Beyond the impossible: Steering consumers away from beef*

PRELIMINARY AND INCOMPLETE WORK

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Abstract

The effect of meat consumption on the environment is well-documented, yet little is known about the effect of policies targeting environmentally harmful food choices. We build a structural model of the demand for meat, which allows us to study three different policies: a 50% reduction of beef products on retail shelves, an environmental tax reflecting the environmental costs of food products, and advertisements for plant-based products that increase consumers' valuation of them. We also analyze the supply side to estimate how prices would change in equilibrium under these policies. We find that limiting beef products alone does not reduce emissions significantly; its benefits can be easily matched with a small tax on beef, and the consumer welfare loss outweighs the environmental gains. Conversely, the other policies prove to be more effective in reducing emissions. However, we find that the burden of the tax is born disproportionately by underprivileged consumers, and its environmental benefits come mainly from consumers switching to poultry and pork products. Subsidizing these meat products while taxing beef might achieve more progressive results.

*Researcher(s)' own analyses calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researcher(s) and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

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1 Introduction

Climate change stands out as one of the paramount challenges in the 21st century. The emission of 51,000 million tons of greenhouse gases annually underscores the urgency for employing novel technologies and policies to curb these emissions. Notably, advancements in various sectors, such as energy, transportation, and food production, have showcased promising developments. Wind and solar energy technologies have experienced a significant cost reduction, while electric vehicles have gained competitiveness due to enhanced performance and reduced pricing. Moreover, plant-based meat substitutes have improved in taste, closely resembling the flavor of meat without compromising their cruelty-free nature. At the same time, policies have played a crucial role. For instance, Chile has mandated that all firms generate 20% of their energy from renewables by 2025, and China's strategic subsidies since 2009 have propelled it to the forefront of electric vehicle sales and production globally.

Numerous areas still hold potential for improvement in reducing emissions, particularly within food consumption. Notably, animal agriculture contributes to 18% of GHG emissions, with an additional estimated 4% arising from the global dairy sector (O'Mara 2011). However, there is a noticeable absence of policies aimed at addressing the high pollution levels associated with certain foods. While some countries have implemented policies targeting food known to be detrimental to human health (as studied by Barahona et al. (2020) in Chile), there remains a lack of focus on the pollution externalities of food consumption, distinct from nutritional considerations. If consumers substitute some consumption across meat products, there is potential to significantly reduce emissions.

In this paper, we study the potential impact of various policies on altering meat consumption habits. We evaluate the effectiveness of the policies to reduce GHG emissions while also exploring their potential socioeconomic implications. To assess these policies, credible demand estimates across numerous products at a detailed level are essential. Therefore, we develop a structural model of demand for thousands of meat products, seeking a balance between flexibility and generality while maintaining computational feasibility.

Specifically, we follow a two-step MLE-BLP estimation (Goolsbee and Petrin (2004), Chintagunta and Dube (2005), and Illanes and Moshary (2023)). This model allows for the estimation of substitution patterns among different product types, accounting for heterogeneity in consumer tastes. Recognizing that consumers with diverse socioeconomic backgrounds may exhibit preferences for different meat types and might respond differently to price fluctuations or product alterations, we incorporate demographic variables such as income, education, and race into the analysis. Furthermore, we develop a supply-side framework to recover marginal costs and estimate equilibrium prices. This allows us to estimate how firms might adjust pricing in counterfactual scenarios, a key factor in policy evaluation overlooked in prior literature addressing similar concerns.

Our research is centered in Chicago, a major U.S. city with diverse demographics.[1] Indeed, demographic factors play a crucial role in consumers' decisions between meat and plant-based products. Specifically,

1. To validate these findings, results from Houston, Los Angeles, and New York will be incorporated in the paper soon.

individuals with a college education or higher tend to favor environmentally friendly options and are willing to pay more for these products. Similarly, high-income shoppers like high-end plant-based products like Beyond, but do not like other (cheaper) plant-based products as much.

When it comes to product elasticities, although there is noticeable substitution between products within the same meat category, there is also significant substitution observed across various types of meat. This suggests that there is potential for policies to influence consumers to opt for different meat choices.

To understand the potential impact of various policies in encouraging environmentally cleaner choices, we leverage the estimated parameters from the demand model to explore three counterfactual scenarios: first, a 50% restriction on beef product sales; second, a carbon tax on products that internalizes the environmental harm caused during food production; and third, a situation where promotional campaigns for plant-based products positively influence how consumers value them.[2]

Results show that a restriction on beef products is not a good solution. First, consumer welfare loss (-$17 million) is larger than the environmental benefits coming from the policy ($12 million), and an analogous level of emission reduction can be achieved with a small carbon tax of $4 per ton of CO_2 emitted.

Regarding the other policies, both the tax implementation and the increase in the valuation of plant-based products demonstrate potential for achieving significant emissions reductions, possibly up to 50% or more. However, for a substantial number of consumers to substitute meat with plant-based products and thereby have a positive impact on emissions, there must be a considerable increase in the valuation of these products.

A carbon tax, conversely, appears as a more plausible solution. A reduction of 50% on emissions can be achieved by implementing a $38 per ton of CO_2 emitted carbon tax. This reduction primarily stems from beef products, given their comparatively higher pollution levels, experiencing a considerable price hike, prompting consumers to shift toward pork and poultry alternatives. However, this tax would disproportionately impact underprivileged consumers, with minorities requiring double the compensating variation compared to white consumers after the tax implementation. Therefore, we plan to study a counterfactual where a carbon tax on beef products is implemented, paired with a subsidy on pork and poultry products. This solution might not be as detrimental for disadvantaged consumers.

The data comes from the NielsenIQ Retail Scanner (RMS) and NielsenIQ Consumer Panel (Homescan) provided by the Kilts Center at the University of Chicago. RMS contains prices and quantities sold for a wide variety of products across many cities in the United States, whereas Homescan includes consumer purchases through time alongside their demographics (such as race, income, and education level). We manually identify roughly 129,000 meat and plant-based products and aggregate them into approximately 2,300 products for traceability.

This paper aligns closely with recent literature exploring the environmental impact of changes on dietary

2. Tonsor, Lusk, and Schroeder (2021) demonstrate that chicken secured its position as the most-bought meat in the U.S. not solely due to price cuts but predominantly because of health and safety marketing. We draw from this fact to construct the counterfactual on promotional campaigns for plant-based products.

habits and the implementation of a meat consumption tax (Briggs et al. 2013; Briggs et al. 2015; Springmann et al. 2016; Springmann et al. 2018; Kehlbacher et al. 2016). While Katare et al. (2020) suggest that education alone might not effectively guide consumers toward environmentally friendlier choices, advocating for the necessity of a Pigouvian tax, all these studies collectively indicate substantial potential for reducing emissions through changes in food consumption behavior. However, none of these studies have thoroughly examined both the extensive (how many consumers would switch their meat choices?) and intensive (the degree of switching) impacts of such a tax. Our paper, incorporating realistic substitution patterns that consider consumer diversity, assesses the actual potential for emissions reduction achievable, not only concerning the tax but also with other policy measures. To the best of our knowledge, this is the first study to comprehensively explore meat choices and their environmental consequences in this manner.

The closest existing paper to ours is Simon (2021), which employs a nested logit model of food consumption to assess their impact on emissions. Leveraging extensive data on marginal costs, she explores potential emissions reductions if dietary habits uniformly changed across Europe. However, this and all cited studies, predominantly focus on the partial equilibrium of the market, examining how consumer demand might alter in various scenarios without delving into how firms would adapt under diverse policy implementations. A tax could be partially or fully passed through to consumers, contingent upon the responsiveness of demand and the competitiveness within the market. These disparities could yield distinct policy implications. Thus, models neglecting the supply side of the market might yield biased estimations of the potential gains or losses from a policy. Our paper incorporates firms' capacity to react to taxes or shifts in consumer perceptions regarding certain foods, enabling them to adjust prices accordingly. Additionally, by incorporating diverse consumer characteristics, we can evaluate how policies differentially impact consumer welfare across demographics.

The remainder of this paper is organized as follows. Section 2 provides background information on emissions by meat type and briefly explains meat consumption patterns in the U.S. In Section 3, we describe the data employed for the empirical analysis. In Section 4, we introduce the chosen demand and supply specifications. Section 5 provides an explanation of the estimation procedure and identification. We present the results in Section 6. The counterfactual policies are explained, and their results are shown in Section 7. Section 8 concludes.

2 Background and setting

In this section, we provide background information on climate change, how animal husbandry is related to it, and why the U.S. is an ideal country to conduct our empirical analysis.

2.1 Emissions by meat type

Agriculture contributes to 18% of global greenhouse gas emissions (O'Mara 2011), with animal husbandry ranking as the most polluting activity within this sector. However, not all animals have an equal impact on emissions. The quantity of greenhouse gases produced varies depending on the type of animal raised. Consequently, Poore and Nemecek (2018) synthesized extensive data encompassing farms, processors, packaging types, and retailers to estimate the environmental impact associated with various food products. Table 1 provides a selection of their findings relevant to this study.

The table underscores the significance of choices in food consumption. On average, cattle emit more than five times the amount of greenhouse gases compared to poultry or pork, and over 25 times more than tofu. Furthermore, there is a substantial disparity in land usage between different types of meat. For instance, a chicken requires 2 calories of grain for every calorie of meat obtained, while a cow needs 6 calories per portion of meat. Increased beef consumption consequently escalates the demand for farming to sustain cattle, potentially contributing to deforestation and other environmental impacts.

Table 1: Difference in greenhouse gases emissions and land use by protein rich products

	GHG Emissions (kg CO_{2eq})		**Land Use ($m^2 year$)**	
	10th Pc	**Mean**	**10th Pc**	**Mean**
Beef	20	50	42	164
Pork	4.6	7.6	4.8	11
Poultry Meat	2.4	5.7	3.8	7.1
Crustaceans (farmed)	5.4	18	0.4	2.0
Fish (farmed)	2.5	6.0	0.4	3.7
Tofu	1.0	2.0	1.1	2.2
Grains	1.0	2.7	1.7	4.6

Source: Poore and Nemeck (2008)

Therefore, countries characterized by high levels of beef consumption, which is sourced from cattle, will have a larger impact on emissions.

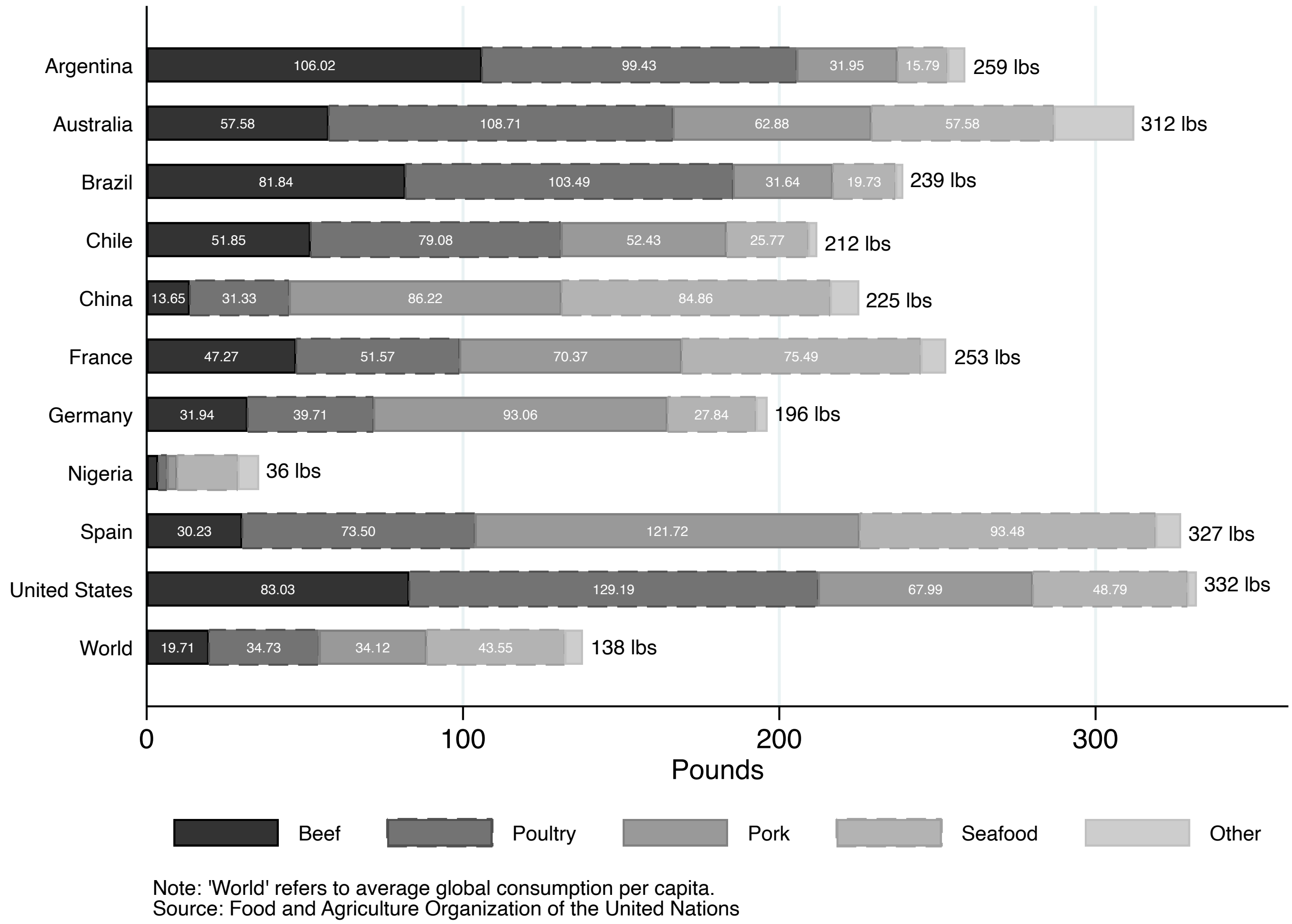
2.2 Meat consumption in the United States

The U.S. stands as one of the world's leading consumers of meat. In terms of beef consumption, the country holds the second position, following closely behind Argentina. For a comparative perspective among nations, Figure 1 provides a snapshot of meat consumption in 2019 across select countries.[3]

The per capita consumption of total meat, amounting to 332 pounds, stands at approximately 240% of the global average of 138 pounds. Spain closely follows the United States in this consumption trend, with the

3. Figure 1 reflects "available for consumption"; actual consumption might be lower after accounting for food wastage.

Figure 1: Average meat consumption per capita by country



U.S. surpassing other developed nations like Germany or France by a significant margin. This discrepancy could partly be attributed to the relatively low share of consumer expenditure allocated to food. Relative to income, the United States has one of the world's lowest food prices. Consequently, this stark contrast sets the country apart not only in beef consumption but also in the consumption of other meat types. Therefore, such substantial and varied purchases of meat provide an ideal scenario for estimating meat consumption demand.

3 Data

We now describe the data that informs the econometric specification and furthermore report the observed heterogeneity in consumers' tastes for different meat types.

3.1 Product characteristics and market definitions

Our primary data sources include the NielsenIQ Retail Scanner (RMS) and NielsenIQ Consumer Panel (Homescan) datasets, obtained through the Kilts Center at the University of Chicago. The RMS dataset provides weekly records of revenue and sales quantity for around 5 million distinct products across 31,500 stores throughout the United States. On the other hand, the Homescan dataset encompasses purchase decisions made by approximately 60,000 households, some of which overlap with the stores featured in the RMS dataset.

For our analysis, we concentrate on four major U.S. cities throughout the year 2019: Chicago, Houston, Los Angeles, and New York. While we refer to them as cities, these names correspond to the "Scantrack Markets" defined by NielsenIQ. By using their market designation, we can accurately utilize the projection factors tailored for each panelist. Each city represents a different geographical region within the U.S.—midwest, south, west coast, and east coast—allowing us to account for diverse demographic distributions across the country.

The following section outlines key specifics of our data.

Products. Out of nearly five million products within the dataset, approximately 235,000 are categorized as either meat or plant-based items.[4]

However, the dataset often lacks specific meat identification (such as beef, poultry, etc.) for these products. To address this, we manually classify each product type by cross-referencing the provided Universal Product Code (UPC) description in the data with a recommended website provided by the Kilts Center, allowing us to discern product names from UPCs.

We successfully identify the meat type (beef, poultry, pork, seafood, or plant-based) for 129,000 products, which collectively represent between 75-79% of sales volume and revenue in each city.[5]

For computational tractability, we aggregate products based on their meat category, brand, the concept of "resemblance flavor" (pertaining exclusively to plant-based products)[6], and clusters for size and price range.

In our product definition, the meat category typically aligns with the product's meat type, except for beef and plant-based products. Beef is further subdivided into three categories: "high-" and "low-" quality cuts (e.g., T-bone steak versus ground meat), or "prepared food," denoting assembled meals containing beef (e.g., frozen beef steak with roasted potatoes). This detailed breakdown enables a more nuanced estimation of substitution patterns toward beef, considering its substantial environmental impact, as discussed in the previous section.

4. It is important to note that our definition of plant-based products encompasses vegetarian or vegan options capable of substituting meat, excluding items like vegetables, rice, or plain pasta while encompassing selections such as tofu sandwiches and vegetarian hamburgers.

5. We exclude 8,000 products that involve mixtures of multiple meats (e.g., beef and turkey sausages) or uncommonly purchased meats like duck, ostrich, veal, among others.

6. "Resemblance flavor" accounts for instances where a product specifically aims to mimic the flavor of beef or chicken.

On the other hand, plant-based products are partitioned into two categories: Beyond Meat products and others, labeled simply as "plant-based." Beyond Meat is notable for creating substitutes closely resembling the flavor, texture, and appearance of ground beef, sausages, and chicken strips. This division allows us to explore whether meat consumers display a greater tendency to substitute toward plant-based options that more closely emulate the flavors of meat or whether other simpler plant-based alternatives suffice.

Table 2 displays the product distribution along with their respective characteristics, specifically for Chicago. Corresponding tables for the remaining cities are available in the Appendix.

Table 2: Product characteristics by meat category, Chicago

	Chicago				
Category	**Products**	**Brands**	**Price (USD)**	**Size (Ounces)**	**Share**
High-End Beef	22	10	7.98	16.66	0.54%
Low-End Beef	223	135	5.98	18.20	10.25%
Prepared Food with Beef	234	143	4.25	17.29	9.08%
Pork	512	255	4.50	15.33	30.50%
Poultry	597	271	4.96	17.30	35.92%
Seafood	455	220	4.75	10.52	9.90%
Plant-based	190	102	3.79	12.58	3.25%
Beyond	5	1	6.89	11.24	0.56%
Top Products	2,059				95.38%
Composites	179				4.62%
All Products	2,238				100%

Price and size are averages across products. Share is based on ounces sold.

Poultry and pork products notably dominate consumer purchases on average. Although high-end beef products are predictably the most costly, there is a scarcity of these items in the dataset. This scarcity stems from their tendency to be predominantly purchased in random weights[7] without specific UPCs, which are not included in the RMS data. However, the dataset does feature numerous instances of low-end and prepared beef products, with substantial purchase occurrences, as detailed in Table 3.

Each product is observed in at least 80 markets and, on average, across 2,409 instances. Beyond Meat products stand out as considerably more expensive than other plant-based alternatives, and secure a market share akin to high-end beef despite consisting of only 5 products, significantly fewer compared to the 22 products representing high-end beef. This corresponds to the notion that Beyond Meat distinguishes itself from other non-meat alternatives through certain attributes that might not be immediately observable to the econometrician.

Composite Products. Following aggregation, the number of products is reduced to approximately 3,000

7. Random weighted meats refers to products weighted and packed on-site in the butchery section of a retail store.

products. Those with limited appearances across markets (less than 80) or negligible market shares below 0.01%[8] are combined into composite products based on meat category, resemblance flavor, and clusters for size and price range. Products that still meet either of the criteria mentioned post-aggregation are eliminated from the analysis.

It is important to note that not all 3,000 products will be present in every city. For instance, in Chicago, we observe 2,238 products being purchased.

Markets. We define a market as a store-week combination. To estimate the number of consumers visiting each store, we utilize the Food Environment Atlas database sourced from the Economic Research Service of the USDA. This database provides the total count of food-selling stores within each county, enabling us to calculate the portion of stores represented in the RMS dataset. We assume that this share of stores adequately approximates the share of consumers observed purchasing in each county. Furthermore, consumers are assumed to distribute themselves among the observed stores based on the stores' corresponding RMS sales share within the county. The total number of consumers is derived from the American Community Survey 2015-2019 conducted by the Census Bureau.

Stores with exceptionally small market sizes (below 25 customers) or a limited product range (less than 50) are excluded from the analysis.

Table 3: Markets' summary statistics, Chicago

	Chicago			
	Mean	**SD**	**Min**	**Max**
by Market				
Products	222.0	96.0	45	423
Brands	122.0	54.7	26	223
Consumers	7,751.9	6,973.7	58	48,053
Product's Shares	0.0007	0.002	0.0001	0.15
by Product				
Markets	2,409.0	3,828.1	80	23,931

Table 3 shows the variation in available choice sets within stores across Chicago. On average, each store offers 222 products out of a total of 2,238. This large number of products per market results in small shares, driving the creation of composite products.

Additionally, the table highlights the recurring appearances of products across different markets. On average, a product is observed in 2,409 store-weeks. This variability in choice sets and the repeated observation of products will significantly help the econometric model in accurately estimating the demand specification parameters.

8. Market size is defined as the product of the number of customers visiting a store and the average weekly meat consumption in the U.S.

Consumer demographics. Data sourced from the American Community Survey 2015-2019 conducted by the Census Bureau is employed to acquire consumer demographics at the zip3 level. The zip3 level corresponds with the store location data available in NielsenIQ's RMS and Homescan datasets.

Table 4: Demographic attributes by city

	Percentage of Population		
	Minority	**College**	**High Income**
Chicago	34.73	38.73	26.37
	(12.92)	(10.25)	(13.85)
New York	36.55	42.77	42.75
	(18.43)	(11.16)	(22.27)
Los Angeles	43.25	31.76	25.34
	(9.62)	(10.90)	(14.81)
Houston	33.63	32.22	24.79
	(9.86)	(5.43)	(12.37)

Minority refers to share of non-white population. College is the share of population with at least some college education. High income corresponds to the share of population with income above $100,000.

The selected demographics for the empirical analysis are consistent with the information available in the Homescan data for the panelists. Three key demographics will be utilized: minority (referring to the non-white population), college education (indicating whether an individual in the household holds a college degree or higher), and high income (denoting households with a monthly income of $100,000 or more).

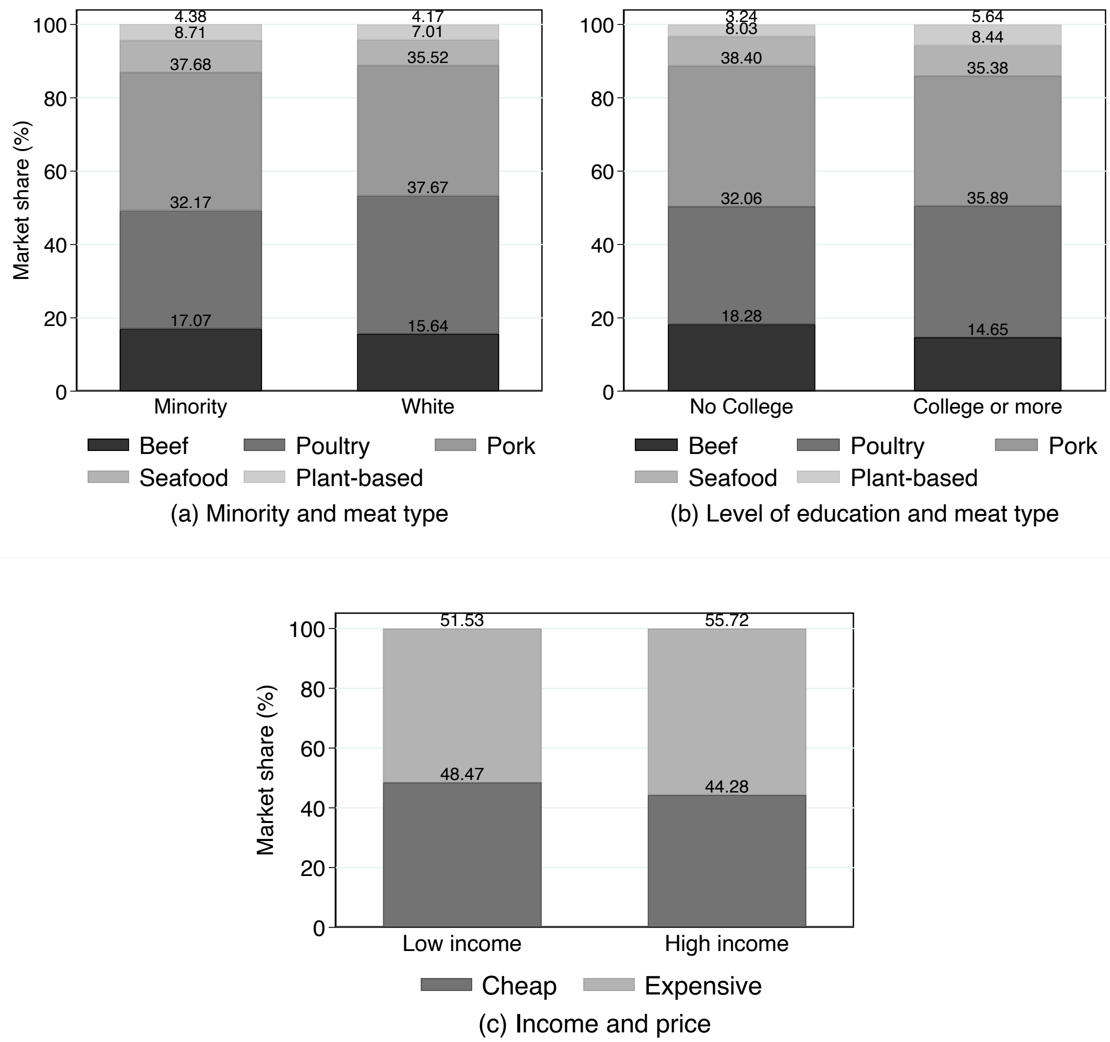
Diversity in demographics among cities is evident. Table 4 highlights the variance: New York boasts a greater proportion of highly educated and affluent residents, whereas Los Angeles has a larger share of minority populations. Chicago and Houston exhibit similar average demographics, yet Chicago showcases more significant dispersion within the city. Analyzing various cities with distinct demographic profiles helps to better comprehend the results, offering broader implications applicable not just to specific cities but to the nation as a whole.

3.2 Evidence of heterogeneity in preferences

To show evidence of taste heterogeneity in meat consumption, we analyze the Homescan dataset, keeping specifically products purchased in RMS for the cities under study. Figure 2 demonstrates how the market shares of various product attributes vary across demographics for Chicago.[9] Panels (a) and (b) examine the differences in shares by race and education level, respectively.

In Panel (a), minorities exhibit a slight preference for beef compared to white customers, while displaying the opposite tendency toward poultry. However, when it comes to plant-based products, racial differences

9. Comparable figures for other cities can be found in appendix C



(a) Minority and meat type

(b) Level of education and meat type

(c) Income and price

Figure 2: Market share of different product attributes by demographics, Chicago

appear less significant. In contrast, Panel (b) suggests that highly educated customers tend to favor plant-based products and poultry. This preference can be explained by college-educated individuals valuing more products perceived as healthier and more environmentally friendly than beef and pork.

Panel (c) illustrates price preferences based on income. A product is labeled as “cheap” if its price falls below the average price of its meat type; otherwise, it is considered “expensive.” Naturally, high-income customers exhibit less price sensitivity and, consequently, tend to purchase more expensive products on average compared to low-income customers.

When assessing the diversity in preferences across cities, panels (b) and (c) typically depict consistent trends: individuals with college education lean toward “cleaner” alternatives, and high-income consumers display lower price sensitivity. However, a discrepancy arises in Houston, where plant-based products do not seem to be favored by college graduates over non-graduates.

In contrast, racial preferences, as shown in panel (a), vary across cities. For instance, beef, which garners more attention from minorities in Chicago, is preferred more by white customers in New York, while displaying almost no discrepancy among groups in Los Angeles.

Overall, Figure 2 elucidates that policies favoring plant-based products, altering food prices, or restricting beef consumption will affect consumers differently based on their demographics. Therefore, a model incorporating such diversity could offer more realistic insights into how consumers might respond to distinct policies aimed at reducing emissions from food consumption.

3.3 Bundling and stockpiling behavior

In each market, as presented in Table 3, consumers typically have an average choice among approximately 200 products.[10] This might raise concerns about whether consumers purchase one or multiple products during each shopping trip. However, Table 5 indicates that, in most instances, consumers tend to select only one product.

It is important to note that the aggregation of 129,000 products into approximately 2,300 could potentially result in artificially lower bundle sizes. Nevertheless, given that aggregation was performed separately for each category (and brand) if consumers frequently bundled multiple types of meat together, the median bundle size would likely surpass one.

Table 5: Bundling and stockpiling behavior across cities

	Meat products			**Any product**
	Median bundle size	**Mean bundle size**	**Purchase every (weeks)***	**Purchase every (weeks)***
Chicago	1	1.66	3.06	1.13
New York	1	1.58	3.47	1.13
Los Angeles	1	1.72	2.89	1.13
Houston	1	1.73	2.74	1.16

*Refers to time it takes to consumers to deplete their stock of accumulated products.

Another question arises concerning whether these products are considered storable. Columns three and four in Table 5 display the average number of weeks it takes for consumers to revisit a store and purchase meat (or plant-based) products or any product, respectively. The data suggests that consumers typically visit a store nearly every week to buy any product but make meat purchases every 2 or 3 weeks. This pattern implies that consumers tend to stockpile meat products, although not for extended periods of time.

In the subsequent section, we address the trade-offs inherent in modeling bundling and stockpiling behaviors and their relevance within our framework.

10. Similar figures for other cities can be found in Table C2 in the Appendix

4 Model of demand and supply for meat

This section provides a description of the demand and supply specifications chosen. We use a discrete-choice model to estimate meat demand, and in Appendix B, we discuss on the rationale behind this modeling approach.

4.1 Demand

To account for the heterogeneity in tastes observed in the previous section, we use random-coefficient estimation. While discussions on the mixed-logit are well documented in the literature (Berry, Levinsohn, and Pakes 1995; Nevo 2000, 2001), we provide a brief description focusing on important aspects for our empirical analysis.

We define a store-week combination as a market and index it by $t \in \mathcal{T}$. There are J products, indexed by $j \in \mathcal{J}$, and one outside good.[11] Utility derived by consumer $i \in \mathcal{I}$ when purchasing product j in market t is

$$u_{ijt} = \alpha_i p_{jt} + \beta_i x_{jt} + \eta_j + \lambda_t + \xi_{jt} + \varepsilon_{ijt} \tag{1}$$

where x_{jt} represents product characteristics (meat type and size), p_{jt} is the price of product j on market t, η_j is a product fixed effect that controls for the unobserved the national mean valuation of its characteristics, ξ_{jt} is a store-week-product specific deviation from this mean and ε_{ijt} is a mean-zero stochastic term. ξ_{jt} assumes that there are market-specific unobservable components common to all consumers, and will be treated as error terms.

α_i, β_i are individual-specific coefficients that are defined as

$$\begin{pmatrix} \alpha_i \\ \beta_i \end{pmatrix} = \begin{pmatrix} \alpha_0 \\ \beta_0 \end{pmatrix} + \Gamma D_i$$

Γ is a diagonal matrix of coefficients that measures how tastes for meat vary with demographics D_i (race, education, income). We do not allow the individual characteristics to consist of demographics that are unobserved. In Appendix F, we show the results for specifications with unobserved individual-level random coefficients distributing as multivariate normal, demonstrating they are statistically insignificant.

We denote the mean utility level (i.e., the portion of utility that does not depend on i) by $\delta_{jt} = \alpha_0 p_{jt} + \beta_0 x_{jt} + \eta_j + \lambda_t + \xi_{jt}$, and the part that depends on i by $\mu_{ijt} = [p_{jt}, x_{jt}]' * (\Gamma D_i)$. Assuming ε_{ijt} follows a Type I extreme Value distribution, we have that the market share for product j in market t is given by

$$s_{jt} = \int_{D_t} s_{ijt}\, dP_d(D_i) = \int_{D_t} \frac{exp(\delta_{jt} + \mu_{ijt})}{1 + \sum_k exp(\delta_{kt} + \mu_{ikt})}\, dP_d(D_i) \tag{2}$$

11. See section 5.2 for a discussion on the outside option.

4.2 Supply

For the supply side, the strategy is to use the demand estimates jointly with an assumption on pricing rules to recover unobserved marginal costs. Let firm f's profit function be given by:

$$\Pi_f = \sum_{j \in \mathcal{J}_f} (p_j - c_j) M s_j(\mathbf{p}) - C_f \tag{3}$$

where $\mathcal{J}_f$ is the set of products owned by firm f, and $s_j(\mathbf{p})$ is the market share (dependent on the vector all market prices $\mathbf{p}$), M is the market size and C_f the fixed cost of production. The first-order conditions, assuming a pure-strategy Bertrand-Nash equilibrium in prices, are

$$s_j + \sum_{k \in \mathcal{J}_f} (p_k - c_k) \frac{\partial s_k}{\partial p_j} = 0, \qquad \forall j \in \mathcal{J}_f \tag{4}$$

Let Ω be the firms' response matrix, with element $(j,k) = \frac{\partial s_k}{\partial p_j}$ if k and j are produced by the same firm, or 0 otherwise. Stacking up the first order conditions given by equation 4 and rearranging terms

$$\mathbf{p} = \mathbf{c} + \underbrace{\Omega(\mathbf{p})^{-1} s(\mathbf{p})}_{\text{markup}} \tag{5}$$

From where the vector of marginal costs $\hat{\mathbf{c}}$ can be easily retrieved.

We use equation 5 and the estimated $\hat{\mathbf{c}}$ to retrieve equilibrium prices in counterfactual scenarios. For instance, in the case of a carbon tax on food, the extent to which this tax is passed through to consumers—or potentially absorbed by firms—relies on market competitiveness. This equation delineates how firms might react under different circumstances.

5 Estimation

In this section, we elaborate on the estimation procedure, identification of parameter estimates, and price endogeneity concerns.

The objective is to estimate the taste parameters that govern demand substitution patterns. We adopt a two-step estimation procedure akin to approaches found in studies such as Goolsbee and Petrin (2004), Chintagunta and Dube (2005), and Illanes and Moshary (2023). This involves using a household model in tandem with a store-level model to recover the demand parameters while addressing price endogeneity.

In the first step, we estimate the parameters Γ via maximum likelihood estimation using household-level data. We define the density of consumer i's observed sequence of choices across markets as

$$\mathcal{L}_i(Y_i | X, \Gamma) = \prod_{t=1}^{T} \prod_{j=0}^{J} s_{ijt}(X_t, \delta_t(\Gamma), \Gamma)^{Y_{ijt}} \tag{6}$$

where $Y_i = (Y_{1i}, \ldots, Y_{Ti})'$, $Y_{ijt} = 1$ if product j is chosen on market t, with $j = 0$ the outside good. The corresponding log-likelihood is as follows

$$\ell(Y;\Gamma) = \sum_{i=1}^{I} \sum_{t=1}^{T} w_{i,t} \sum_{j=0}^{J} Y_{ijt} * \log[s_{ijt}(X_t, \delta_t(\Gamma), \Gamma)] \tag{7}$$

where $w_{i,t}$ is the weight of household i in market t given by NielsenIQ expansion weights. The estimation proceeds by searching for the values of Γ that maximize equation 7.

Note that δ is taken as given for the log-likelihood construction because it is derived through an inner loop within each Γ iteration. With a given set of Γ values, there exists a unique set of mean utilities δ (Berry 1994). Employing a Nested Fixed Point method, we numerically search for the mean utility values, δ, that match with the observed market shares (at the store-week level) for given values of the Γ parameters.[12]

Given the asymptotic normality from the maximum likelihood estimator, and assuming the model is correctly specified, the standard errors for the parameters Γ estimated in the first stage are given by the following variance-covariance matrix

$$\hat{V} = \left(\frac{\sum_{i=1}^{I} \sum_{t=1}^{T} w_{i,t} \sum_{j=0}^{J} Y_{ijt} * \frac{\partial \log[s_{ijt}(X_t,\delta_t(\Gamma),\Gamma)]}{\partial \Gamma} \frac{\partial \log[s_{ijt}(X_t,\delta_t(\Gamma),\Gamma)]}{\partial \Gamma'}}{\sum_{i=1}^{I} \sum_{t=1}^{T} w_{i,t}} \right)^{-1}$$

The second step involves retrieving α_0 and β_0 from the estimated δ product-specific intercepts. As pointed out in Section 4.1, the mean utility is constructed as

$$\delta_{jt} = \alpha_0 p_{jt} + \beta_0 x_{jt} + \eta_j + \lambda_t + \xi_{jt} \tag{8}$$

It is important to consider the potential endogeneity between prices (p_{jt}) and ξ_{jt}. If there is a positive correlation between these elements, the model might underestimate consumers' average responsiveness to prices. Since the parameters enter linearly in Equation 8, employing an instrumental variables (IV) approach would effectively address this concern.

To get the standard errors for $\hat{\alpha}_0$ and $\hat{\beta}_0$, we apply the delta-method and obtain the variance-covariance matrix

$$\hat{V}_{\text{2ndStage}} = P_{IV} \frac{\partial \delta}{\partial \Gamma} \hat{V} \frac{\partial \delta}{\partial \Gamma'} P'_{IV} \tag{9}$$

where P_{IV} is the projection matrix coming from Equation 8, and

$$\frac{\partial \delta}{\partial \Gamma} = -\frac{\partial\, s_{jt}}{\partial \delta}^{-1} \frac{\partial\, s_{jt}}{\partial \Gamma} \tag{10}$$

is computed by applying the implicit function theorem.

12. It is important to highlight the benefits of utilizing store-aggregated shares instead of household sample aggregate shares. This approach eliminates concerns regarding feasibility constraints caused by sparseness in the observed purchases in any given store-week. Moreover, it circumvents potential issues associated with sampling errors at the household panel level, both in estimating Γ and in computing δ.

5.1 Instruments and identification

In this section, we delve into the identification of parameters from the two-step estimation procedure. We start by addressing identification in the first stage.

For a given Γ, δ is pinned down by the Berry-inversion. Concerning Γ, its estimation benefits from two distinct sources of variation.[13] One stems from consumers with varying demographics making choices among products with diverse characteristics within a given market. The second source arises from the fluctuation in prices and choice sets observed across different markets for identical consumer demographics. This enables observation of scenarios where minority consumers, within a market, may favor particular product characteristics over non-minority consumers. Additionally, it sheds light on how low-income individuals might alter their product choices in response to price changes while high-income consumers remain unchanged in their decisions.

Recovering δ and Γ in the initial step of estimation is not impacted by bias stemming from price endogeneity. This stage benefits from mean utilities that condition for ξ, mitigating such concerns.

In contrast, the second stage of the estimation does suffer from endogeneity issues. Firms base their pricing decisions on all product characteristics, including both observed (x_{jt}) and unobserved (ξ_{jt}) factors. Consequently, prices are not randomly assigned, needing instrumental variables to prevent biased parameter estimates.

We use product fixed effects to capture product characteristic valuations (observed and unobserved) that remain constant over time. Furthermore, we incorporate market fixed effects to capture unobserved determinants of demand (seasonal and/or aggregate shocks to the food industry).

The remaining econometric error within ξ_{jt} accounts for shifts in unobservable consumer preferences and changes in unobserved product characteristics not linked to seasonal or market-specific factors. To instrument for these, we employ input costs—such as weekly or monthly grain and animal feed prices—interacted with meat type indicators. This method, similar to Berto Villas-Boas (2007), allows inputs to enter the production function of each meat type differently. Since different animals are fed diverse grains, and plant-based products use distinct inputs from animal feed, this approach captures these distinctions. While input prices are directly associated with product prices, they are not relevant to consumer valuation of the products. Hence, the IV approach allows for the identification of parameters in the second stage of the estimation process. Table D1 in Appendix D shows that our instruments are not weak.

5.2 Outside good definition

In section 3.1, we outlined a market as a store-week combination and detailed the methodology for estimating the assumed number of customers visiting each. However, the market size is not quantified by the number of customers; instead, it is determined by the total meat consumption within that market over a week.

13. See Berry and Haile (2020) for details on identification.

Using 2019 per capita meat consumption data from the USDA, I calculate the total ounces of meat purchased per week by summing the consumption of all consumers in a market. This measurement encompasses every ounce of meat consumed by individuals. Consequently, the outside option would encompass any meat (or plant-based) product either eaten at restaurants or bought from NielsenIQ retail stores as a random weight non-UPC product.

For counterfactual policy assessments, we assign emissions levels to each ounce of meat, obtained from table 1. To determine the total emissions in a market, an assumption about the emissions associated with an ounce of the outside option must be made. We assume that the composition of meat products within the outside option mirrors the observed shares in that market (store-week). Consequently, the emissions of the outside option will be a weighted sum of the emissions from each meat type (including plant-based products), with the weights determined by the observed market shares.

6 Results

Table 6 presents the results from our preferred mixed logit model specification.[14] The estimated parameters are precise, and reveal that high- and low-end beef products are preferred over the seafood reference category. Conversely, prepared food with beef tends to be less valued on average than seafood, mirroring a similar trend with the combined pork-poultry category.[15] Notably, Beyond Meat products exhibit a higher average valuation compared to the reference seafood category, differing from the rest of the plant-based products, which show a lower average valuation.

The model also reveals diverse tastes across demographics. More educated consumers value environmentally friendly products like plant-based, Beyond, and pork-poultry items more than consumers without a college education. Similarly, high-income shoppers exhibit a preference for pork-poultry and are willing to invest in "cleaner" options by opting for Beyond products. However, they do not favor other (less expensive) plant-based products as much as lower-income groups do. Moreover, higher-income and educated demographics seem less responsive to price changes, likely due to their willingness to pay more for healthier, albeit pricier, food choices. In addition, these types of consumers might also be less price elastic simply due to income effects.

Allowing for taste heterogeneity has a significant impact on predicted consumer responses, varying notably across demographics. Table 7 shows an average own-price elasticity of -2.7, with considerable heterogeneity both within and across meat categories. Interestingly, Beyond, high- and low-end beef products tend to display higher elasticity than others on average. The own-price elasticity for composite products closely mirrors the overall average, providing reassurance since composite products are an aggregate of smaller-share products.

14. Tables D1 and D2 in Appendix D detail the IV first stage outcomes and the fit of the mixed logit model, respectively.

15. As pork and poultry products have comparable environmental impacts, they are grouped together since substitution to any of these two categories would have similar environmental effects on counterfactual results.

Table 6: Demand Estimates

	$\alpha_0,\ \beta_0$	Demographic Interactions (Γ) Minority	Educ $\geq$ College	Income $\geq 100K$
Price	-0.5387	-0.1397	0.0146	0.0680
	(0.0096)	(0.0075)	(0.0078)	(0.0077)
Constant	-6.6545	0.2017	-0.2316	-0.0817
	(0.0028)	(0.0646)	(0.0644)	(0.0656)
High End Beef	0.7569	-0.6794	-0.9363	-0.1281
	(0.0053)	(0.2659)	(0.2258)	(0.2247)
Low End Beef	0.5177	-0.0095	-0.4513	-0.2020
	(0.0034)	(0.0640)	(0.0691)	(0.0705)
Prepared Food Beef	-0.7805	-0.2829	-0.0292	0.0997
	(0.0030)	(0.0870)	(0.0880)	(0.0877)
Pork-Poultry	-0.0964	-0.3684	0.1101	0.2611
	(0.0023)	(0.0553)	(0.0560)	(0.0558)
Plant Based	-0.3429	-0.8686	0.5037	-0.6074
	(0.0027)	(0.1022)	(0.0986)	(0.1088)
Beyond	0.0638	1.0700	0.8774	1.1056
	(0.0070)	(0.1687)	(0.1819)	(0.1643)
Composite	0.1661	-0.1156	0.1184	0.1085
	(0.0014)	(0.0322)	(0.0313)	(0.0314)
Size	0.0978	0.0463	-0.0050	-0.0028
	(0.0002)	(0.0014)	(0.0014)	(0.0015)
Summer	0.0204			
	(0.0015)			

Comparing these findings to prior literature, the average own-price elasticities in this model appear higher (in absolute value). However, this difference can be accounted for. For instance, while Simon (2021) analyzes consumer choices through a nested logit model, our mixed logit model allows for substitution patterns that are not driven by a functional form but by the differences in the price sensitivity of consumers.[16] Therefore, it is reasonable to expect that we can capture higher price elasticities. Lusk and Tonsor (2016), on the other hand, relies on experimental choice data, which typically reflects lower price sensitivity compared to real purchase scenarios. This disparity arises as consumers are typically more price elastic during actual purchases than in online survey experiments.[17]

Additionally to own-price elasticities, cross-price elasticities are crucial in this study to understand potential consumer substitution away from "dirtier" products in various scenarios. Drawing from Miravete, Seim, and Thurk (2020), we calculate a ratio and best substitute metrics for each product category. The ratios denote cross-price elasticities between products within a category (e.g., high-end beef) and products

16. See Nevo (2000) for a detailed explanation of the differences between the nested and mixed logit models.
17. For a detailed distribution of elasticities across product categories, refer to Appendix E, figure E1.

Table 7: Price Elasticities by category and composite

	Price elasticity (ε_{jj})		Cross-price elast. (ε_{ji})	
	Average	SD	Ratio	Best subst.(%)
By category:				
High-End Beef	-3.23	1.45	1.20	28.30
Low-End Beef	-3.27	1.46	1.21	23.91
Prepared Food with Beef	-2.39	1.55	1.12	17.12
Pork-Poultry	-2.71	1.29	1.05	46.88
Seafood	-2.52	1.63	1.06	16.35
Plant Based	-2.40	0.85	1.47	57.27
Beyond	-3.94	0.95	4.00	83.33
By composite:				
Composites	-2.84	1.45	—	—
All products	-2.70	1.39	—	—

"Ratio" is the average cross-price elasticity among products of a characteristic (e.g., Beyond) relative to the average cross-price elasticity among products that do not have that characteristic. Values greater than one indicate that consumers are more likely to substitute toward a product that shares the characteristic in question (e.g., same category). "Best Subst." is the percent of products that share a characteristic (e.g., same category) where the best substitute (i.e., the product with the largest cross-price elasticity) also shares that characteristic (e.g., is of the same category).

outside that category (e.g., plant-based). For product j, the calculation for $Ratio_j^c$ involves

$$Ratio_j^c = \frac{\frac{1}{|\mathcal{C}_j^c|}\sum_{i\neq j, i\in\mathcal{C}_j^c}\varepsilon_{ji}}{\frac{1}{|\mathcal{C}_j^{-c}|}\sum_{i\neq j, i\in\mathcal{C}_j^{-c}}\varepsilon_{ji}},$$

where ε_{ji} is the average cross-price elasticity between products i and j, and $\mathcal{C}_j^c$ refers to the products which share category c with product j. For instance, j is a plant-based product, then $\mathcal{C}_j^c$ is the set of all plant-based products, and $|\mathcal{C}_j^c|$ is its cardinality. $Ratio_j^{c=plant-based}$ is the ratio of the average cross-price elasticity among plant-based products and product j against the average cross-price elasticity among all other category products with product j. Values greater than one indicate that consumers are more likely to substitute toward another product within that specific category.

Table 7 also illustrates the "Best substitute" metric, representing the probability that the product (other than j) with the highest cross-price elasticity shares the same characteristic c as product j. This statistic ranges from 0 to 100, with higher values indicating a greater percentage of products within category c having the best substitute categorized also as c.

The table reveals that plant-based products exhibit a high probability of being substituted with other plant-based items, particularly noteworthy with Beyond products, where items within the same brand are frequently chosen as substitutes. While beef products often find substitutes within their category more than pork-poultry or seafood (i.e., have a higher "Ratio"), their best substitutes frequently come from other categories. In fact, beef products tend to be substituted with pork-poultry items when their prices increase.[18]

All ratios being above one affirm that the estimation captures typical patterns observed in the food market. It is reassuring to note that meat demand is sensitive to prices, indicating consumers' willingness to alter their preferred meat category in response to price fluctuations. This sets the stage for examining counterfactual policies that modify prices or product valuations, driving consumers to choose other products and potentially reducing emissions from food choices. The upcoming section delves into an analysis of various policies, considering their potential impact on emissions reduction and their regressive nature.

7 Policy study

In this section, we outline, analyze, and compare various policies aimed at mitigating the environmental impact of food consumption, focusing on the city of Chicago.[19] Three distinct policies are under scrutiny: a limitation on 50% of beef product sales, a tax that internalizes environmental externalities in food prices, and a hypothetical scenario where advertisements for plant-based and Beyond products positively impact their attractiveness and desirability (i.e., an increase on their mean utilities).

To compute the outcomes of these counterfactual policies, we back out the products' marginal costs utilizing the supply-side model elaborated in Section 4.2. The estimated marginal costs and mark-ups are presented in Appendix E.

When a policy is implemented, one should expect firms to adjust their prices in order to maximize profits. To solve for this pricing equilibria, we draw on the engineering literature, particularly inspired by Morrow and Skerlos (2011) as recommended by Conlon and Gortmaker (2020), whose method involves a fixed-point approach specifically tailored to mixed logit demands.[20] To estimate marginal costs and the new equilibrium prices, we assume perfectly competitive markets.

We now describe each counterfactual in greater detail before presenting the outcomes.

- **Restriction on beef products**: Animal welfare laws can stipulate the maximum number of animals allowed per square foot in breeding spaces. For instance, California passed a law in 2018 requiring breeding pigs to be confined to an area with at least 24 square feet of space to allow them to move freely. Assuming that most farmers cannot expand their breeding spaces, this restriction could significantly limit the volume of available meat products for consumption. This counterfactual scenario aims to explore the potential effects of laws that directly or indirectly restrict the display of beef products on store shelves, examining their impact on consumer welfare and environmental outcomes.

  To analyze this scenario, we randomly select beef products without replacement from the pool available and remove the chosen items from all markets across the city. The process halts when 50% of the

18. This aligns with the historical trends depicted in Figure A1 in Appendix A, indicating the increase in poultry market shares attributed to competitive pricing and successful marketing strategies.
19. Results for Los Angeles, New York, and Houston will be included in a future version of the paper.
20. To handle potential singular matrices, which might pose an issue due to the inversion of a diagonal matrix of demand derivatives that could approach zero, we employ the Moore-Penrose pseudoinverse to solve for price equilibria.

total ounces of beef available in the city, not within each individual market, are withdrawn from the shelves. We then compute the new market shares and equilibrium prices for each product-market. To minimize the influence of random product selection on these counterfactual outcomes, this procedure is repeated 100 times. Subsequently, we compute the mean meat category share consumed across various demographic groups.

Importantly, in this counterfactual, we do not consider changes in the cost structure of firms caused by the restriction. For instance, reducing output might impact the economies of scale of beef companies during production, potentially increasing their costs and, consequently, their prices. Since the change in prices we estimate only comes from reduced competition, this might lead to an underestimation of the policy's impact on beef prices.

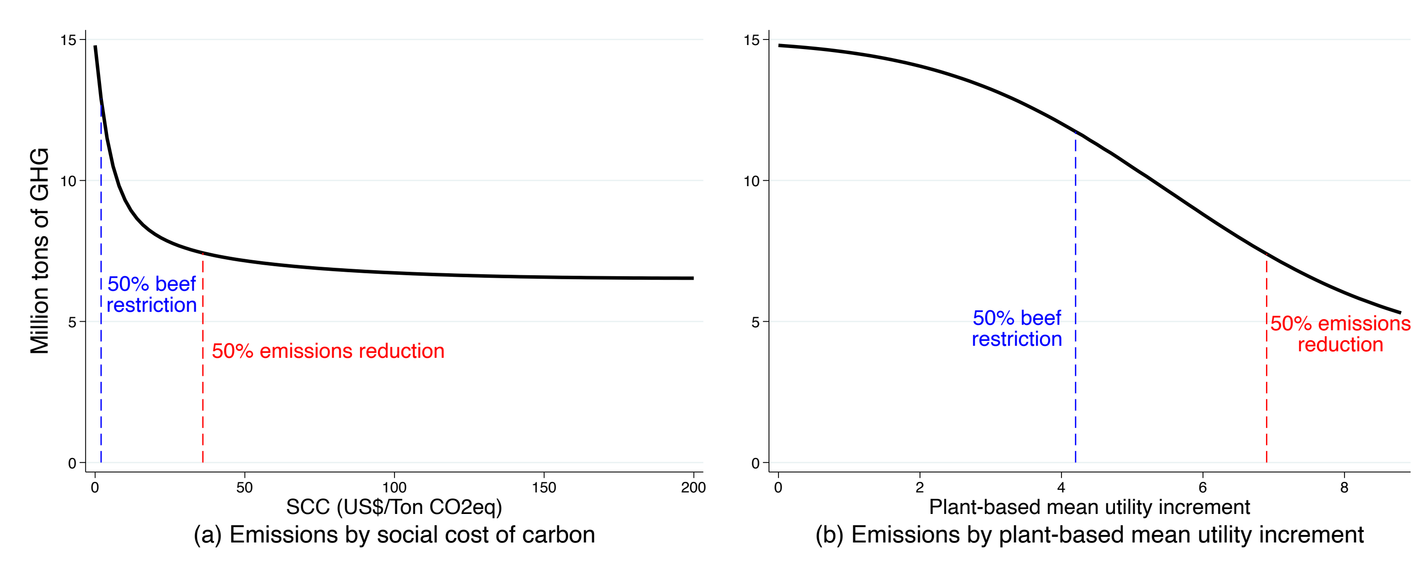
- **Food tax on emissions**: The social cost of carbon (SCC) quantifies the monetary value of damages caused to society by an additional metric ton of CO_2. We investigate the potential shifts in emissions and market shares under varying SCC values, ranging from \$0 to \$200 per tonne of CO_{2eq}.[21] Leveraging data from table 1, we compute the CO_{2eq} emissions attributed to the production processes of each product. For most meat categories, except high- and low-end beef products, we assume an 80% composition by the meat they represent. However, for "Prepared Food with Beef," we consider it to be composed of 50% beef. Since the rest of the meat categories are an aggregation of high- and low-end meat cuts and some prepared food, I assume they are composed of 80% by the meat they represent.[22] Incorporating the social cost of carbon into prices, we derive new price equilibria and subsequently estimate the revised levels of emissions and market shares.

- **Mean utility increment for plant-based and Beyond products**: Figure A1, outlined in Appendix A, illustrates the upward trajectory of chicken consumption, attributing its rise not solely to price reductions but primarily to successful health and safety marketing, as highlighted by Tonsor, Lusk, and Schroeder (2021). This counterfactual explores the potential emissions reduction if similar marketing strategies were implemented for plant-based and Beyond products, augmenting the mean utility of these products, and allowing firms to adjust prices accordingly.

For each value of the social cost of carbon, a corresponding emissions tax is imposed on food products based on their respective t-CO_{2eq} emitted during manufacture. As the SCC increases, the tax rises, making more polluting foods relatively more expensive compared to less polluting ones. This motivates price-sensitive consumers to opt for environmentally friendlier food choices, leading to reduced emissions from food consumption. Panel (a) of Figure 3 demonstrates the emission changes across various SCC values. Initially, there is a significant decline at low SCC levels, followed by a stabilization of emissions despite higher tax levels. Notably, a social cost of carbon of \$4 reduces emissions to the same level as a 50%

21. The U.S government social cost of carbon current value is \$51 per tonne of CO_{2eq}, but recent comprehensive research (Rennert et al. (2022)) estimates it to be around \$185/t-CO_{2eq}.
22. These assumptions are maintained in the "Restriction on beef products" counterfactual.

Figure 3: Greenhouse gases emissions over different policies



restriction on beef products, while a value of $38 halves emissions. Given the current U.S. carbon price of $51 per tonne of CO_{2eq}, integrating the environmental costs into food prices could cut emissions from food consumption by over 50%.

The stabilization of emissions occurs as consumers increasingly favor the outside option due to rising product prices. However, as detailed in Section 5.2, the composition of meat products within the outside option reflects observed market shares. As prices rise, consumption tends to converge, with pork-poultry and plant-based products taking the lead in market shares owing to their comparatively lower emissions. Consequently, the cumulative emissions from both inside and outside goods stagnate.

Moreover, Figure 3 illustrates the shift in emissions associated with different values of the mean utilities (δ) of plant-based products (panel (b)). As the valuation for plant-based products increases, consumers switch consumption toward these products, resulting in decreased emissions. Panel (b) indicates that incremental reductions in emissions are modest at lower levels of the mean utility of plant-based products but exhibit more substantial decreases as this value increases. Raising the mean utility of plant-based and Beyond products by 4.3 would yield an emissions reduction comparable to the beef restriction counterfactual, while a boost of 7.0 would reduce emissions in half.

As market shares fluctuate as we change the social cost of carbon or mean utility of plant-based products, we opt to compare market shares across policies at two distinct benchmarks: first, when they attain equivalent levels of emissions reduction as the beef restriction policy (about 20% fewer emissions than the baseline), and second, when they achieve a 50% reduction in emissions. Table 8 exhibits the change in market shares for each policy. Panel (a) corresponds to the emissions reduction achieved through beef restriction, while panel (b) centers on the scenario targeting a 50% reduction in emissions. To minimize assumptions related

Table 8: Emissions and meat consumption change across different policies

(a)	Policies comparison at emissions reduction given by beef restriction			
	Baseline	**Beef Restriction**	**SCC = US$4.0**	$\delta_{plant-based}$ **+ 4.30**
*Shares**				
High-End Beef	3.14%	2.07%	2.07%	1.78%
Low-End Beef	15.69%	9.41%	8.34%	11.25%
Prepared Food with Beef	7.36%	4.54%	7.33%	5.44%
Pork-Poultry	51.99%	59.37%	58.34%	37.40%
Seafood	19.88%	22.43%	21.70%	13.75%
Plant Based	1.28%	1.46%	1.47%	22.74%
Beyond	0.66%	0.73%	0.74%	7.64%
Emissions (Million tons of GHG)	14.75	11.69	10.51	11.44

(b)	Policies comparison at 50% emissions reduction			
	Baseline	**Beef Restriction**	**SCC = US$38.0**	$\delta_{plant-based}$ **+ 7.00**
*Shares**				
High-End Beef	3.14%	—	0.12%	0.40%
Low-End Beef	15.69%	—	0.23%	5.32%
Prepared Food with Beef	7.36%	—	3.23%	3.24%
Pork-Poultry	51.99%	—	71.37%	20.65%
Seafood	19.88%	—	21.39%	6.40%
Plant Based	1.28%	—	2.35%	50.00%
Beyond	0.66%	—	1.31%	13.98%
Emissions (Million tons of GHG)	14.75	—	7.28	7.13

*To abstract results from outside option assumptions, shares presented are conditional on purchase.

to the outside option, only conditional purchase shares are included, assuming an equivalent distribution of meat shares for both outside and inside goods.

Panel (a) demonstrates a close resemblance in share levels between beef restriction and a social cost of carbon set at $4. Notably, the emissions difference (nearly 1 million tons of GHG less with the tax) predominantly stems from a 1% variance in the low-end beef share, underscoring the impact even a slight reduction in beef consumption can exert.

On the other hand, panel (b) reveals distinct disparities between the baseline and the policies' shares. Both policies achieve similar emission levels but with considerable deviations in their shares. With an SCC of $38, consumption predominantly revolves around poultry-pork and seafood. Conversely, elevating the mean utility of plant-based products (unsurprisingly) directs consumption more toward these items. Comparing the outcomes from both counterfactuals highlights an intriguing point: maintaining low-end beef consumption demands substantial quantities of plant-based products to lower emissions to a level achieved by a diet focusing on poultry-pork and seafood. This underscores that shifting from beef consumption to poultry-pork and/or seafood could yield a significant impact, revealing that a shift toward plant-based products is not the sole solution to reduce emissions.

After examining the environmental impacts of the policies, it is crucial to evaluate their costs, who would

Table 9: Welfare change and cost-benefit of the different policies in comparison with baseline

(a)	Policies comparison at emissions reduction given by beef restriction		
	Beef Restriction	**SCC = US$4.0**	$\delta_{plant-based}$ **+ 4.30**
Compensating variation			
High Income	$0.12	$0.23	-$0.67
Low Income	$0.15	$0.29	-$0.53
Minority	$0.19	$0.42	-$0.61
White	$0.12	$0.20	-$0.54
College educated	$0.10	$0.20	-$0.75
Not college educated	$0.16	$0.31	-$0.46
Cost-benefit evaluation (Millions of dollars)			
Emissions Reduction	$12.24	$16.98	$13.26
Consumer Welfare	-$17.69	-$45.10	$74.85
Firms' Profits	-$8.22	-$79.70	-$22.35
Government Revenue	—	$23.99	—
Overall	-$13.66	-$83.84	$65.76

(b)	Policy comparison at 50% emissions reduction		
	Beef Restriction	**SCC = US$38.0**	$\delta_{plant-based}$ **+ 7.00**
Compensating variation			
High Income	—	$1.04	-$2.89
Low Income	—	$1.12	-$2.29
Minority	—	$1.65	-$2.09
White	—	$0.83	-$2.61
College educated	—	$0.92	-$3.06
Not college educated	—	$1.21	-$2.08
Cost-benefit evaluation (Millions of dollars)			
Emissions Reduction	—	$283.98	$289.71
Consumer Welfare	—	-$140.62	$316.27
Firms' Profits	—	-$115.65	$92.80
Government Revenue	—	$57.78	—
Overall	—	$85.49	$698.78

bear them, and whether they outweigh their benefits. Table 9 displays the compensating variation required by each demographic group in each counterfactual scenario. Across all policies, lower-income individuals, minorities, and less-educated consumers fare worse compared to their counterparts. As expected, all consumers experience an improvement in the counterfactual where the mean utility of plant-based and Beyond products increases. Specifically, college-educated individuals benefit the most, aligning with their preference for plant-based products, as demonstrated in Figure 2. Regarding a tax on food emissions, minorities need twice the compensation compared to white consumers to reach indifference between a tax and the baseline scenario, regardless of the SCC level (either $4 or $38). Simultaneously, the relative disparity in compensating variation between individuals without and with a college education increases, while the relative difference between low and high-income consumers decreases as the tax amount rises.

In assessing the overall cost-effectiveness of each policy, it is noteworthy that as the social cost of carbon increases, the environmental benefits outweigh the decline in consumer welfare. At lower tax values, despite potential emission reductions, the costs outweigh the benefits. Yet, with a larger tax, the environmental benefits alone surpass the reduction in consumer welfare and firms' profits. The implications of restricting beef are analogous to implementing a low SCC tax.

Each policy presented here unfortunately exhibits regressiveness, burdening underprivileged demographics despite the shared responsibility of emission reduction among all consumers. As a next step, exploring how these policy implications vary across different cities is important. Additionally, studying two more counterfactuals—where only a tax on beef emissions is implemented, and the resulting revenue subsidizes plant-based/Beyond or pork-poultry products—could potentially alleviate the load carried by disadvantaged consumers in these new scenarios.

8 Concluding remarks

Addressing climate change is urgent, and a significant amount of emissions stem from food production. While numerous studies advocate for dietary shifts toward less environmentally harmful foods, few have explored whether individuals are willing to make such changes and to what extent. As far as we know, this is the first paper to address this important question.

We employ a demand and supply model, aiming to estimate rich substitution patterns among meat products. Our findings underscore substantial taste heterogeneity across products, and consumers have differing responses based on demographics.

With the estimated primitives from the demand model, we examine the hypothetical outcomes of three policies: restricting beef product sales, implementing a food emissions tax, and significantly boosting consumer valuation of plant-based products through advertising. Our analysis suggests that a beef product restriction might not yield substantial emission reductions, easily matched by a modest tax, and could result in greater welfare loss than environmental gains. Conversely, both the emissions tax and the heightened valuation of plant-based products display potential for significant emission reductions.

Furthermore, we observe that the net benefits of a food tax increase with its magnitude. However, the cost of this tax falls disproportionately on underprivileged consumers. A more progressive outcome might be attainable through a policy subsidizing plant-based or poultry-pork products while imposing a tax on beef.

The tax's benefits primarily stem from consumers shifting toward poultry-pork products. While seemingly switching to pork-poultry is the most practical and impactful solution to emission reduction, its long-term efficacy should be assessed, especially considering ongoing concerns about animal welfare within the poultry industry.

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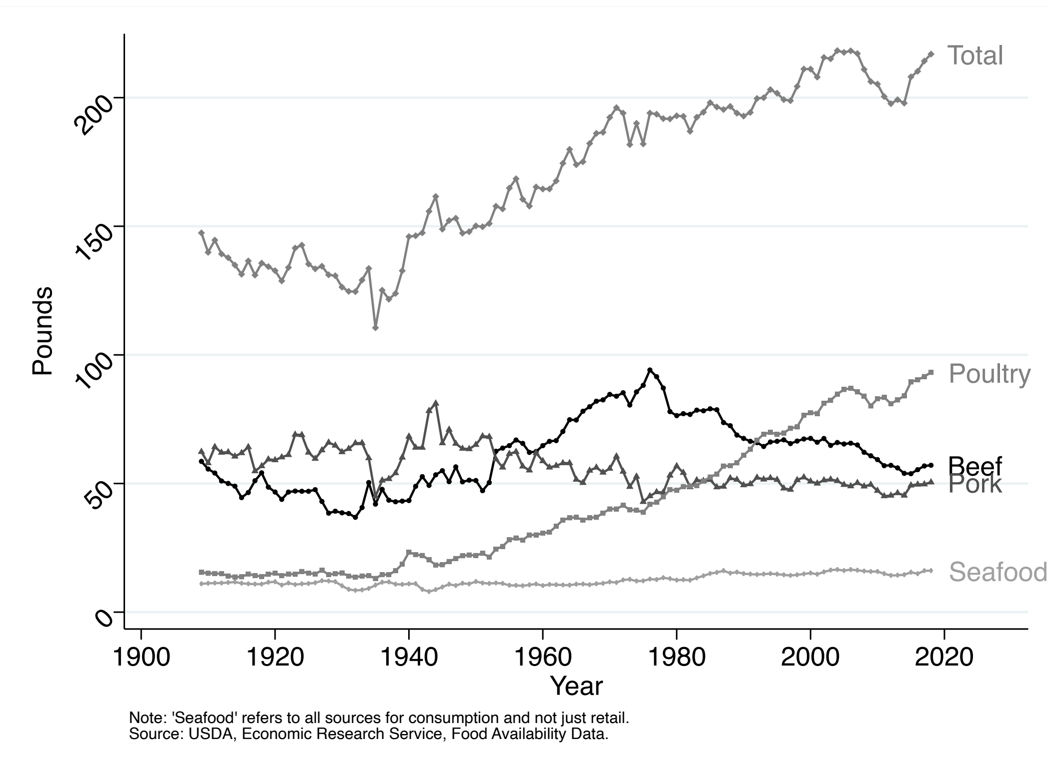
Appendix

A U.S. meat purchases through time

In Section 2, we highlighted the high levels of meat consumption in the U.S. This section now explores the evolving preferences for different types of meat over time. Figure A1 shows the average meat consumption per capita for each specific meat type.

Figure A1: Average meat consumption per capita throughout time



The graph depicts that seafood and pork consumption have remained stagnant throughout time. Since 1980, per capita beef consumption has declined, while poultry consumption has doubled. Encouraging consumers to shift away from beef products holds significant environmental benefits, as highlighted in Table 1. Specifically, two key factors drive the trends observed in Figure A1 regarding beef and poultry: a decrease in poultry production costs and the impact of health and safety marketing. Approximately one-third of the decline in beef demand can be attributed to decreased poultry prices, while the remaining two-thirds are credited to health and safety marketing (Tonsor, Lusk, and Schroeder 2021).

While an econometrician can observe prices, health and safety perceptions associated with a product remain unobservable. By utilizing a structural demand model, we estimate the relative influence of price against other unobservable determinants in driving consumer purchase decisions. This information is crucial in identifying the most effective approach to incentivize the substitution from beef to plant-based products or other meats with lower emissions.

B Potential demand models for meat consumption

In this section, we provide a concise overview of potential demand model specifications applicable to our framework. We delve into the advantages and challenges associated with each model.

Previous literature on demand estimation for food consumption (Tiffin and Arnoult 2010; Kehlbacher et al. 2016) has often utilized modified versions of the Almost Ideal Demand System (AIDS, Deaton and Muellbauer (1980)).[23] However, as highlighted by Chaudhuri, Goldberg, and Jia (2006), the AIDS model faces limitations when dealing with a varying number of products. Originally developed for broad commodity categories consistently consumed by all consumers, AIDS struggles with widely varying choice sets in the data. Since our framework consists of multiple markets with substantial variability in the choice sets, using AIDS would necessitate further aggregation of products. This could potentially absorb crucial price variation that would, in turn, significantly influence the estimation of essential substitution patterns.

There could be a potential concern about our demand specification, discrete choice model, considering that food products might often be purchased in bundles. This would entail modeling the scenario as a multi-product choice problem. While several innovative approaches have emerged for estimating demand with large choice sets and bundles, many focus solely on panel data (Iaria and Wang 2020, 2021; Lanier, Large, and Quah 2022). However, such data might be considerably sparse, lacking the comprehensive store-level information available in RMS data. For instance, A. Wang (2021) proposes a model that considers complementarities between products but is not well-suited for the extensive number of products we analyze.

Other models like the one proposed by Lewbel and Nesheim (2019) present a general discrete-continuous choice model, but they assume exogenous prices, whereas price endogeneity is prevalent in our dataset. There are also studies like Ershov et al. (2021), which use similar data to ours to estimate a multi-product choice model for sodas and chips, though their model does not allow for more than two different products (one unit each) to be bundled together. This approach would still underestimate the potential complementarities that meat products present.

In addition, it is challenging to envision two different types of meat being complementary, even if they are purchased together. In this scenario, bundling likely stems from preferences for variety in households or shopping logistics rather than synergies in consumption. Thus, assuming that meat products act as substitutes seems reasonable. Therefore, the advantages of exploring complementarities between products using a multi-product choice model do not seem to outweigh the complexities introduced in this context.

Policies affecting a specific type of meat should prompt consumers to switch to other types. Moreover, the paper presents evidence that supports the absence of significant bundling across different meat types. Consequently, we chose to model demand using a discrete choice approach.

23. Other examples of using AIDS to estimate a demand system for food consumption appear in the Public Health literature (Briggs et al. 2013; Briggs et al. 2015).

Employing a discrete-choice model assumes all products act as substitutes, potentially leading to overestimating cross-price elasticities in cases where some products exhibit complementarity. However, as indicated in Table 5, bundling does not appear to be a significant concern. Consumers tend to buy a single product per trip, supporting the notion that considering different meat types as substitutes is a reasonable assumption.

Stockpiling behavior, however, might still be a factor to consider. Static demand estimates of long-run price elasticities may be misestimated for storable goods that experience frequent sales (Hendel and Nevo 2006, 2013; E. Y. Wang 2015). Research by Hendel and Nevo (2006) suggests static demand estimates might (i) overstate own-price elasticities by around 30%, (ii) underestimate cross-price elasticities by up to five times, and (iii) exaggerate substitution to the outside good by over 200%. Since this paper aims to evaluate consumers' willingness to shift towards eco-friendly meat products, underestimating cross-price elasticities could set lower bounds on the policy effects analyzed. Thus, accounting for stockpiling behavior might actually magnify the effects of a policy that demonstrates significant positive impacts on emission reduction.

C Descriptive tables and figures for Houston, Los Angeles and New York

In this appendix section, we present the characteristics of products and markets for additional cities. Table C1 indicates a similar distribution of category shares across cities. Pork and poultry consistently appear as the preferred category, followed by beef and seafood. Additionally, the number of products available correlates with the city's density, with Houston offering less than half the products available in New York.

Despite all four cities leaning towards more progressive choices historically (voting consistently for progressive parties that do not deny climate change), there is a notable disparity in the consumption patterns of plant-based products in Houston compared to the other cities. The urban-rural divide seems to impact consumer preferences, nudging individuals in more rural areas towards meat products rather than plant-based or Beyond options.

Table C2 demonstrates that despite Houston's lower population density, NielsenIQ has data from stores in counties that, on average, are more populated compared to counties in Los Angeles, New York, or Chicago. Additionally, New York and Los Angeles exhibit similar average choice set sizes, but markets in New York display greater variance.

For Houston, Figure C1 illustrates that race and education level seem to have minimal influence on consumers' decisions regarding different meat types. However, income evidently plays a significant role. Low-income consumers prioritize cheaper products much more than high-income consumers do.

Unlike Houston, Figure C2 highlights that in Los Angeles, race and education significantly influence consumers' decisions regarding meat purchases. Minorities and non-college-educated consumers tend to prefer pork, while their counterparts lean more toward poultry products. College-educated individuals show a higher preference for plant-based products compared to those without a college education, and this trend

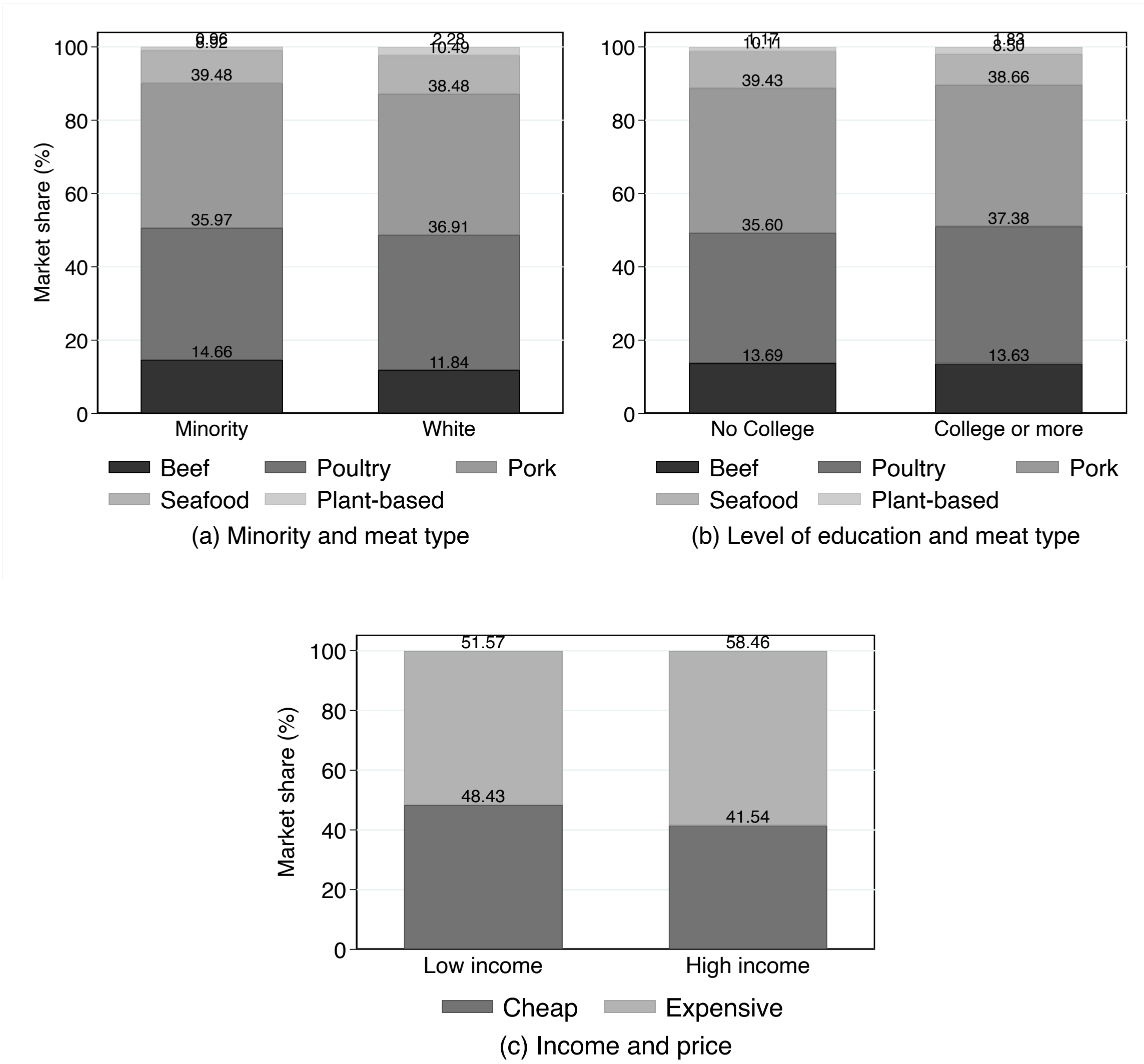


Figure C1: Market share of different product attributes by demographics, Houston

Table C1: Product characteristics by meat category, Houston - Los Angeles - New York

	Houston				
Category	**Products**	**Brands**	**Price (USD)**	**Size (Ounces)**	**Share**
High-End Beef	16	8	6.85	16.89	0.63%
Low-End Beef	147	84	5.25	18.94	15.59%
Prepared Food with Beef	127	84	3.91	17.28	7.91%
Pork	343	173	4.26	17.81	30.77%
Poultry	361	168	4.64	18.89	32.40%
Seafood	250	130	4.99	13.87	10.74%
Plant Based	87	55	3.64	16.47	1.64%
Beyond	5	1	7.06	11.29	0.32%
Top Products	1,185				88.33%
Composites	151				11.67%
All Products	1,336				100%
	Los Angeles				
Category	**Products**	**Brands**	**Price (USD)**	**Size (Ounces)**	**Share**
High-End Beef	26	13	7.58	16.41	0.56%
Low-End Beef	273	110	6.25	20.52	14.71%
Prepared Food with Beef	212	121	4.48	17.56	4.14%
Pork	535	232	4.72	17.01	27.75%
Poultry	607	261	5.10	18.74	39.04%
Seafood	453	197	5.36	13.43	9.30%
Plant Based	234	122	3.97	15.75	3.80%
Beyond	5	1	7.02	11.16	0.70%
Top Products	2,173				96.30%
Composites	172				2.70%
All Products	2,345				100%
	New York				
Category	**Products**	**Brands**	**Price (USD)**	**Size (Ounces)**	**Share**
High-End Beef	33	22	8.77	15.88	0.65%
Low-End Beef	305	156	7.17	18.77	10.79%
Prepared Food with Beef	240	138	4.93	16.39	8.49%
Pork	630	278	5.40	13.89	24.46%
Poultry	724	303	5.42	17.03	35.80%
Seafood	796	361	5.78	11.88	15.02%
Plant Based	287	146	4.52	12.51	4.15%
Beyond	6	1	7.30	10.96	0.64%
Top Products	2,849				97.78%
Composites	172				2.22%
All Products	3,021				100%

Price and size are averages across products. Share is based on ounces sold.

extends to minorities versus white individuals. Interestingly, income appears less influential in Los Angeles, with low-income consumers showing a slightly higher preference for cheaper products, but the difference is not substantial.

Figure C3 illustrates that, similar to Chicago, all demographics play a crucial role in understanding meat preferences. Minorities exhibit a clear preference for plant-based products, while white consumers lean more

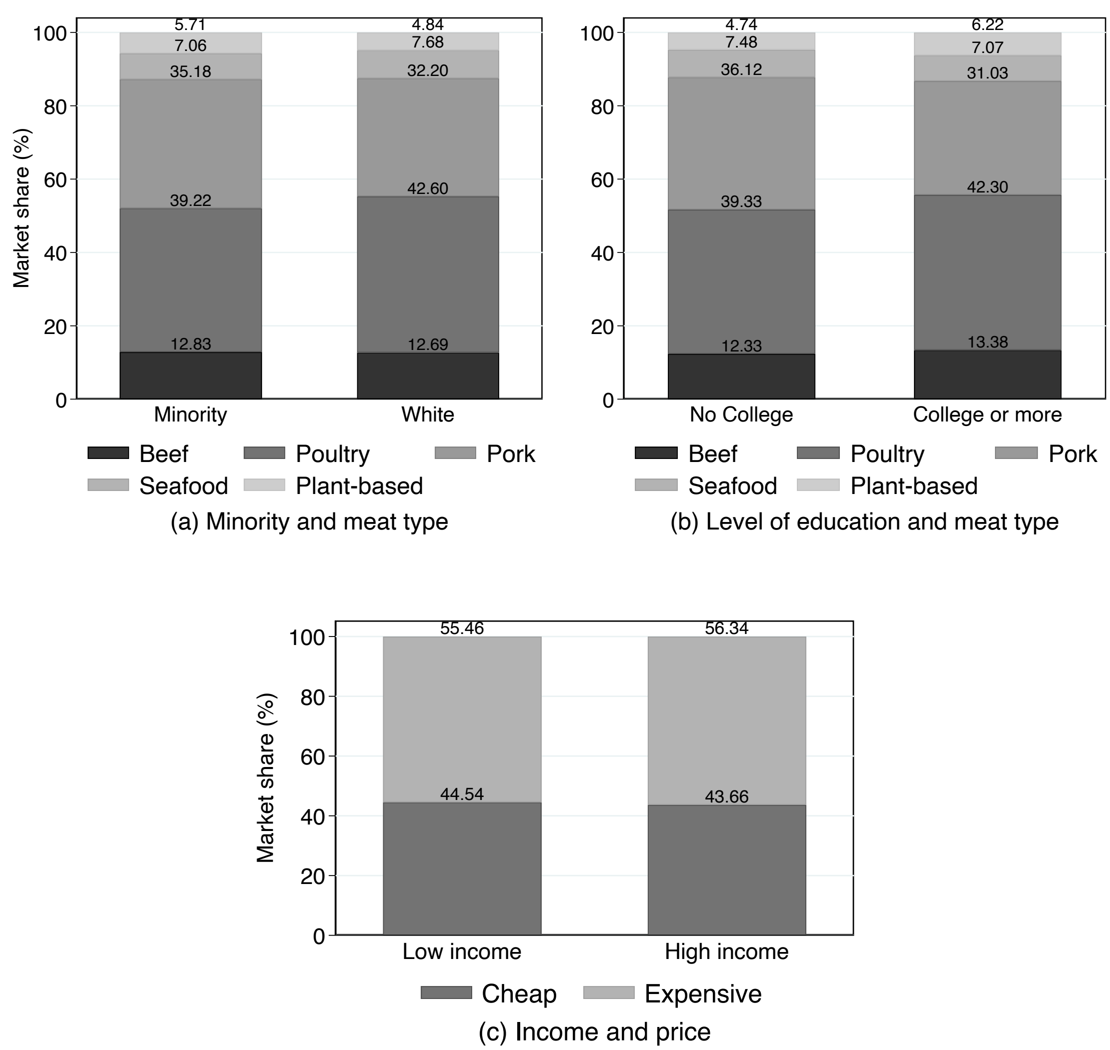


Figure C2: Market share of different product attributes by demographics, Los Angeles

Table C2: Markets' summary statistics, Houston - Los Angeles - New York

	Houston			
	Mean	**SD**	**Min**	**Max**
by Market				
Products	137.3	49.4	49	358
Brands	83.0	30.17	24	168
Consumers	16,892.4	15,888.3	180	90,117
Product's Shares	0.0005	0.0009	0.0001	0.066
by Product				
Markets	1,311.3	2,049.2	80	13,422
	Los Angeles			
	Mean	**SD**	**Min**	**Max**
by Market				
Products	240.4	68.2	38	416
Brands	114.6	34.1	19	209
Consumers	7,876.8	5,092.9	55	40,309
Product's Shares	0.0007	0.002	0.0001	0.13
by Product				
Markets	5,025.0	8,353.8	80	47,767
	New York			
	Mean	**SD**	**Min**	**Max**
by Market				
Products	241.5	114.0	40	573
Brands	121.4	51.5	28	244
Consumers	4,319.7	4,762.0	33	41,599
Product's Shares	0.001	0.004	0.0001	0.32
by Product				
Markets	2,852.5	4,710.7	80	30,970

towards seafood. The disparity in plant-based preference between college-educated and non-college-educated individuals is striking, representing the widest gap among the four cities. The same pattern holds for pork and seafood preferences. Regarding income, the impact of price disutility is significant, with low-income consumers showing a clear tendency to choose more affordable products.

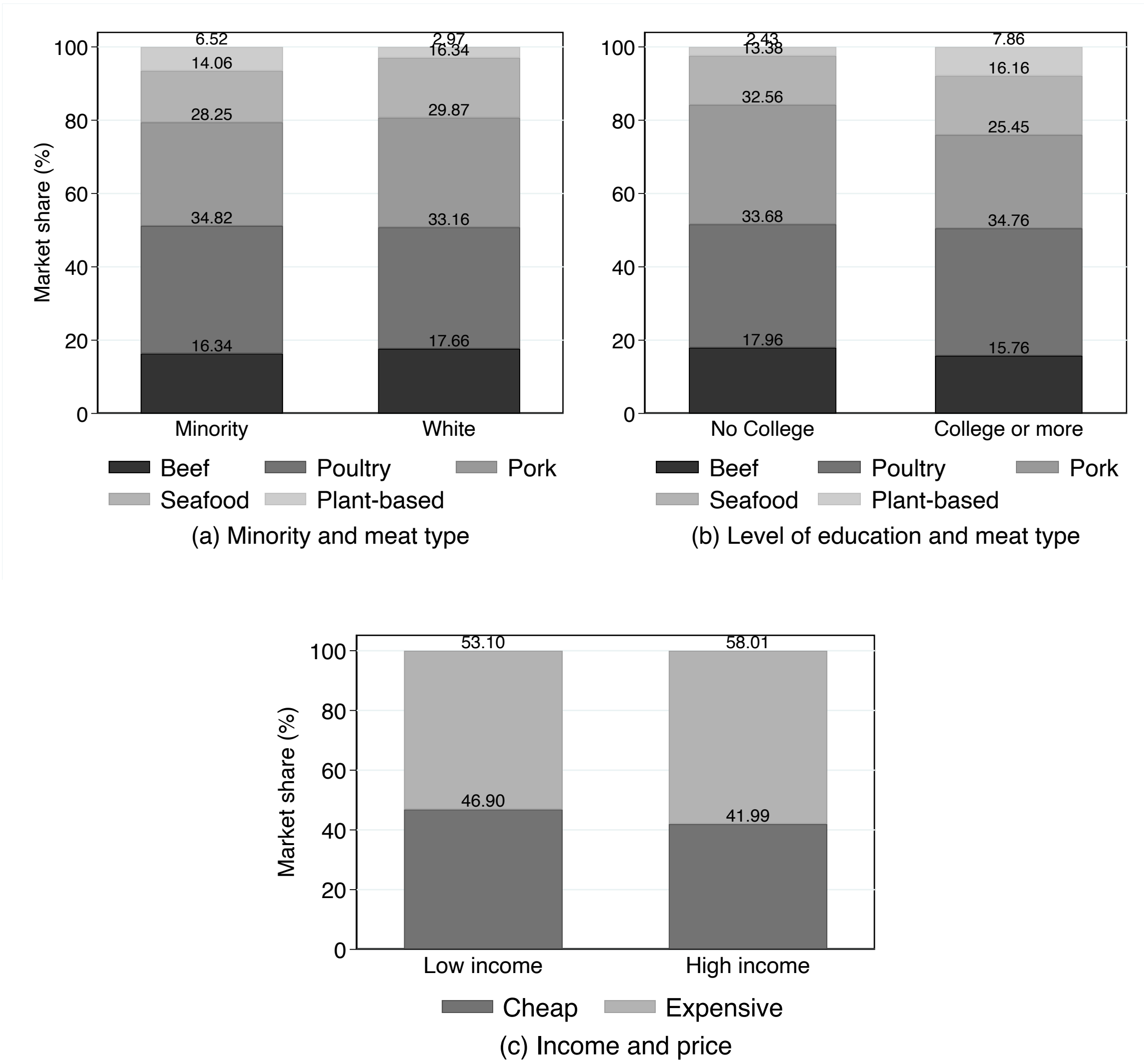


Figure C3: Market share of different product attributes by demographics, New York

D Instrumental variables regression's first stage results and mixed logit model fit

In this section, we showcase the findings derived from the initial stage of our instrumental variables regression, along with the goodness of fit evaluation for the structural model.

The results of the first stage in our IV regression analysis performed for Chicago are presented in table D1. The high R^2 value indicates that the instruments account for a substantial variance in prices. Moreover, the elevated F-statistic suggests a robust instrument relevance. Coefficients, reflecting interactions between animal feed/grain and respective meat categories, generally exhibit the anticipated positive sign and significance. While the instruments pass the under- and weak-identification tests, they fail the over-identification test, raising some concerns that necessitate attention.

Table D1: IV first stage regression results

	Coef.	*S.D.*	*t*	$P > \|t\|$	*[95% Conf.*	*Interval]*
Hay	0.42	0.18	2.65	0.008	0.11	0.73
Wheat	-4.23	0.07	-58.84	0.000	-4.37	-4.09
Corn	1.40	0.13	11.23	0.000	1.16	1.65
Soy	2.92	0.07	39.57	0.000	2.78	3.07
Rapeseed	2.02	0.06	31.97	0.000	1.89	2.14
Flaxseed	1.39	0.04	37.39	0.000	1.31	1.46
Fish Meal	-0.11	0.02	-6.22	0.000	-0.14	-0.07
Canola Oil	0.82	0.13	6.39	0.000	0.57	1.07
Constant	0.27	0.002	152.18	0.000	0.266	0.272
Controls:	Product FE, Market FE					
$\mathbf{R^2}$	0.9123					
F-stat	3,160.12					
N	4,559,754					
	Statistic			*Decision*		
Underidentification test	8,895.305			Reject. Model is identified.		
Weak identification test	742.468			Reject. Not weakly identified.		
Overidentification test	4,319.783			Reject. Model is overidentified.		

Table D2 demonstrates a robust model fit specific to Chicago. The first column depicts the data, while the second and third columns represent the model's estimates. The model assesses shares from both RMS data and panelist data (second and third column respectively).

Overall, table D2 exhibits a close fit for shares, average sizes, and prices of products purchased, for both RMS and panelists data.

Table D2: Model Fit

	RMS Data	**RMS Model**	**Homescan Model**
Inside Share	13.99%	13.99%	14.72%
Purchase Price	5.29	5.25	5.48
Purchase Size	20.17	19.91	21.42
Cond. Share High-End Beef	1.08%	1.06%	1.10%
Cond. Share Low-End Beef	11.39%	11.39%	11.99%
Cond. Share Prepared Food Beef	6.43%	6.47%	5.05%
Cond. Share Pork-Poultry	67.27%	67.01%	68.58%
Cond. Share Seafood	10.43%	10.54%	10.09%
Cond. Share Plant Based	2.76%	2.95%	2.59%
Cond. Share Beyond	0.62%	0.59%	0.60%
Cond. Share Composite	38.71%	38.50%	41.43%
Share High-End Beef	0.14%	0.14%	0.14%
Share Low-End Beef	1.60%	1.60%	1.85%
Share Prepared Food Beef	1.00%	1.00%	0.77%
Share Pork-Poultry	9.39%	9.39%	10.13%
Share Seafood	1.47%	1.47%	1.43%
Share Plant Based	0.33%	0.33%	0.32%
Share Beyond	0.07%	0.07%	0.08%
Share Composite	5.32%	5.32%	6.19%

"Cond." refers to "Conditional on purchase"

E Estimated elasticities, marginal costs and markups

In this section, we present the estimated elasticities, marginal costs, and markup distribution across different meat categories for the city of Chicago.

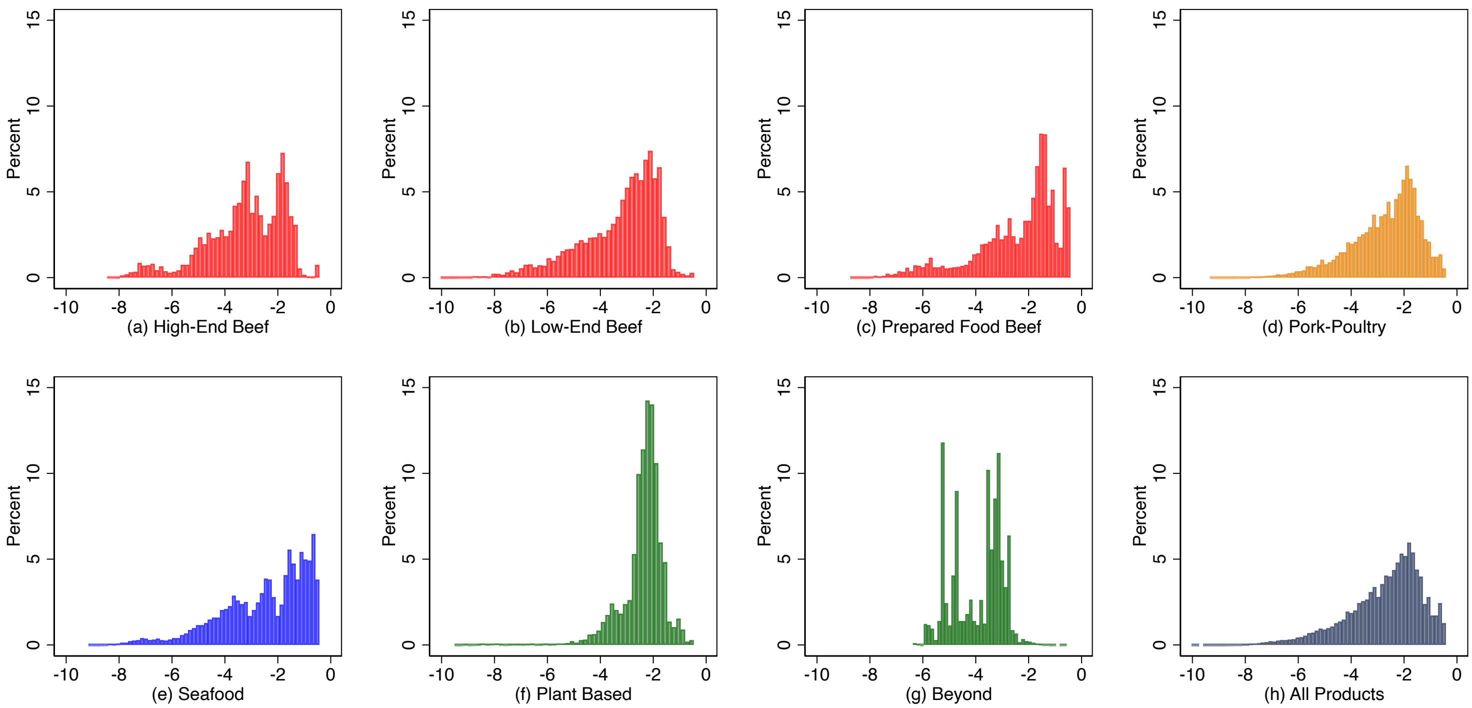


Figure E1: Distribution of elasiticities by meat category

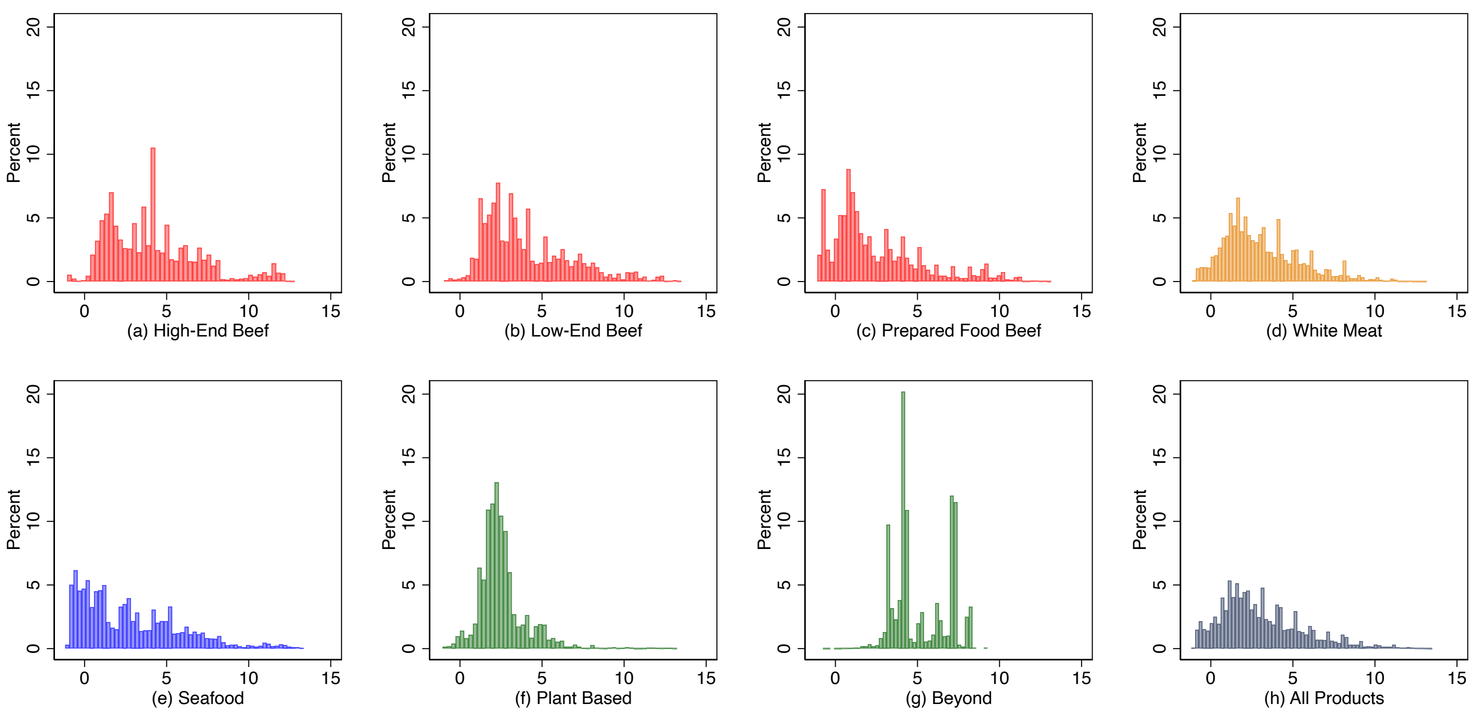


Figure E2: Distribution of marginal costs by meat category

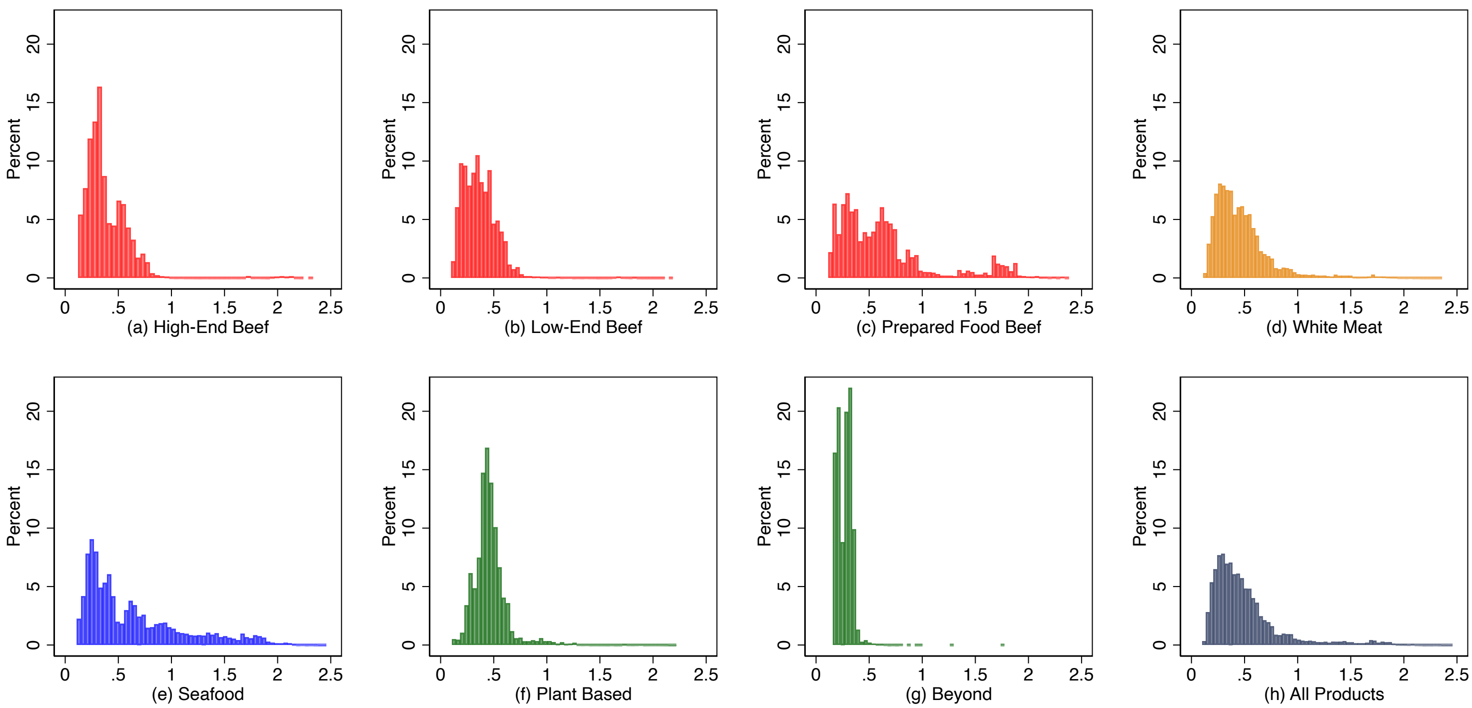


Figure E3: Distribution of mark-ups by meat category

F Robustness checks

In this section, we present other demand specifications, where we include individual-level random coefficients.

(Robustness check tables coming soon)

Table E1: Diversion ratios by meat category

	Diversion ratios						
Price change	**High-End Beef**	**Low-End Beef**	**Prepared Food with Beef**	**Pork-Poultry**	**Seafood**	**Plant Based**	**Beyond**
High-End Beef	—	0.0018	0.0017	0.0017	0.0017	0.0016	0.0013
Low-End Beef	0.0182	—	0.0172	0.0168	0.0168	0.0148	0.0169
Prepared Food with Beef	0.0075	0.0108	—	0.0105	0.0105	0.0062	0.0068
Pork-Poultry	0.1045	0.1109	0.1099	—	0.1089	0.0931	0.1171
Seafood	0.0147	0.0155	0.0153	0.0154	—	0.0133	0.0148
Plant Based	0.0034	0.0036	0.0036	0.0036	0.0037	—	0.0039
Beyond	0.0007	0.0011	0.0013	0.0014	0.0012	0.0009	—