences due to national pricing practices of the main retailers in these countries. In contrast, for the United States, we account for differences at the state-level, and household price indices are weighted accordingly.

Estimation We estimate the system implied by Equations (S.7) and (S.8), treating $\log\left(Y_{ht}^{\text{cpg}}\right)$ as endogenous. Because of robustness and the high-dimensionality of our demand system, and as is common in the empirical demand literature (e.g., Blundell and Robin, 1999; Hausman et al., 1994), we estimate the share equations individually using 2SLS, rather than estimating the full system by 3SLS. We instrument $\log\left(Y_{ht}^{\text{cpg}}\right)$ with log income, household-size and year indicators, demeaned within household. Finally, our primary interest is in measuring δ_Y and ϕ_j. In this context, we can replace $\sum_{k=1}^{K} \omega_k \log P_t^k$ with a time-fixed effect γ_t, which accounts for the price effects of all possible commodity groups k.[22], [23]

Estimates and Comparison with Reduced Form Table S.3 shows the estimates of the key parameters in the structural model. The effect δ_Y of the log of income on the log of budget for grocery purchases is estimated to be small for each country. In addition, per country the

[21] We include the following aisles: beef & lamb, cheese, deli meat and cheese, fish and seafood, meat, 50% beef and lamb+50% meat (only in Germany and the Netherlands), milk, butter & eggs, yogurts, meat alternatives, and dairy alternatives.

[22] As we make the simplifying assumption that ω_k is identical across households, the time-fixed effect γ_t is common across households too.

[23] When we include CPI indices for food, non-food, general merchandise, etc., we obtain substantively identical results.

table lists the estimates of ϕ_j which give the effect of income on expenditure shares of aisle j, while accounting for food prices. These estimates are very small too in each country.

– insert Table S.3 here –

Table S.4 compares the estimated greenhouse gas elasticities obtained from the reduced-form model and the structural demand model. Although the two approaches differ along several dimensions, the elasticities implied by the two-stage structural demand model are overall very similar to those from the reduced-form analysis, if somewhat larger. One important difference is that the structural model imposes multistage budgeting, with households first allocating income across expenditure classes in the first stage and next across grocery aisles. The model includes only high-emission aisles and their main substitutes, with all other categories combined into a single aisle. The structural estimates may also depend on how products are aggregated into aisles, as well as on the AIDS functional form, in which income affects emissions through grocery budget and aisle expenditure shares and does not allow for non-monotonic income responses. Despite these differences, both estimates show that the implied effect of income on emissions is very small, thereby confirming our main result that income changes have an economically small effect on greenhouse gas emissions from households' food baskets and their causal effect is much smaller than the ones reported from previous literature on cross-sectional studies.

– insert Table S.4 here –

Replication of Structural Model using Administrative Data This section replicates the main reduced-form analyses for the Netherlands using administrative income records instead of self-reported household income. The results are presented in Table S.5 and reinforce the conclusions presented in the main manuscript: we find small income elasticities for both reduced form and structural estimates.

– insert Table S.5 here –

Table S.1: Observations of Panelists over Time

	YouGov	Consent	Match
year	N	N	N
2011	6,125	3,335	3,333
2012	8,976	5,081	5,077
2013	9,098	5,473	5,469
2014	9,141	5,929	5,926
2015	9,192	6,379	6,369
2016	8,980	6,688	6,677
2017	8,943	7,157	7,149
2018	8,845	7,749	7,741
2019	9,669	8,942	8,932
2020	9,524	9,349	9,332
2021	9,451	9,381	9,367
2022	9,141	9,052	9,034

Table S.2: Summary Statistics Panelists

	Matched Panelists			Non-Matched Panelists			Difference		
Characteristic	M	SD	P50	M	SD	P50	*t*	*p*	*D*
Age	52.61	15.15	53.00	49.02	17.96	47.00	19.935	0.000	0.216
Household Size	2.15	1.19	2.00	2.12	1.22	2.00	3.219	0.001	0.029
Income	2,461.04	1,104.77	2,200.00	2,144.34	998.06	2,000.00	31.446	0.000	0.301
Environmental Impact	3,860.95	2,336.06	3,356.11	3,574.42	2,330.06	3,001.08	13.674	0.000	0.123

Table S.3: Selected Structural Estimates

	DE		NL		US	
	est.	s.e.	est.	s.e.	est.	s.e.
δ_Y	0.0404	(0.0037)	0.0620	(0.0061)	0.0297	(0.0025)
$\phi_{\text{beef/pork mix}}$	-0.0001	(0.0002)	-0.0001	(0.0003)	-	-
$\phi_{\text{beef and lamb}}$	0.0045	(0.0005)	0.0081	(0.0008)	0.0810	(0.0014)
ϕ_{cheese}	-0.0051	(0.0008)	-0.0098	(0.0014)	0.0025	(0.0007)
$\phi_{\text{dairy alternatives}}$	-0.0004	(0.0000)	0.0012	(0.0007)	0.0002	(0.0001)
ϕ_{deli}	0.0121	(0.0013)	0.0042	(0.0013)	0.0083	(0.0008)
ϕ_{fish}	0.0025	(0.0006)	-0.0021	(0.0009)	0.0128	(0.0008)
$\phi_{\text{other meat}}$	0.0116	(0.0011)	0.0137	(0.0016)	0.0778	(0.0014)
$\phi_{\text{meat alternatives}}$	-0.0004	(0.0003)	0.0018	(0.0007)	-0.0001	(0.0002)
$\phi_{\text{milk, butter, eggs}}$	-0.0064	(0.0009)	0.0058	(0.0014)	-0.0140	(0.0009)
$\phi_{\text{other foods}}$	-0.0168	(0.0020)	-0.0197	(0.0032)	-0.1610	(0.0031)
ϕ_{yoghurt}	-0.0015	(0.0004)	-0.0030	(0.0012)	-0.0074	(0.0006)

Note: Estimates for income and budget effects $\delta_Y and \phi_j$ in each country are collected from Equations (S.7) and (S.8) respectively, which in addition to household income and budget, account for household heterogeneity in budget and preferences, as well as for the (own and cross) effects of aisle prices.

Table S.4: Comparison of Reduced Form vs. Structural Estimates of the Income Elasticity of GHG Emissions

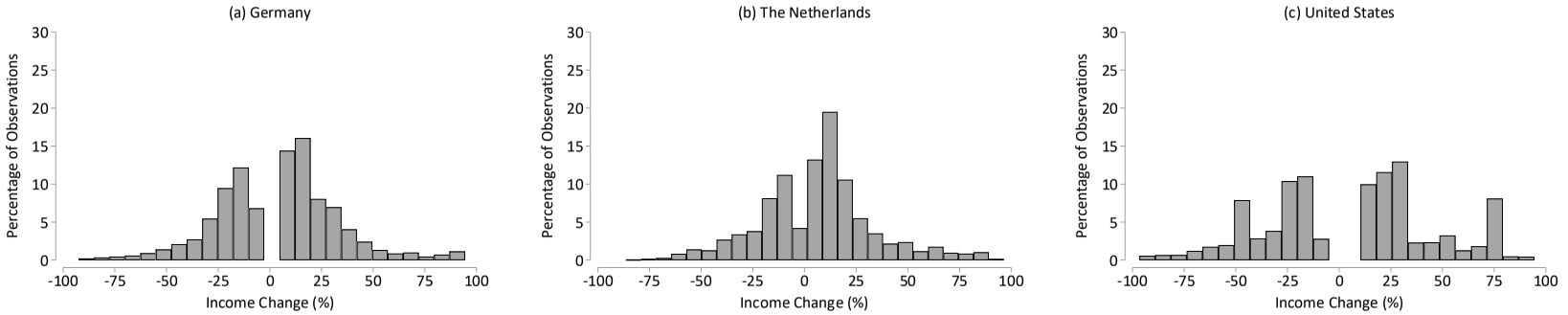
	DE		NL		US	
	Estimate	s.e.	Estimate	s.e.	Estimate	s.e.
η_E structural	0.0411	(0.0037)	0.0642	(0.0062)	0.0422	(0.0043)
η_E reduced-form	0.0239	(0.0053)	0.0388	(0.0074)	0.0097	(0.0034)
η_I structural	0.0018	(0.0002)	0.0029	(0.0004)	0.0164	(0.0025)
η_I reduced-form	0.0072	(0.0025)	0.0085	(0.0041)	-0.0044	(0.0020)

Table S.5: Replication of Reduced Form vs. Structural Estimates of the Income Elasticity of GHG Emissions with Administrative Income

	NL (Administrative Income)	
	Estimate	s.e.
η_E structural	0.0498	(0.0051)
η_E reduced-form	0.0237	(0.0060)
η_I structural	0.0021	(0.0004)
η_I reduced-form	0.0061	(0.0032)

Note: Income is measured using administrative data collected by Statistics Netherlands and matched to YouGov panelists. See data section.

Figure S.1: Histograms of Conditional Household Income Changes



Web Appendix: The Income Elasticity of Households' Greenhouse Gas Emissions: The Case of Grocery Consumption

October 12, 2026

1 Additional Tables and Figures

1.1 Effects of Income Changes on Shopping Behavior

The modest estimates of income elasticity of environmental impact of food purchases align with our further investigation into how income changes influence food purchasing behavior itself. Specifically, we analyze the impact of within-household income variation on factors such as the number of store visits, purchase volume, total household expenditure, and the average price paid per equivalent unit. Consistent with our earlier findings –and using the same empirical framework– Table 1 shows that household income has only a small effect on shopping behavior in terms of trip frequency, total volume purchased or total spending. We conduct the analyses in Table 1 as a complement to our main models, as they alone cannot fully capture the income elasticity of environmental impact. Specifically, they do not account for shifts between high-emission foods (e.g., beef) and lower-emission alternatives (e.g., plant-based meat substitutes) independent of total quantities purchased.

– insert Table 1 here –

1.2 Short-Term versus Longer-Term Income Variation

Section 3.4 of the main manuscript examines whether the income elasticity differs for more persistent income changes. We construct three longer-term income proxies from each household's own experienced income trajectory, based on a three-year window that smooths over year-to-year variation. Whereas we present these results in a figure in the main manuscript, Table 2 provides the full regression table for these analyses for total environmental impact and Table 3 for environmental intensity. For completeness, Table 4 replicates these analyses using administrative income.

– insert Table 2 here –

– insert Table 3 here –

– insert Table 4 here –

1.3 Replication of Heterogeneity Analyses with Administrative Data

In this section we replicate our heterogeneity analyses for income levels, emission levels, and generation-specific time trends using administrative income data and controlling for wealth. Table 5 shows the results of this specification for total emissions and emission intensity.

Heterogeneity across Income Levels Replicating our findings for heterogeneity between high- and low-income households, we find that lower-income households exhibit a slightly higher income elasticity of total environmental costs than their higher-income counterparts when using income from administrative data. In terms of GHG intensity we find a reverse pattern where higher-income groups react somewhat stronger in terms of emission intensity to income changes (Column 1). Overall, these findings corroborate our earlier conclusion that there are no economically meaningful interactions between income changes and emissions, suggesting that baseline income level does not moderate the income-emissions relationship substantively.

Heterogeneity across Emission Levels Using administrative income, we do not find any meaningful differences in the income elasticity of emissions from household grocery consumption for households with lower vs. higher baseline emission levels, both in terms of overall emissions and emission intensity, providing further support for our earlier conclusion that baseline emission level does not moderate the income-emissions relationship in any substantive way (Column 2).

Heterogeneity across Generations As previously described for our analyses of the three countries, the income effect on environmental impact may be confounded by generation-specific developments in consumption over time. We replicate these analyses using administrative income and controlling for wealth. We do not find any meaningful changes in the income elasticity coefficients when accounting for generation-specific time trends in our model ($\eta_E = 0.020,$ s.e. $= 0.007$ and $\eta_I = 0.004,$ s.e. $= 0.004$) (Column 3).

– insert Table 5 here –

Table 1: The Effect of Income on Shopping Behavior

	Log number of trips			Log volume			Log value			Log price		
	DE	NL	US	DE	NL	US	DE	NL	US	DE	NL	US
Log income	-0.003	-0.002	-0.002	0.017	0.030	0.014	0.040	0.061	0.027	0.024	0.031	0.012
	(0.004)	(0.007)	(0.003)	(0.005)	(0.007)	(0.003)	(0.004)	(0.007)	(0.003)	(0.004)	(0.003)	(0.001)
Constant	4.749	4.899	4.488	13.125	13.161	13.172	11.513	11.587	7.268	-1.612	-1.574	-5.903
	(0.032)	(0.053)	(0.023)	(0.040)	(0.053)	(0.026)	(0.032)	(0.050)	(0.024)	(0.028)	(0.026)	(0.012)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Panelist fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.881	0.885	0.820	0.856	0.896	0.834	0.872	0.888	0.828	0.850	0.902	0.833
adj R^2	0.847	0.859	0.778	0.814	0.873	0.795	0.835	0.864	0.787	0.806	0.880	0.793
Observations	285,950	106,945	466,754	285,950	106,945	466,754	285,950	106,945	466,754	285,950	106,945	466,754

Note: Controls include social group and household size. Time fixed effects are at the yearly level. Standard errors are clustered at the household level.

Table 2: The Effect of Income on Grocery-Related GHG Emissions

	DE				NL				US			
	Current	Forward	Centered	Backward	Current	Forward	Centered	Backward	Current	Forward	Centered	Backward
Log income	0.024	0.039	0.028	0.012	0.039	0.057	0.051	0.034	0.010	-0.012	-0.003	0.018
	(0.005)	(0.011)	(0.011)	(0.012)	(0.007)	(0.012)	(0.012)	(0.012)	(0.003)	(0.006)	(0.007)	(0.007)
Constant	7.635	7.371	7.490	7.690	7.638	7.349	7.469	7.695	7.385	7.425	7.619	7.547
	(0.041)	(0.084)	(0.083)	(0.087)	(0.057)	(0.088)	(0.087)	(0.092)	(0.030)	(0.055)	(0.058)	(0.063)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Panelist fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.848	0.842	0.844	0.838	0.892	0.902	0.907	0.902	0.805	0.820	0.827	0.834
adj R^2	0.803	0.808	0.809	0.801	0.868	0.882	0.888	0.882	0.759	0.777	0.785	0.790
Observations	285,950	212,855	211,010	191,761	106,945	85,838	83,859	76,721	466,754	323,501	323,545	288,890

Note: Forward, centered, and backward refer to three-year income proxies covering t, t+1, t+2 (discounted at 3 percent annually), t−1, t, t+1, and t−2, t−1, t, respectively. Income is deflated by the country-specific CPI. Controls include social group in year t and household size in each year of the corresponding income window. Time fixed effects are at the yearly level. Standard errors are clustered at the household level.

Table 3: The Effect of Income on Grocery-Related GHG Emissions per 100 g.

	DE				NL				US			
	Current	Forward	Centered	Backward	Current	Forward	Centered	Backward	Current	Forward	Centered	Backward
Log income	0.007	0.019	0.018	0.016	0.009	0.024	0.019	0.019	-0.004	-0.010	-0.007	-0.001
	(0.003)	(0.005)	(0.005)	(0.005)	(0.004)	(0.007)	(0.007)	(0.007)	(0.002)	(0.004)	(0.004)	(0.004)
Constant	-0.886	-0.984	-0.964	-0.936	-0.917	-1.033	-0.974	-0.979	-1.181	-1.149	-0.935	-0.973
	(0.019)	(0.040)	(0.040)	(0.040)	(0.031)	(0.052)	(0.052)	(0.052)	(0.018)	(0.034)	(0.036)	(0.038)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Panelist fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.768	0.757	0.760	0.766	0.812	0.815	0.818	0.822	0.728	0.740	0.751	0.763
adj R^2	0.699	0.703	0.707	0.713	0.771	0.778	0.782	0.785	0.664	0.677	0.690	0.700
Observations	285,950	212,855	211,010	191,761	106,945	85,838	83,859	76,721	466,754	323,501	323,545	288,890

Note: Forward, centered, and backward refer to three-year income proxies covering t, t+1, t+2 (discounted at 3 percent annually), t−1, t, t+1, and t−2, t−1, t, respectively. Income is deflated by the country-specific CPI. Controls include social group in year t and household size in each year of the corresponding income window. Time fixed effects are at the yearly level. Standard errors are clustered at the household level.

Table 4: The Effect of Income on Grocery-Related GHG Emissions using Administrative Income Data

	Total Emissions				Emission Intensity			
	Current	Forward	Centered	Backward	Current	Forward	Centered	Backward
Log income	0.020	0.041	0.026	-0.010	0.008	0.008	0.016	0.019
	(0.007)	(0.013)	(0.013)	(0.013)	(0.004)	(0.007)	(0.007)	(0.007)
Log wealth	0.006	0.007	0.007	0.006	0.002	0.002	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	7.650	7.309	7.504	7.969	-0.950	-0.953	-1.035	-1.045
	(0.071)	(0.128)	(0.132)	(0.135)	(0.037)	(0.072)	(0.071)	(0.068)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Panelist fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Time fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.899	0.917	0.919	0.911	0.808	0.828	0.827	0.826
adj R^2	0.880	0.900	0.902	0.893	0.772	0.793	0.792	0.790
Observations	72,324	51,149	52,123	53,239	72,324	51,149	52,123	53,239

Note: Forward, centered, and backward refer to three-year income proxies covering t, t+1, t+2 (discounted at 3 percent annually), t−1, t, t+1, and t−2, t−1, t, respectively. Income is deflated by CPI. Controls include social group in year t and household size in each year of the corresponding income window. Time fixed effects are at the yearly level. Standard errors are clustered at the household level.

Table 5: Heterogeneity Analyses with Administrative Income and Wealth Controls

	Total Grocery-Related GHG emissions			Grocery-Related GHG emissions per 100 gr.		
	(1)	(2)	(3)	(1)	(2)	(3)
Log income	0.041	0.015	0.020	-0.008	0.002	0.004
	(0.010)	(0.008)	(0.007)	(0.005)	(0.004)	(0.004)
Log wealth	0.006	0.004	0.005	0.001	0.001	0.000
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Log income * high baseline	-0.061	0.003		0.036	0.009	
	(0.016)	(0.009)		(0.008)	(0.005)	
Constant	7.436	7.610	7.442	-0.790	-0.914	-0.884
	(0.104)	(0.082)	(0.093)	(0.053)	(0.046)	(0.048)
Controls	✓	✓	✓	✓	✓	✓
Time fixed effects	✓	✓	✓	✓	✓	✓
Panelist fixed effects	✓	✓	✓	✓	✓	✓
Generation x time fixed effects						✓
R^2	0.899	0.922	0.900	0.808	0.816	0.810
Adj R^2	0.880	0.907	0.881	0.772	0.781	0.773
Observations	72,324	72,324	71,981	72,324	72,324	71,981

Note: Controls include social group and household size. Time fixed effects are at the yearly level. Standard errors are clustered at the household level. (1) accounting for baseline income level (2) accounting for baseline emission level (3) using generation-specific time trends