To Beef, or Not To Beef: Trade, Meat, and the Environment

Dora Simon*

Last Updated: November 28, 2024. Latest version here.

Abstract

How can food consumption choice reduce emissions? I estimate a demand model using purchasing data of meat and other protein rich products from a European retailer and combine it with data on production and transport emissions. In counterfactual exercises, I analyze the reaction of consumers to food consumption policies. I find that buying local only decreases emissions by around 2% compared to the status quo. Vegetarian scenarios lead to the largest decrease in emissions of more than 20%. Pigouvian taxes lead to emissions reductions of 8-21%. These findings underscore the role of consumer choices in shaping food-related emissions.

1 Introduction

A first order priority in the fight against global warming is to drastically reduce greenhouse gas emissions. As the agricultural sector is the second largest contributor to emissions (IPCC, 2014), food consumption behavior lies at the heart of the strategies to reduce climate change. A representative survey in eleven EU countries finds that more than half of consumers pay attention to the impact of their food choices on the environment (BEUC, 2020).

How can food consumption choice reduce emissions? The effect of food consumption on total emissions depends both on the emissions intensity (emissions per kg) of different food products and on the quantity consumed of each product. With the aim of calculating counterfactual scenarios on the quantity of food consumption, I estimate a partial equilibrium model of meat demand. As meat is the largest contributor to emissions of the agricultural sector (Gerber et al., 2013), I obtain weekly purchasing data of meat and other protein rich products from an exclusive cooperation with a European retailer. The quality of the data enables me to estimate own- and cross-price elasticities with a credible instrumental variable strategy. Combining the purchasing data with data on production and transport emissions intensities (Poore and Nemecek, 2018) allows me to gauge the effect of different food consumption scenarios on the environment.

The counterfactual scenarios in this paper lead to three main findings. My counterfactuals include popular, supposedly eco-friendly consumption behaviors like buying local (or autarky in the language of a trade

*Dora Simon: University of Stavanger, Kjell Arholms gate 23, 4021 Stavanger, dora.simon@uis.no. I am grateful to my advisors Ralph Ossa and Gregory Crawford, as well as to Emily Blanchard and Simon Lepot for feedback and support during the course of this project. I also thank Meredith Fowlie, Joseph Shapiro, David Yanagizawa-Drott, Lorenzo Casaburi, David Hemous, Nir Jaimovich, Alessandro Ferrari, Joachim Voth, as well as other participants at the seminars at the University of Zurich, the University of California, Berkeley, the University of Bern, the University of Stavanger, and the NBER Summer Institute for helpful comments and suggestions.

economist) and vegetarianism, as well as Pigouvian taxes which are proportional to the emissions intensities of a product and often favored by economists[1]. First, I find that buying local only leads to a 2% decrease in emissions from food consumption compared to the status quo. Free trade on the other hand leads to an increase in emissions. The reason is that the current tariff scheme taxes highly polluting foods the most, and thus contributes to lower emissions. Second, the vegetarian scenarios all lead to a decrease in emissions of around 20%. A scenario where people can purchase all meat products except beef and cheese yields a larger decrease in emissions than vegetarianism where cheese is allowed. Third, Pigouvian taxes lead to substantial decreases in emissions as well (9-21% depending on the level of the tax), while allowing all foods to be consumed. Overall, this paper shows that vegetarianism or Pigouvian taxes have a larger potential to reduce emissions from food consumption than buying local.

Three stylized facts emerge from the emissions data. First, transport emissions intensities are a low share of overall emissions intensity of a product. The only case where transport emissions are relevant is with air transport. Even then, the production emissions make up the larger part of emissions. Second, production emissions intensities do not only vary across food types, but also across countries. For each food type, it would be possible to halve the emissions intensity by producing with the production technology of the country with the lowest emissions intensity. Third, the variation in production emissions intensities across food types is large. On average, meat products have six times higher production emissions intensities than vegetarian products. More specifically, beef is the most polluting meat type and has a ten times higher emissions intensity than chicken, the least polluting meat type. These stylized facts show that the key question when talking about decreasing emissions from food consumption is "To Beef or Not To Beef?"

To analyze the impact of food consumption behavior on meat demand, I estimate a discrete choice model (Berry, 1994; McFadden, 1974). The purchasing data for estimating the model stem from a unique cooperation with a European retailer. As the retailer wishes to stay anonymous, I will use the convention in the trade literature and call the country Home. I obtain weekly revenues, quantities, marginal costs, and product characteristics like the origin of the products on a bar code level. In the words of Bresnahan (1997), obtaining marginal cost data is "rare and lucky." The quality of the data ensures a credible identification strategy using high quality instrumental variables for estimating meat demand. I focus on the protein-rich food types of poultry, pork, beef, veal, lamb, fish, cheese, eggs, legumes, and tofu. The model is estimated using a nested logit specification with food types as nests. Contrary to a standard logit specification, this allows the cross-price elasticities within nests to be different than across nests. In intuitive terms, the cross-price elasticity between domestic and imported beef is allowed to be higher than the cross-price elasticity between beef and chicken. In my main specification, I estimate demand and supply jointly with GMM, where I model the supply side as the pricing equation of the multiproduct monopolist retailer. This allows the price of each product to react to the prices of all the other products. Without a supply side, the price of the domestic

[1] Around 35% of respondents of a representative food consumption survey of 11 EU countries associate sustainability with local supply chains and over 50% consider cutting down red meat consumption due to environmental reasons(BEUC, 2020).

products would stay the same in a buy local scenario, for example. This might lead to an overestimation of the environmental effects of the policy, if in reality the domestic products would experience a price increase and thus lower consumption. In the main specification, the price of domestic products is allowed to adjust to this lack of competition.

The identification of a nested logit model relies on overcoming potential endogeneity concerns of two predictors. First, the price variable might be endogenous due to correlation with the error through unobserved product characteristics. Products with higher levels of unobserved product characteristics might be priced higher. To overcome this omitted variable bias, I instrument for the price using marginal costs. Marginal costs as measured by the European retailer represent production costs and are not sensitive to particular demand fluctuations. As they only influence the quantities purchased through their effect on price, the exclusion restriction holds. Second, the nested logit model is estimated by adding a within group market share as a predictor. For example, this variable measures the market share of domestic beef with respect to the market share of all beef products and suffers from omitted variable bias as well. Products with higher levels of unobserved product characteristics might have a higher within group market share. I instrument for the within group market share with a proxy for advertisement of the other products in a group. Advertisement of products on sale, for instance through stickers on the products, increases the demand for those products even beyond the price effect of sales. Additionally, it might influence the within group market shares. If for example all other beef products are on sale, but domestic beef is not, the within group market share of domestic beef should decrease. The instrument for the within group market share is the average number of products with sale stickers of other products within the group. The exclusion restriction is that advertisement of other products does not influence the utility for the product in question. The estimated own-price elasticities range between -0.2 and -8.5.

Combining the estimates of the model with the emissions data, I calculate several counterfactual scenarios. These hypothetical scenarios quantify the consumers' reaction to different policies. I discuss three sets of scenarios: the first considers trade-related scenarios like buy local (or autarky) and free trade. The second category revolves around reducing meat consumption like vegetarianism or a no-beef no-cheese scenario. The third set of scenarios implements Pigouvian taxes that are proportional to the emissions intensity of each product.

The first set of counterfactuals shows that buying local or autarky does not lead to a large decrease in emissions, while free trade might do so. Contrary to popular belief, a naive buy local scenario which assumes that people eat the same amount of each food type in autarky instead of estimating the substitution patterns leads to a small increase in emissions. The reason is that some imported products have lower emissions intensities than domestic ones, so forcing the country to produce them domestically leads to a slight increase in emissions. The estimated buy local scenario leads to a small decrease in emissions. While beef consumption increases under the buy local scenario, other major contributors to emissions like cheese decrease in quantity.

The decrease in emissions is double compared to a scenario with only a demand side and without a supply side. To account for tariffs and quotas, I provide two free-trade scenarios. The first assumes the quota is not binding. The second assumes the quota is binding and uses the ad-valorem equivalent tariffs to calculate the counterfactual. For the first free trade scenario, the emissions increase only slightly by around 0.22%, while the increase is much more pronounced with 45% when using the ad-valorem equivalent tariffs. Beef, lamb and veal have the highest tariffs, thus a decrease in tariffs under a free trade scenario leads to more consumption and overproportionally more emissions.

The second set of counterfactuals addresses excluding meat products from the choice set. Vegetarianism results in a decrease of emissions of around 23%. A related counterfactual considers decreasing beef consumption while all other meat products can be purchased. Since beef is the most polluting product, refraining from it yields a decrease in emissions of 15%. The second largest contributor to total emissions is not a meat product, but cheese. Per kilogram, the emissions intensities of cheese are comparable to those of fish and better than pork or chicken. A scenario without consumption of beef and cheese, but allowing all other meat types leads to a decrease of around 33% in emissions and thus results in a larger decrease than vegetarianism. Thus, the answer to the question posed in this paper is "Not to beef," at least from an environmental perspective.

The third set of scenarios analyzes Pigouvian taxes of 50, 100, and 150 EUR/tCO_2e (tons of CO_2 equivalents). The counterfactual with the lowest level of taxes of 50 EUR/tCO_2e leads to a decrease of around 9%, while the other two scenarios lead to around 16% and 21%, respectively. In these scenarios, all prices increase, because all products are associated with some level of emissions.[2] The prices of greener products increase less, thus there is substitution of consumption towards these greener products.

To assess relevance and external validity, I examine three aspects. First, by holding consumption shares constant and assuming the lowest possible emissions intensity for each food type, I find that emissions could decrease by 9% if production practices improved. This number serves as a lower bound, indicating greater emissions reduction potential from consumption-based policies. Second, I analyze the buy local scenario, considering extremes where Home has the highest and lowest production emissions intensity. If Home were the least efficient, emissions would rise by 38%; if the most efficient, they would decrease by 11%. This suggests that buying local might lead to a small decrease in emissions for greener countries, and a large increase in emissions for dirtier countries. Thus, vegetarianism and Pigouvian taxes seem like more effective policies for decreasing greenhouse gas emissions from food consumption. Third, differences in consumption patterns across countries are mostly due to prices and product traits, with minor variations in preferences. Using European meat consumption data, I find that Home's patterns align with those of other countries. Based on these considerations, I conclude that my results are likely to be representative for most developed European countries.

[2] In a general equilibrium model, the tax revenues would be rebated lump-sum to the households. Since this is partial equilibrium, this mechanism is not explicitly modeled in this setup.

This paper lies at the intersection of international trade and environmental economics. Supply side considerations have been the main focus of the effect of trade on the environment (Cherniwchan et al., 2017). The importance of analyzing the demand side has been acknowledged by many authors in that literature (Cherniwchan et al., 2017; Copeland and Taylor, 1995; McAusland, 2008). Yet, there are only few papers in this area. Some empirical work covers the demand for used or fuel efficient cars, while some theoretical papers analyze the effect of pollution regulation or the trade regime on consumption-generated pollution (Antweiler and Gulati, 2016; Copeland and Taylor, 1995; Davis and Kahn, 2010; McAusland, 2008). While incentivizing clean production can be an important factor to reduce greenhouse gas emissions, consumers are the final step in the supply chain. This paper sheds light on the effect of consumer demand for food on the environment. My findings imply that consumer behavior can have a large impact on reducing emissions. The trade literature has a tradition of gauging the welfare implications of international trade. Taking into account externalities from production and transport emissions, Shapiro (2016) finds that the gains from trade still outweigh the losses from its environmental costs. Further, he finds a negative correlation between the emissions intensity of an industry and tariffs in the US, meaning that greener products have higher tariffs (Shapiro, 2020). My findings in this paper contrast this result. I find larger tariffs for dirtier products in Home, implying that free trade would increase emissions in this setting.

The environmental sciences generally show that transport emissions are a small share of overall emissions of food products. Analyses of buying local for a variety of food products find a decrease in emissions. In spite of these emission reductions from buying local, the role of food consumption behavior emerges as the main determinant of emissions in the agricultural sector. Several authors recognize that a dietary shift away from meat products can lead to lowering emissions more than buying local or improving production emissions. Their counterfactuals deal with the effect of e.g. reducing meat production by half on the environment. (Poore and Nemecek, 2018; Weber and Matthews, 2008) My analysis adds to the debate by estimating the substitution patterns of consumers facing different policy scenarios instead of assuming them. Contrary to the environmental scientists, I show that buying local might harm the environment when taking into account consumer behavior.

To my best knowledge, this is the first analysis of food consumption behavior on the environment. I apply methods from the industrial organization literature (Berry, 1994; Nevo, 2001) with high-quality purchasing data (Bresnahan, 1997) to a question that is important both for international trade and environmental economics. Although the industrial organization literature has examined the effects of food consumption on health and other outcomes (Briggs et al., 2013; Dubois et al., 2017; Edjabou and Smed, 2013; Griffith et al., 2019), this is the first study to assess its impact on climate change within an open economy. In contrast to supply-side studies that evaluate how environmental policies affect upstream emissions (Dominguez-Iino, 2021), my work assesses demand-side policy implications, demonstrating that accounting for consumption behavior is essential to effective climate policy.

This paper is organized as follows. Section 2 describes the data. Some stylized facts are presented in section 3. Section 4 outlines a model of meat demand, and section 5 discusses estimation and presents the regression results. The counterfactual scenarios are presented in section 6. Section 7 discusses relevance and external validity and section 8 concludes.

2 Data

Through an exclusive cooperation with a European retailer, I obtain confidential data on revenues and quantities for food products at the bar code level. As the retailer wishes to stay anonymous, I follow the convention of the international trade literature and call the country "Home." This retailer has a very high market share for food and is the leading seller of meat products in Home. To protect the retailer's anonymity, I will also anonymize all other European countries. The robustness section will address the concerns associated with this anonymity. Contrary to standard scanner data sets, I obtain the marginal costs and the country of origin of all products. What I call "marginal cost" is the wholesale cost of each product. For a subset of products, I have access to the calculation of these wholesale costs and can observe that it contains components related to the true cost of food production and not some demand-driven components. This will be important for identification, as I use these marginal costs as instruments for the price. The country of origin is important to estimate the own- and cross-price elasticities between domestic and imported products and evaluate the effects of trade policy.[3]

There are around 12000 bar code level products from 37 countries in the period of 2017-2019 with a weekly frequency. Product characteristics include country of origin, labels (e.g. organic), brand name (e.g. "European Retailer Premium Brand"), food type (e.g. beef or cheese), sales or promotions, and product category (e.g. ground meat). The data consists of all products that contain exactly one of the food types considered (beef, veal, lamb, pork, poultry, fish, crustaceans, cheese, eggs, tofu, legumes). I exclude products that are a combination of two food types and calculate the weekly average price as revenue divided by quantity.[4] Prices and quantities vary by product, week, and region. The retailer operates in all of the different geographical regions of Home.

I consider both emissions from production and from transportation in the analysis. Production emissions intensities stem from a peer-reviewed meta data of life cycle assessments of food products (Poore and Nemecek, 2018). The subset of the data I am using takes into account emissions related to land use change, crop production for animal feed, raising livestock, processing, packaging, retail, and losses. These production emissions intensities are expressed in tCO_2 equivalents per kg of edible product and vary by food type (beef,

[3]Conducting the analysis with aggregate data from trade statistics or input-output matrices would not allow me to use high-quality instrumental variables like marginal costs. With aggregate data I would not be able to identify consumer demand, but rather processor demand. As the meat types used in restaurants are different from the meat types offered directly to consumers, my data source is best suited to credibly identify consumer demand.

[4]Verifying this calculation with a subset of the data for which exact prices are available shows an accuracy of over 99%.

beef dairy herd, lamb/mutton, poultry, pork, crustaceans, fish, tofu, eggs, cheese, legumes), and country. Appendix section A.1 gives more details on how I combine the data sets.

The transport emissions intensities originate from two different sources. Emissions intensities from air transport come directly from the European retailer. An internal study calculates the greenhouse gas emissions of the transport by airplane in kgCO2e per kg of each product that is flown. This data takes into account distances, weight, and whether the product was transported as belly freight or not. I calculate emissions intensities from other modes of transport (truck, rail, ship) using shares for each mode. For some products, I obtain the mode of transport from the European retailer. For the other products, I work with average modes of transport per food type obtained from customs data. Emissions intensities for each transport mode come from Poore and Nemecek (2018) and are given in kgCO2e per gram of product transported for 1km. I calculate the distances using great circle distances from the Center for International Prospective Studies (Mayer and Zignago, 2006).

For estimating the model, I need to define an outside good. This outside good captures the option not to buy any of the protein-rich products in my data. I define the outside good to be any other food type. This definition allows consumers to substitute away from meat to any other food product - be it a meat substitute or some potatoes. Thereby, I make use of the empirical pattern that most humans eat around 1.5 kg of food every day to define the market size. I obtain data from a representative food consumption survey in Home to match the quantity of the outside good to the quantity consumed by the average Home resident. This results in setting the market share of the outside good to around 85%. I assume that the outside good is domestic and thus, the transport emissions are zero. As for the production emissions intensities, I use the average of all other food types (without drinks) in Poore and Nemecek (2018) that are not available in the data set from the European retailer on prices and quantities. This includes the emissions from fruit, vegetables, and starches.

To match the level of variation of the emissions data and to simplify estimation, I aggregate the bar code level products by food type, continent of origin, and transport mode (flight, truck, rail, ship). I treat Home as its own continent and aggregate the other countries into continents according to seven regions as defined in the World Bank Development Indicators. Leaving the country of origin on the country level instead of aggregating to the continent level would lead to a lot of missing values, as not every food type is represented for every country in the data set on production emissions intensities. This results in a data set with 38 distinct products varying across regions and weeks. Whenever I refer to a "product," I refer to this aggregated product definition unless otherwise stated. I report regressions for both the aggregate and the barcode level product definition.

The majority of price variation comes from variations in marginal costs and sales. There are three types of sales. With standard sales (sales 1), the price is reduced per kg of product. Packaged sales (sales 3) also offer price reductions, but at the same time require the consumer to buy the product in packages (e.g. three

	Food Type	Imported	Transport Mode	Continents	Quantity	Sales 1	Sales 2	Sales 3	Label Organic	Label Local
1	beef	no	internal	1	2169.74	79.46	48.67	18.58	61.98	476.75
2	beef	yes	flight	5	34.66	25.53	126.89	36.08	0.00	0.00
3	beef	yes	mixed	4	9.04	28.52	506.63	65.51	0.00	0.00
4	beef	yes	truck	1	178.34	8.78	56.21	22.60	1.39	0.00
5	cheese	no	internal	1	8573.40	26.98	45.75	2.69	23.30	333.52
6	cheese	yes	mixed	1	689.73	14.08	14.38	1.51	5.67	0.00
7	eggs	no	internal	1	2721.73	4.90	26.29	1.29	99.86	504.52
8	eggs	yes	mixed	1	569.46	1.12	8.15	1.66	0.60	0.00
9	fish	no	internal	1	721.57	35.72	91.55	22.13	54.09	29.19
10	fish	yes	mixed	6	360.56	74.64	587.52	152.96	313.50	0.00
11	lamb	no	internal	1	203.76	31.45	64.34	25.46	0.09	259.09
12	lamb	yes	flight	2	151.14	70.09	45.62	20.73	0.00	0.00
13	lamb	yes	mixed	1	9.79	14.50	310.50	82.16	21.51	0.00
14	legumes	no	internal	1	517.16	1.53	50.97	0.04	63.60	0.64
15	legumes	yes	mixed	1	143.11	4.18	1.13	0.05	15.09	0.00
16	pork	no	internal	1	4146.90	37.57	56.50	10.07	6.41	351.72
17	pork	yes	mixed	1	0.44	0.43	0.00	5.30	0.00	0.00
18	pork	yes	truck	1	6.28	10.93	3.33	31.53	0.00	0.00
19	poultry	no	internal	1	4287.12	31.37	98.21	16.85	7.61	374.60
20	poultry	yes	mixed	1	89.95	19.69	120.28	47.98	0.00	0.00
21	tofu	no	internal	1	246.61	1.85	92.20	12.89	105.78	25.04
22	tofu	yes	mixed	1	64.14	1.65	0.00	15.91	212.06	0.00
23	veal	no	internal	1	80.05	3.78	10.21	2.08	0.20	67.65
24	veal	yes	mixed	1	0.55	2.89	0.00	0.68	0.00	0.00

Note:
This table shows the summary statistics of the aggregated products. The mixed transport mode can be either rail, ship, or truck. Continents are defined according to the World Bankd Development Indicators. The quantity is expressed in tons per 1 mio consumers. Sales and labels are in %.

Table 1: Summary Statistics

sausages instead of one). The third type of sales only occurs when a product is close to expiry. In that case, a product might be discounted with stickers (sales 2).

Table 1 gives some product characteristics by food type[5]. Overall, most food is not imported, thus imported market shares are low. Similarly to other supermarket data (Berto Villas-Boas, 2007; Nevo, 2001), Table 2 shows that aggregate consumer prices vary mostly by product and somewhat by region and over time.

	price
Regional Variation	0.07
Time Variation	0.04
Product Variation	0.50

Table 2: Coefficient of Variation

For the trade regime analysis, I rely on the experts at the European retailer and with their help, categorize the barcode level products according to which trade regime they belong to. There are three types of trade

[5]To respect the retailer's anonymity, I am limited in the types of summary statistics I show in Table 1.

regimes: no restriction, tariff, and tariff-rate quotas. I collect data on the trade restrictions for different products from the trade statistics of Home. Additionally, I gather the ad valorem equivalent (AVE) most favored nation tariff from the Market Access Map (ITC, 2020) of the World Trade Organization. This tariff represents an upper bound as the AVE tariffs are very high.

3 Stylized facts

One wide spread belief is that regional foods are more sustainable than imported ones. This "buy local" concept relies on two implicit assumptions. The first is that transport emissions are important for the overall emissions of a product. The second is that emissions from production are the same across countries.

Combining consumption data from Home with production emissions intensities (Poore and Nemecek, 2018) and transport emissions intensities, Figure 1 shows that transport emissions intensities only account for a small fraction of overall emissions intensities of products consumed. The three products represent median overall emissions intensity per transport mode. A mixed transport mode might be transported via truck, rail, or ship. The product coming only by truck is pork, the other two are beef. While choosing products with higher or lower production emissions intensities would change the proportions of transport and production emissions, the message would be the same: Transport emissions do not play an important role in overall emissions. Figure 16 in the Appendix illustrates this for the case of beef and tofu. Therefore, the first assumption of the buy local concept is flawed.

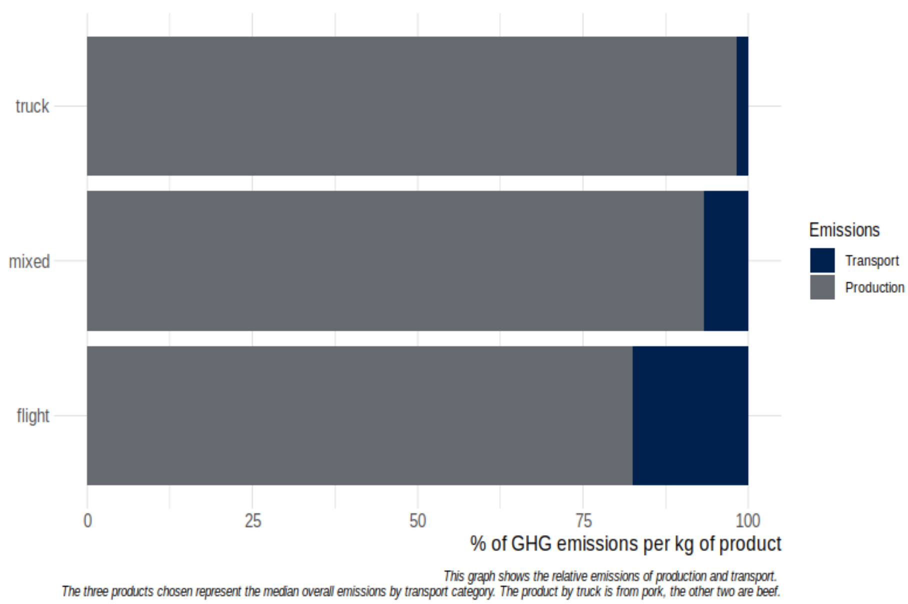


Figure 1: GHG emissions intensities of selected imported meat products

Figure 2 shows the distribution of emissions of producing 1 kg of food across different countries[6]. There are three main takeaways from this graph. First, the emissions intensities of vegetarian products are lower than those of meat products. Therefore, a vegetarian diet yields lower emissions compared to a standard diet. Second, the production emissions intensities vary substantially even within meat products. Substituting beef by poultry or pork could reduce emissions intensities by a factor of 10. The reason for these stark differences is a biological one: Ruminants (cattle, lamb, mutton) have higher emissions intensities because of lower efficiency when converting feed to edible meat (feed-conversion ratio). Third, the emissions intensities vary across countries. For each food type, production emissions intensities could be at least halved if production took place with the technology of low-emissions intensity countries. This suggests that the second assumption of the buy local rule does not hold either.

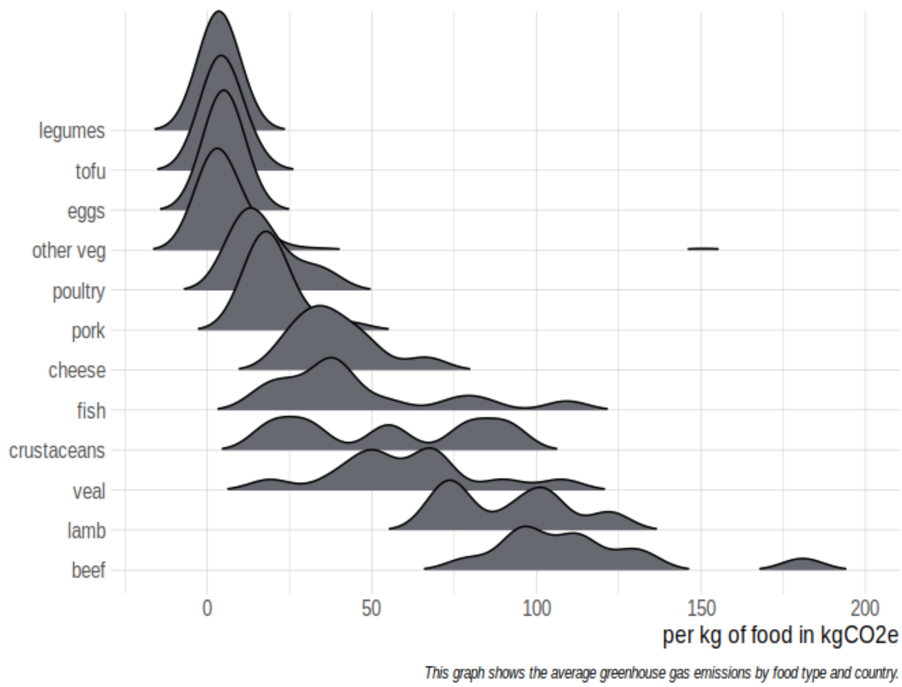


Figure 2: GHG emissions intensities across countries

The figures show that what we eat is much more important than whether our food is local. All this evidence suggests that the fundamental question when talking about decreasing emissions from food consumption is "To Beef or Not To Beef."

[6]These emissions intensities include several stages of the life cycle of a product, including land use change. Depending on whether one views deforestation as a fixed or a sunk cost, land use change should not enter in the environmental cost. Excluding land use change results in lower overall emissions intensities for all products, but the ordering and the spread of emissions intensities across meat types stays the same. See graph 17 in the Appendix.

4 A discrete choice model of meat demand

The previous sections described the data and presented some stylized facts. In this section, I outline a discrete choice model of meat demand. Estimating demand is the basis for gauging the effect of different policies. The goal of this exercise is to estimate consumer's reaction to changes in choice sets and prices which enables me to conduct counterfactual exercises. The model helps to estimate own- and cross-price elasticities of meat products using a nested logit framework (Berry, 1994). First, I present the theoretical model on the demand side. Then, I add the supply side that represents the pricing decision of the firm. Third, I add a dummy version of the model to highlight mechanisms.

4.1 Demand

Consumer i's conditional indirect utility of consuming food product j of product group g in region r and week w is modeled as a linear function of product characteristics (McFadden, 1974):

$$u_{ijrw} = \alpha p_{jrw} + x_{jrw}\beta + \xi_{jrw} + \zeta_{igrw} + (1-\sigma)\varepsilon_{ijrw},$$

where p_{jrw} is the price of good j in market rw, market rw is a region in a certain week, and α is the price sensitivity. The model includes x_{jrw} as a vector of observable product characteristics of product j in market rw, with β being a vector of preferences for the observable product characteristics. Unobservable product characteristics ξ_{jrw} are observable for both consumers and firms, but unobservable to the econometrician. I allow tastes for products in the same group g to be correlated, where ζ_{igrw} is a group error shock and σ is the strength of the correlation of products within a group. A group is defined as a food type (e.g. beef or chicken). The econometric error ε_{ijrw} is assumed to be iid extreme value type 1 distributed. Figure 3 shows a stylized representation of the nesting structure.

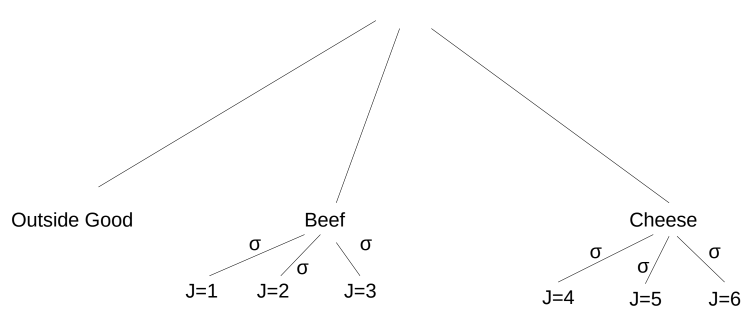


Figure 3: Stylized nesting structure

This discrete choice framework assumes that one product is being chosen among all options. Continuous or multiple-discrete models require individual-level data (Dubé, 2004; Hendel, 1999). While I cannot exclude that consumers choose several products at one occasion, multiple-discreteness is less likely to be present for products with short expiry dates. Conceptually, the utility function can be interpreted to represent utility from a future consumption occasion, with consumers making multiple decisions at each shopping trip. As I have weekly data, a purchasing occasion will be a weekly shopping trip.

The individual utilities u_{ijrw} are aggregated over consumers i to obtain the market share of product j. Since we can only analyze differences in utility and not their absolute levels, I introduce an outside good and set its utility to 0. As described in section 2, this outside good captures the option not to buy any of the protein-rich products. This results in setting the market share of the outside good to around 85%.

The mean utility of food product j is denoted by $\delta_{jrw} = \alpha p_{jrw} + x_{jrw}\beta + \xi_{jrw}$. Assuming that consumers choose the product that maximizes their utility, the probability that consumer i chooses product j in market rw is given by a nested logit form. Summing across consumers yields market shares for market rw: $s_{jrw} = \sum_i s_{ijrw}$.

$$
\begin{aligned}
s_{jrw} &= \int ... \int 1(u_{ijrw} > u_{ikrw} \forall k \neq j) p(\varepsilon_{i1rw}, ..., \varepsilon_{iJrw}, \zeta_{igrw}) \\
&= \frac{1}{1 + (\sum_{k \in g} e^{\frac{\delta_{jrw}}{1-\sigma}})^{1-\sigma}} \text{ if } \quad j = 0 \\
&= \frac{e^{\frac{\delta_{jrw}}{1-\sigma}} (\sum_{k \in g} e^{\frac{\delta_{jrw}}{1-\sigma}})^{-\sigma}}{1 + (\sum_{k \in g} e^{\frac{\delta_{jrw}}{1-\sigma}})^{1-\sigma}} \text{ if } \quad j \in J
\end{aligned}
\tag{1}
$$

4.2 Supply

The supply side should ideally be modeled by an oligopoly where several firms compete with each other. Since I only have data from one firm, I will model supply as a multiproduct monopoly.

The profit function of the firm is

$$
\Pi_{jrw} = \sum_{j \in J} (p_{jrw} - (mc_{jrw} + \tau_j)) s_{jrw} - C,
$$

where J is the set of all products of the firm in given market rw. p_{jrw} is the price of product j in week w in region r, mc_{jrw} is the marginal cost, τ_j is a tax on product j, s_{jrw} is the market share of product j and C is a fixed cost. The tax τ_j is 0 in the baseline model used to estimate the parameters. It will take on different values for the counterfactual scenarios. The first order condition with respect to the price of good j in market rw is

$$0 = s_{jrw} + \sum_{k \in J} (p_{krw} - (mc_{krw} + \tau_j) \frac{\partial s_{krw}}{\partial p_{jrw}})$$

Note that the first order condition takes into account both the own-price effects and the cross-price effects, hence p_{krw} shows up in the equation. Defining S_{jk} as the matrix of own- and cross-price derivatives of the market share and switching to vector notation:

$$S_{jk} = -\frac{\partial s_{krw}}{\partial p_{jrw}}$$

$$0 = s_{rw} - S_{jk}(p_{rw} - (mc_{rw} + \tau_j))$$

The price is a function of the marginal cost, the tax, the matrix of own- and cross-price derivatives, and the market share:

$$p_{rw} = (mc_{rw} + \tau_j) - S_{jk}^{-1} s_{rw} \tag{2}$$

4.3 Intuition

To help with the intuition of the model and the interpretation of the results, this section presents a simpler version of the model. For that, I depart from the nested logit assumption and consider a logit model instead. The intuitions remain the same. For conciseness, I skip the rw market subscript. In a logit framework, the demand equation is given by:

$$s_j = \frac{e^{\delta_j}}{1 + \sum_k e^{\delta_k}} \tag{3}$$

For simplicity, I assume that $\delta_j = \alpha p_j$ and that the number of products k is 2.

The formulas for the own- and cross-price elasticities are given by:

$$\text{OPE} = \frac{\partial s_j(p_j)}{\partial p_j} \frac{p_j}{s_j} = \alpha p_j (1 - s_j)$$

$$\text{CPE} = \frac{\partial s_j(p_j)}{\partial p_l} \frac{p_l}{s_j} = -\alpha p_l (1 - s_l)$$

If the price of one product increases, the quantity of that same product decreases and the quantity of the other product increases. However, in more realistic scenarios, there are several prices that change at the same time. This means that for each product, there might be an own-price effect (its price decreases, so the quantity increases) and a cross-price effect (some other price decreases, so the product's quantity decreases). Depending on the relative magnitudes of these effects, one of the two effects will dominate. Appendix A.2 gives a numerical example.

Adding a simple multiproduct supply side, the profit function is the following:

$$\Pi = (p_j - mc_j)s_j(p) + (p_l - mc_l)s_l(p)$$

The first-order condition is:

$$0 = s_j + (p_j - mc_j)\frac{\partial s_j}{\partial p_j} + (p_l - mc_l)\frac{\partial s_l}{\partial p_j}$$

Rearranging yields the pricing equation:

$$p_j = mc_j + \frac{1 - \alpha s_l(p_l - mc_l)}{\alpha(1 - s_j)} \tag{4}$$

Equation 4 allows us to identify another effect which refers to dropping products from the choice set. Intuitively, if there are less competitors, a product's price should increase. Setting the market share of good l, s_l, to 0 leads to an increase in the price of good j.[7] I call this the competition effect. In a sense, this is the reverse of the cross-price elasticity effect: Consumers are willing to buy more of product l if product j's price increases, and the retailer is willing to increase the price of product j if product l is not available.

5 Identification and estimation

The demand side can be estimated via OLS. When including the supply side, both demand and supply have to be estimated via GMM. Both procedures are outlined below.

5.1 Demand only estimation via OLS

Estimating the market shares s_{jrw} is complicated by the fact that the econometric error enters nonlinearly. I solve for the mean utility δ_{jrw} by inverting the market shares and estimate the following linear equation (Berry, 1994):

$$ln\frac{s_{jrw}}{s_{0rw}} = \delta_{jrw} + \sigma ln\frac{s_{jrw}}{s_{grw}} = \alpha p_{jrw} + x_{jrw}\beta + \sigma ln\frac{s_{jrw}}{s_{grw}} + \xi_{jrw}$$

[7]Recall that α is negative. Thus, the numerator is 1 + a positive quantity, and the denominator is negative. Setting s_l to 0 results in subtracting a smaller quantity.

where $\frac{s_{jrw}}{s_{grw}}$ is the market share of product j within food type g in market rw and the unobserved product characteristic ξ_{jrw} is the error term. The observed product characteristics x_{jrw} include labels, brands, and sales variables. I refer to these variables as "controls" in the next equation. Table 3 shows the median market shares for the median domestic and imported food type.

	Food Type	Imported	Market Share	Group Market Share	Within Group Market Share
1	beef	0	1.21	1.36	90.98
2	beef	1	0.11	1.36	0.35
3	cheese	0	4.94	5.35	92.63
4	cheese	1	0.41	5.35	7.37
5	eggs	0	1.53	1.93	84.73
6	eggs	1	0.32	1.93	15.27
7	fish	0	0.42	0.61	69.07
8	fish	1	0.20	0.61	1.02
9	lamb	0	0.08	0.19	48.93
10	lamb	1	0.08	0.19	25.00
11	legumes	0	0.29	0.38	77.18
12	legumes	1	0.08	0.38	22.82
13	pork	0	2.98	2.98	99.88
14	pork	1	0.00	2.98	0.11
15	poultry	0	2.57	2.62	98.49
16	poultry	1	0.03	2.62	1.52
17	tofu	0	0.14	0.18	79.47
18	tofu	1	0.03	0.18	20.53
19	veal	0	0.28	0.28	98.61
20	veal	1	0.00	0.28	1.42

Note:

This table shows the median market shares across markets and products in percent. A group is a food type.

Table 3: Market Shares Summary Statistics

The parameters α and σ might both suffer from endogeneity which can be solved using an instrumental variable approach. First, I explain the types of biases that arise for each parameter. Second, I propose instrumental variables to obtain unbiased estimates of α and σ. The estimating equation in the case of demand-side only estimation is:

$$ln\frac{s_{jrw}}{s_{0rw}} = \alpha p_{jrw} + \sigma ln\frac{s_{jrw}}{s_{jgrw}} + \theta_g + \theta_{year} + \theta_{quarter} + \theta_r + controls + \xi_{jrw},$$

where $\frac{s_{jrw}}{s_{0rw}}$ is the relative market share of product j. p_{jrw} is the price of good j in region r in week w. $\frac{s_{jrw}}{s_{jgrw}}$ is the within group market share, where a group is defined as a food type. This is the variable that makes this a nested logit, excluding it would leave us with a logit specification. θ_g, θ_{year}, $\theta_{quarter}$, and θ_r are group, year, quarter, and region fixed effects. The control variables include labels, brands, and sales variables.

The main variable of interest is the price coefficient α. This coefficient might be upward biased, since higher values of the unobserved characteristics in the error term might be associated with a higher price. Including fixed effects that vary by region, year, and quarter help to control for demand shifts caused by spatial components, yearly trends, and seasonal variation. The within group market share $\frac{s_{jrw}}{s_{grw}}$ measures the market share of e.g. domestic beef with respect to the market share of all beef products. It is correlated with the unobserved product characteristic ξ_{jrw} in the error and thus endogenous. Products with more desirable characteristics might have a higher market share within their group.

A valid instrument for the price should be relevant and exogenous. I use the marginal cost for each product as an instrument for the price. In the words of Bresnahan (1997), obtaining marginal cost data is "rare and lucky." This instrument is relevant because it is part of the price. The exogeneity condition will hold if the instrument is uncorrelated with the error term. Marginal costs as measured by the European retailer represent production costs and are not sensitive to particular demand fluctuations. According to internal price calculations that are available for a subset of the products, the largest part of the marginal cost is the raw material, followed by processing costs (cutting in the case of meat), and some smaller costs for packaging, logistics, transport, and tariffs, if applicable. The exclusion restriction is that marginal costs influence market shares only through their effect on the price. This might be violated if there are unobserved variables that influence both marginal costs and consumer demand. As I control for an extensive set of product characteristics, I do not worry about omitted variables that affect marginal costs.

To instrument for the within group market share, I create a proxy for advertisement of other products in a group. I use a variable about sales to create this instrument. These sales are planned months in advance, so they are not correlated with the demand shock. To be clear, all price effects of sales are included in the price. Therefore, the inclusion of sales variables only affects the market share of good j through an advertisement effect. The advertisement of products on sale takes the form of stickers or banners on products which will grab the consumer's attention and make the product more likely to be purchased. The instrument will be correlated with the denominator of the within group market share in the estimating equation. Relevance is given as the advertisement of products on sale, for example through stickers on the products, influences the demand for those products. If for instance all other beef products are on sale, but domestic beef is not, the within group market share of domestic beef should decrease. The exclusion restriction is that stickers on other beef products only influence the demand for domestic beef through their effect on the other products' demand. This might be violated if the utility of domestic beef is affected by a sticker on imported beef.

$$proxy\ for\ sales = mean_{rw,k \neq j \in g}(sales)$$

I calculate the instrument as the mean percentage of revenue from products on sale in market rw for food type g, where I exclude product j from the calculation. I use the standard sales for creating the instrument as opposed to packaged sales or expiry sales. Using packaged sales leads to similar results. Expiry sales are not planned ahead and are likely to be correlated with demand. An increase in expiry sales means that consumers buy less of a product than expected. Figure 18 in the Appendix shows the variation in the instrument and the within group market share. The correlation is negative: When the instrument increases, the within group market share decreases. This happens because for higher levels of the instrument, other products in the same group become more attractive, thus the within group market share of product j decreases.

5.2 Joint estimation of supply and demand via GMM

Estimating demand is important, but it does not take into account the pricing behavior of the firm. Equation 2 shows that the demand parameters α and σ also enter the pricing equation on the supply side. Therefore, a joint estimation via GMM might lead to more credible results. Including a supply side also improves the counterfactual scenarios. Calculating counterfactuals only using the demand side implicitly implies that the prices of the goods not affected by a policy do not change. For a buy local scenario, for example, it is expected that the domestic prices would increase as a response to less competition.

The demand and supply moments are created by multiplying the residual demand and supply by the instrumental variables from the previous section. The residual demand is based on equation 1, while the residual supply is based on equation 2:

$$\text{Residual Demand} = ln\frac{s_{jrw}}{s_{0rw}} - \text{constant}_D - \alpha p_{jrw} - x_{jrw}\beta - \sigma ln\frac{s_{jrw}}{s_{grw}} - \xi_{jrw}$$

$$\text{Residual Supply} = p_{jrw} - \text{constant}_S - \theta mc_{jrw} - S_{jk}^{-1} s_{rw}$$

5.3 Regression results

This section shows the regression results for the nested logit model and the corresponding elasticities. In Table 4, I show the results for three versions of nested logit regressions. Column 1 shows an OLS nested logit model without instruments, column 2 shows an IV nested logit model with marginal costs and the advertising proxy as instruments, columns 3 and 4 show the respective first stages, and column 5 shows the joint estimation of supply and demand with GMM. All columns include continent, food type, quarter, year, and regional fixed effects, and a set of controls.[8] The control variables include the percentage of products with a brand name (e.g. “European Retailer Premium Brand”) and the percentage of products with different types of labels (e.g. “organic”). Most labels and brands are omitted due to space constraints, but shown in Table 21 in the Appendix. The sales variables represent different types of sales and enter with differing signs. As noted before, the price effect of sales is captured by the price variable. Therefore, all three sales variables represent the effects of advertisements related to sales, e.g. special shelf placement or stickers on products. The standard sales (sales 1) and packaged sales (sales 2) variables combine price reductions with advertisements. Thus, a higher share of sales increases the market share of a product. The expiry sales (sales 3) represents sales due to a product being close to its expiry date. The retailer only uses this type of sales if consumers purchased less of a product than expected. Therefore, a higher share of expiry sales indicates lower demand than expected and thus decreases the relative market share.

[8] Interacting the fixed effects or including week-of-the-year fixed effects does not alter the results.

Table 4: Nested Logit, IV, and GMM Regressions

	Dependent variable:				
	relative MS		price	within group MS	joint estimation
	NL	NL IV	FS 1	FS 2	GMM
	(1)	(2)	(3)	(4)	(5)
Price	-0.004^{***}	-0.016^{***}			-0.06^{***}
	(0.0002)	(0.001)			(0.001)
Within Group MS	0.935^{***}	0.621^{***}			0.503^{***}
	(0.002)	(0.014)			(0.022)
Sales 1	0.797^{***}	2.133^{***}	-15.315^{***}	4.809^{***}	2.737^{***}
	(0.023)	(0.066)	(0.540)	(0.078)	(0.106)
Sales 2	-0.500^{***}	-1.999^{***}	-24.475^{***}	-3.796^{***}	-5.104^{***}
	(0.024)	(0.074)	(0.544)	(0.078)	(0.119)
Sales 3	0.282^{***}	0.674^{***}	-7.961^{***}	1.531^{***}	0.346^{***}
	(0.009)	(0.021)	(0.210)	(0.030)	(0.033)
Label Organic	-0.205^{***}	-0.132^{***}	10.833^{***}	-0.085	-0.698^{***}
	(0.016)	(0.024)	(0.394)	(0.057)	(0.039)
Label Local	0.057^{***}	0.394^{***}	-8.741^{***}	1.272^{***}	0.643^{***}
	(0.013)	(0.023)	(0.309)	(0.045)	(0.037)
Marginal Cost			0.900^{***}	-0.038^{***}	1.315^{***}
			(0.004)	(0.001)	(0.003)
Advertising Proxy			-4.478^{***}	-3.379^{***}	
			(0.816)	(0.118)	
F-Statistic			4954	1282	
Observations	39,262	39,262	39,262	39,262	39,262

Note: *p<0.1; **p<0.05; ***p<0.01
Includes quarter, year, region, continent, and food type fixed effects, labels, and brands.
This table shows a regression of the relative market share (relative MS) on prices, the within group market share (within group MS), and other product characteristics.

The first column presents a nested logit model with food types as nests and without instrumental variables. The coefficient of interest is the price coefficient which is negative and significant. Adding the marginal cost and the proxy for advertisement as instruments in column 2 results in a more negative price coefficient. This confirms the suspicion that the price coefficient is upward biased. The coefficient on the within group market share is larger than 0. This implies that the substitution patterns between products in the same nest are somewhat higher than across nests. The magnitudes cannot be interpreted in an intuitive way. Therefore, I turn to the elasticities later.

Column 3 and 4 show the first stage estimates for the nested logit regression. Increasing marginal costs by 1 € results in a consumer price increase of around 0.90 € in column 3. For the within group market share first stage in column 4, the proxy for advertisement enters negatively. Increasing the proxy of advertisement of other products decreases the denominator of the regressor and thus increases the within group market share. In other words, the group becomes more desirable, so the within group market share of product j decreases. The F-statistics are large in both first stages.

Column 5 shows the results for the joint estimation of demand and supply, including both instruments. The price coefficient gets even more negative, while the within group market share decreases slightly. The coefficient on the marginal cost implies that for a 1 € increase in marginal costs, the price increases by 1.30 €. This estimate is in line with pass-through rates in the previous literature on pass-through in different types of markets (Bonnet and Réquillart, 2013; Genakos and Pagliero, 2022; Hanson and Sullivan, 2009; Miller et al., 2017). This specification controls for fixed effects, so the true pass-through rate would be the fixed effects plus my estimates.

This specification accounts for consumer preferences for more environmentally friendly products as long as these preferences are captured by food type and continent fixed effects. Alternatively, the greenhouse gas emissions intensities for each product could enter the utility function. As emissions intensities vary across continents and across products, my setup does not allow to estimate a coefficient on emissions intensity. A specification in Appendix Table 23 where instead of continent fixed effects I only control for domestic or imported products and include greenhouse gas emissions intensity shows that the coefficients of interest do not change and that the coefficient on emissions intensity is very low. As consumers do not observe emissions intensities, but rather product characteristics like food type and country of origin, I do not include emissions intensities in the main specification.

As mentioned in section 2, all these regressions are run on the aggregated data. Appendix table 22 shows the demand-only regressions on the barcode level data. The results are similar to the aggregated data, except that the brandname dummies are siginificant on the barcode level. Many brands are food type specific (e.g. a brandname for chicken), so there is little variation in the aggregated data. Therefore, I choose to still include them in the aggregated regressions. I report both OLS and IV regressions, with and without product fixed effects.

	Group	OPE NL	CPE Within Group	CPE Across Groups	Share switched to OG
1	Beef Dom	-2.8201	0.0018	0.0170	7.9459
2	Beef Imp	-8.4887	0.0529	0.0002	7.8636
3	Cheese Dom	-1.0559	0.0025	0.0272	8.2728
4	Cheese Imp	-1.2562	0.0317	0.0025	8.0734
5	Eggs Dom	-0.4888	0.0009	0.0038	7.9792
6	Eggs Imp	-0.4044	0.0032	0.0006	7.9336
7	Fish Dom	-2.5625	0.0027	0.0054	7.8758
8	Fish Imp	-3.4189	0.0097	0.0001	7.9250
9	Lamb Dom	-2.3344	0.0009	0.0010	7.8569
10	Lamb Imp	-5.8026	0.0036	0.0007	7.8164
11	Legumes Dom	-0.2133	0.0001	0.0003	7.8657
12	Legumes Imp	-0.2190	0.0003	0.0001	7.8578
13	Pork Dom	-2.2787	0.0004	0.0340	8.3347
14	Pork Imp	-6.1662	0.0834	0.0001	8.1541
15	Poultry Dom	-1.7954	0.0006	0.0242	8.0687
16	Poultry Imp	-2.2936	0.0295	0.0004	7.9519
17	Tofu Dom	-0.5824	0.0001	0.0004	7.8494
18	Tofu Imp	-0.5233	0.0004	0.0001	7.8474
19	Veal Dom	-3.1585	0.0001	0.0041	8.8211
20	Veal Imp	-7.0524	0.0098	0.0001	8.8139

Note:

This table shows the own- and cross-price elasticities of the gmm nested logit specification.

Table 5: Nested Logit Elasticities Ad

The own- and cross-price elasticities are given in Table 5. In the case of several products (several continents to import from or several transport categories), I present the median elasticity of the group. The own-price elasticities range between -0.2 and -8.5. This is slightly higher than other's findings in the meat market (Anders and Mőser, 2010; Eales and Unnevehr, 1988; Reed et al., 2003; Yang et al., 2018). However, none of these papers estimates demand and supply jointly. The own-price elasticities based on the demand-only estimates (not reported) are more in line with the previous literature.

The second column shows the cross-price elasticities for products within the same group, e.g. between domestic and imported beef. The third column shows the cross-price elasticities for products outside the group, e.g. between beef and chicken. Allowing for higher cross-price elasticities within groups is a feature of the nesting structure. Without nesting, all cross-price elasticities would take the logit form of column 3. The reason for these low cross-price elasticities lies in the data structure: low market shares for the imported products yield low cross-price elasticities. I report the formulas for calculating the elasticities in a nested logit setup in the Appendix in section A.4. The share switched to the outside good in the fourth column is around 7%. This represents the share of the food budget that consumers substitute to the outside good when the price of product j changes (Berry et al., 1995).

6 Counterfactuals

The previous sections outlined a discrete choice model for meat demand, discussed identification and presented the regressions results. In this section, I use the estimates of the model to analyze some counterfactual scenarios. These hypothetical scenarios rely on changing the choice set or the prices and comparing the outcome to the status quo. I introduce three sets of scenarios: the first considers trade-related scenarios like buy local (or autarky) and free trade. The second category revolves around reducing meat consumption like vegetarianism or a no-beef no-cheese scenario. The third set of scenarios implements Pigouvian taxes, so taxes that are proportional to the emissions intensity of each product.

Buying local and vegetarianism are popular, supposedly eco-friendly strategies, as evidenced by a representative survey of food consumption and sustainability (BEUC, 2020). Often, counterfactuals in economic models are perceived as policies imposed by the government. However, they can also be viewed as self-imposed restrictions. In this context, the vegetarian scenario would correspond to all consumers voluntarily imposing mental taxes on meat. While some of these counterfactuals may seem extreme, they illustrate the potential environmental impact if these popular movements were to be fully embraced.[9] Conversely, the conventional economic approach is to account for the externality from emissions and impose a Pigouvian tax.

I structure the analysis in five subsections. First, I explain how the counterfactuals are calculated. Second, I show the status quo of food consumption and the related total emissions. Third, I discuss several trade-related policies, revolving around buy local (or autarky) and free trade. Fourth, I analyze policies related to reducing meat consumption, including a no beef, a vegetarian, and a no beef no cheese scenario. Fifth, I discuss three Pivouvian tax scenarios.

Figure 4 summarizes the counterfactuals. It shows the average yearly change in emissions for each counterfactual scenario compared to the status quo. The left panel shows the trade-related scenarios. Overall, the buy local scenarios have a small impact on emissions compared to the free trade, vegetarian, and Pigouvian tax scenarios. Contrary to popular belief, buying local only decreases emissions slightly by around 2%. The naive buy local scenario which leads to an increase of around 0.2% does not take into account the own- and cross-price elasticities and relies on ad-hoc assumptions instead. The free trade scenario leads to a small increase in emissions which becomes very large when considering ad valorem equivalent tariffs. The vegetarian scenarios all lead to a decrease in emissions. Surprisingly, a no beef no cheese scenario yields the largest decrease in emissions, although all other meat products can be consumed in this scenario. The Pigouvian tax scenarios all refer to different values of the social cost of carbon per ton of CO_2e. At 150 EUR/tCO_2e, the emissions decrease is slightly above 20%, and thus of similar magnitude as the vegetarian scenario.

[9] Calculating extreme counterfactuals stretches the interpretation of the elasticities that only hold for local changes.

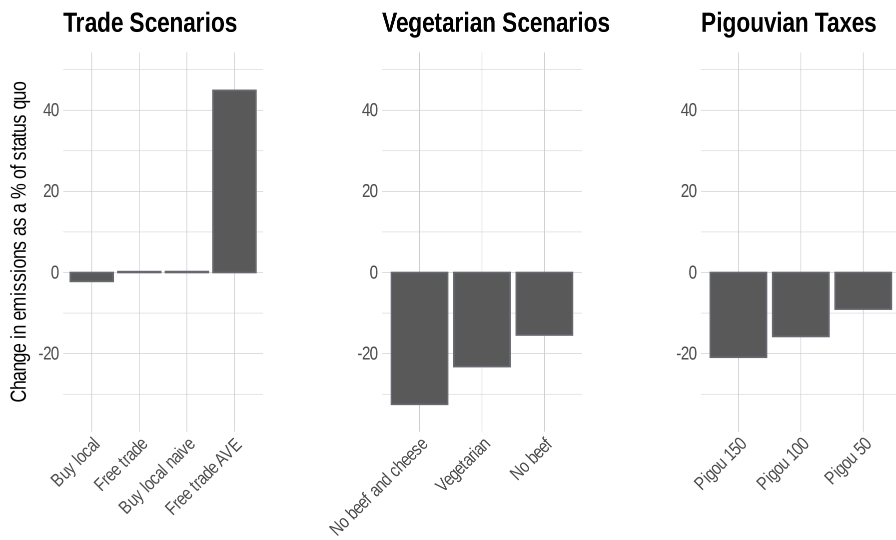


Figure 4: Summary of counterfactuals

6.1 Calculation of counterfactuals

In a standard demand-only model, one would run counterfactuals by either changing the price or dropping some of the data points (e.g. imported products for a buy local counterfactual) and predicting the left-hand side. Since this model estimates demand and supply jointly, I cannot simply predict the left-hand side of the regression in order to run counterfactuals. The reason is that the price enters both demand and supply. Hence, I need to find the new equilibrium jointly. I do so using a fixed-point algorithm based on equations 1 and 2 that takes into account both demand and supply. The algorithm will the determine the new price based on both the demand and the supply equation, taking into account consumer preferences and the pricing behavior of the retailer.

6.2 Status quo

Table 6 shows the current consumption patterns in Home. As implied by the column for the outside good, the protein-rich products considered in my sample account for only 16% of total consumption in terms of quantities while yielding more than 50% of emissions. Beef and cheese are the highest contributors to emissions. While beef only represents around 1.5% of consumption in terms of quantity, it is responsible for around 15% of emissions. I will compare all counterfactual scenarios to this status quo. As the discrete choice model compares quantities relatively to an outside good, the total amount of food consumed will not change in any of the counterfactuals.

	Type	Quantity		Emissions	
		in 1000 kg	%	in 1000 tCO2e	in %
1	Beef	2392	1.47	272361	14.78
2	Cheese	9283	5.69	450617	24.45
3	Eggs	3301	2.02	19251	1.04
4	Fish	1079	0.66	40692	2.21
5	Lamb	364	0.22	35319	1.92
6	Legumes	662	0.41	1898	0.10
7	Pork	4140	2.54	77230	4.19
8	Poultry	4376	2.68	45855	2.49
9	Tofu	313	0.19	1233	0.07
10	Veal	82	0.05	5458	0.30
11	Outside Good	137123	84.07	893054	48.46
12	Total	163115	100.00	1842968	100.00

Note:
This table shows the consumption patterns in the status quo. The quantity is expressed in tons per 1 mio consumers.

Table 6: Status Quo

6.3 Trade-related counterfactuals

6.3.1 Buy local

The buy local or autarky scenario would imply that the import of any protein-rich product to Home is prohibited[10]. Alternatively, this scenario can be interpreted as a complete adherence to the buy local idea. In any case, consumers would not purchase imported protein-rich foods in autarky.

A first naive counterfactual in assesses a buy local scenario without modeling consumer behavior explicitly. To gauge the impact of buying local on the environment without an economic model, the researcher must make some assumptions. Buying local implies that no imported products are purchased, so transport emissions fall to 0. What will consumers buy instead of the imported goods? A straight-forward assumption is that they would buy the same overall quantities of different food types which are now all produced domestically.

Table 7 shows the results of such a counterfactual. I show the quantity for an average year per 1 mn consumers both in the status quo (before) and in the counterfactual (after), as well as the related emimssions. The fourth and seventh column show the change in the counterfactual in percent. This naive counterfactual would yield a perhaps surprising result: Overall emissions from food consumption do not change much, if anything they increase by around 0.2%. For most food types, the emissions decrease. For those products, this implies that Home is ecologically more efficient than the producers of imported products. This is however not true for cheese and lamb, for example. For those two food types, the emissions increase when completely produced in Home. Overall, this leads to a slight increase in emissions.

The previous naive counterfactual makes the strong assumption that consumers would buy the same amount

[10] Discrete choice models express quantities in terms of an outside good. Consequently, my autarky counterfactuals will focus on protein-rich products while assuming no change in the outside good. Thus, the import mix for the outside good remains constant, even in an autarky scenario.

Table 7: Naive Buy Local Counterfactual

	Quantity (in mt.)			Emissions (in 1,000 mtCO2e)		
Type	Before	After	Δ%	Before	After	Δ%
Beef	2,392	2,392	0	272,361	271,458	-0.33
Cheese	9,283	9,283	0	450,617	455,374	1.06
Eggs	3,301	3,301	0	19,251	18,395	-4.44
Fish	1,079	1,079	0	40,692	41,348	1.61
Lamb	364	364	0	35,319	37,482	6.12
Legumes	662	662	0	1,898	1,881	-0.9
Pork	4,140	4,140	0	77,230	77,253	0.03
Poultry	4,376	4,376	0	45,855	44,473	-3.01
Tofu	313	313	0	1,233	1,192	-3.34
Veal	82	82	0	5,458	5,435	-0.42
Outside Good	137,123	137,123	0	893,054	893,054	0
Total	163,115	163,115	0	1,842,968	1,847,345	0.24

Note.— This table shows a naive buy local scenario, assuming that all imported food types will be produced in Home in an autarky scenario and ignoring the estimated cross-price elasticities. The values are for an average year per 1 mio. consumers. The 'before' column refers to the free trade scenario, the 'after' column to the counterfactual values.

of every food type if imported products were not available. Now we turn to the more sophisticated analysis, where instead of relying on ad-hoc assumptions, we use the model to gauge the effects of the counterfactual scenarios. This means that the own- and cross-price elasticities are estimated instead of just guessed, and that the pricing behavior of the retailer is allowed to respond to the counterfactuals. For the buy local counterfactual, this means that the own- and cross-price elasticities matter for determining the demand for the domestic products, and the prices of these domestic products are allowed to change as a response to a buy local or autarky policy.

Table 8 reveals that overall emissions would not change much in a model-based buy local scenario. Contrary to the naive scenario which found a slight increase in emissions, the buy local scenario shows a decrease in emissions of around 2%. Some products show an increase in their consumption after autarky, while others are consumed less. The changes in consumption patterns match the price changes in the counterfactual, as shown in Figure 5. This figure shows the average price in grey and the average counterfactual price in yellow.[11] Veal for example shows an increase in consumption and thus an increase in emissions. The reason is that the veal price drops, and consumers are relatively elastic with respect to veal (see elasticities in Table 5). Thus, they increase their consumption by a large amount. Two food types exhibit a perhaps surprising pattern: For beef and pork, the quantities consumed increase, although the prices increase. In both cases, the cross-price effect from a price increase for other products (e.g. cheese or legumes) dominates the own-price effect. Section 4.3 explains these effects in more detail.

Estimating this model with only the demand side makes use of the elasticities, but does not allow for the

[11] To protect the European retailer's anonymity, I omit the axis marks on the y-axis.

Table 8: Buy Local Counterfactual

	Quantity (in mt.)			Emissions (in 1,000 mtCO2e)		
Type	Before	After	Δ%	Before	After	Δ%
Beef	2,392	2,650	10.78	272,361	300,727	10.41
Cheese	9,283	7,473	-19.5	450,617	366,595	-18.65
Eggs	3,301	2,306	-30.13	19,251	12,853	-33.23
Fish	1,079	1,110	2.86	40,692	42,760	5.08
Lamb	364	276	-24.21	35,319	28,408	-19.57
Legumes	662	426	-35.72	1,898	1,209	-36.3
Pork	4,140	4,744	14.58	77,230	88,517	14.61
Poultry	4,376	4,474	2.25	45,855	45,472	-0.83
Tofu	313	224	-28.2	1,233	856	-30.6
Veal	82	119	45.23	5,458	7,894	44.63
Outside Good	137,123	139,312	1.6	893,054	907,313	1.6
Total	163,115	163,115	0	1,842,968	1,802,603	-2.19

Note.— This table shows a buy local counterfactual in which only domestic products can be purchased. The values are for an average year per 1 mio. consumers. The 'before' column refers to the status quo, the 'after' column to the counterfactual values.

prices of the domestic products to adjust. Table 24 in the Appendix shows that the overall emissions would also decrease, but by only around 1%. Although the magnitudes are small, taking into account the supply side doubles the effect on emissions.

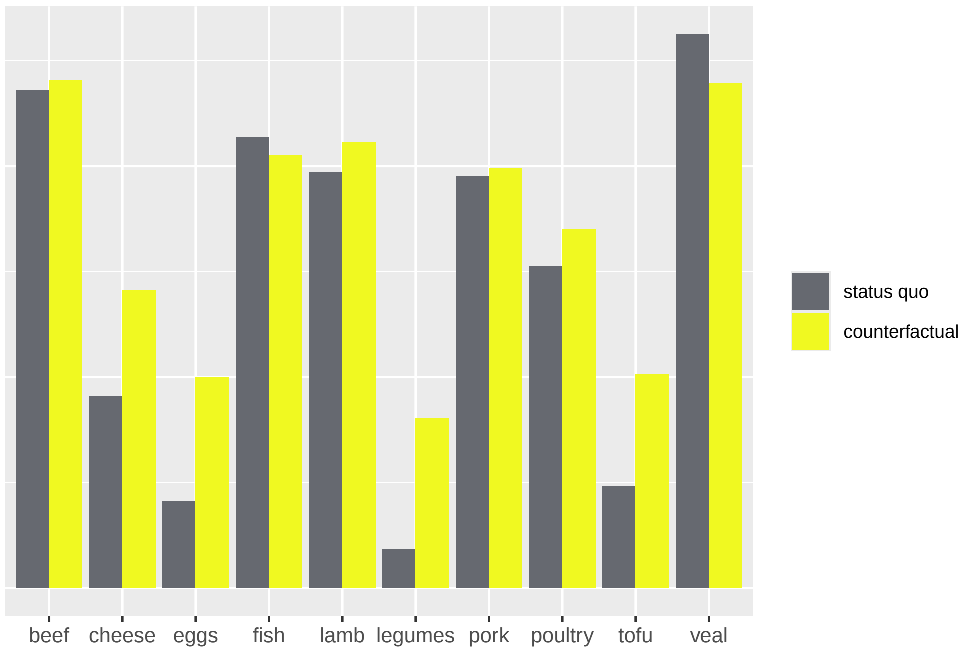
6.3.2 Free trade

The previous section considered buy local or autarky. This section deals with the opposite scenario: free trade. Analyzing a free trade scenario involves determining the tariffs for each imported product. These tariffs will then act like a negative tax in the model. Thus, the tariffs will be subtracted from the marginal cost in equation 2. I assume that Home is a small open economy and takes prices as given. There are three types of trade regimes for the products in my data set: no restriction, tariff, and tariff-rate quotas. Figure 6 illustrates these different tariff regimes.

The small open economy assumption implies that the price of products without a tariff is a world price and would not change under free trade (point 3 in Figure 6). For products with a tariff, the solution is simple: One can just use the existing tariffs for each product. A subset of products is subject to a tariff-rate quota (point 1 in Figure 6). The quantity that can be imported is restricted by a quota and combined with a tariff. The tariffs on within-quota quantities are relatively low, while the tariffs for quantities outside of the quota are very high. The quota is binding and all imports occur within the quota. Simply subtracting the tariff would yield point 2 in Figure 6 and not the free trade price in point 3.

Because of the products subject to a tariff-rate quota, I provide two scenarios. In the first, I subtract the tariff. This will represent a lower bound of tariff changes under free trade. In the second, I gather data on the ad valorem equivalent (AVE) most favored nation tariff from the Market Access Map of the World Trade

Figure 5: Prices in Buy Local Counterfactual



Note: This figure shows the median price for each food type. The grey bars show the price in the status quo, the yellow bars show the price in the counterfactual. The light blue bar refers to the price without the ad-valorem equivalent tariff, the dark blue bar to the price without the within-quota tariff.

Organization. This tariff represents an upper bound as the AVE tariffs are very high.

The free trade scenario in Table 9 shows a modest increase in emissions of around 0.22%. The reason is that both the beef and the veal price drop under a free trade scenario, and these are among the three most polluting food types. Figure 7 shows the prices for the status quo, under the free trade counterfactual, and the free trade prices under a full pass-through assumption. As pass-through is estimated to be larger than one, the counterfactual price is usually lower than the full pass-through price (blue bars). The veal price decreases by around 25%. Yet, the consumption of veal only increases slightly. This suggests that the cross-price effect from the price decrease of beef and other products is relatively strong.

Comparing the prices in the Free Trade Counterfactual based on the within-quota tariffs (Figure 7) with the Ad Valorem Equivalent scenario (Figure 8) shows a much larger decrease in prices for beef and lamb. This implies that the demand for beef and lamb increases tremendously in that scenario, yielding an overall increase in emissions of 46% in Table 9. Here, we observe an interesting phenomenon: The price decrease for beef and lamb is very large, and the own-price elasticities are high for these products (see 5). Therefore, the consumption of beef and lamb increases strongly. Figure 8 suggests that the prices for most other products either decreased or stayed the same. The own-price elasticities for those products would imply that the quantities for the other products should increase. In this case, however, the cross-price elasticity of beef and lamb dominates the own-price elasticities of other products: The consumption of all other products decreases

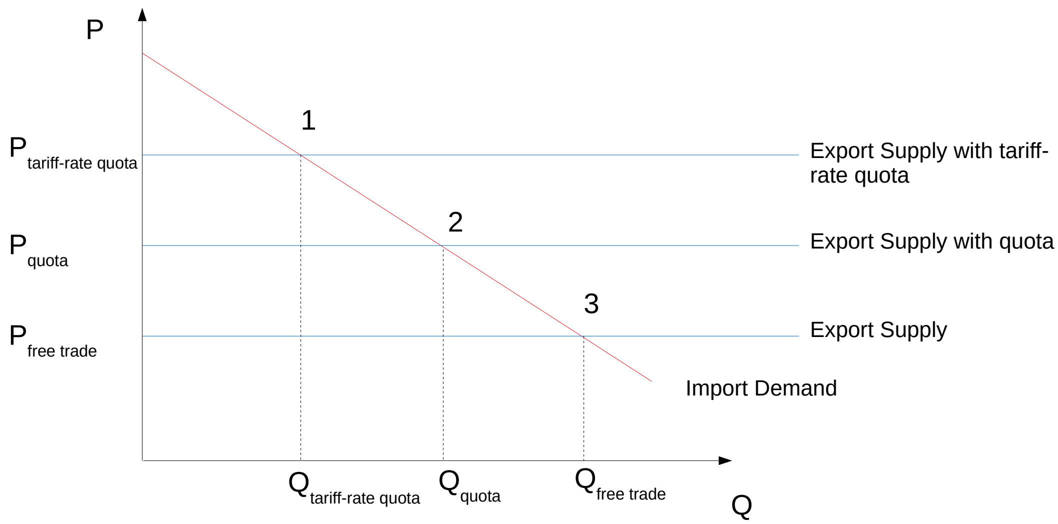


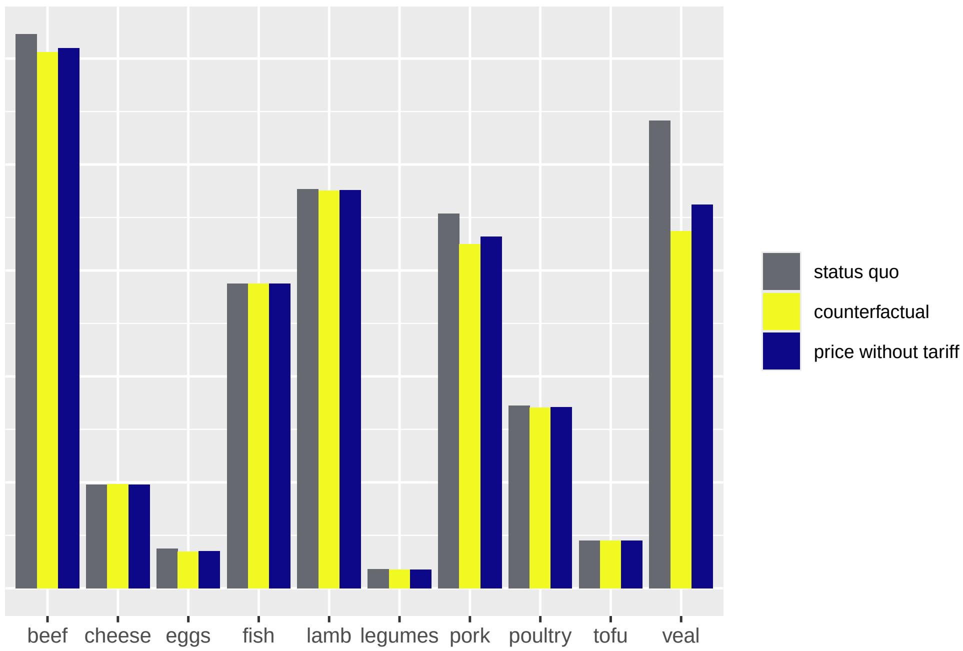
Figure 6: Prices under different tariff regimes

Table 9: Free Trade Tariff Counterfactual

	Quantity (in mt.)			Emissions (in 1,000 mtCO2e)		
Type	Before	After	Δ%	Before	After	Δ%
Beef	2,392	2,423	1.31	272,361	276,180	1.4
Cheese	9,283	9,279	-0.05	450,617	450,404	-0.05
Eggs	3,301	3,321	0.61	19,251	19,422	0.89
Fish	1,079	1,078	-0.05	40,692	40,670	-0.05
Lamb	364	368	1.02	35,319	35,632	0.89
Legumes	662	663	0.12	1,898	1,901	0.13
Pork	4,140	4,141	0.02	77,230	77,227	0
Poultry	4,376	4,376	0	45,855	45,925	0.15
Tofu	313	312	-0.05	1,233	1,232	-0.05
Veal	82	84	2.77	5,458	5,788	6.05
Outside Good	137,123	137,069	-0.04	893,054	892,701	-0.04
Total	163,115	163,115	0	1,842,968	1,847,082	0.22

Note.— This table shows a free trade counterfactual in which the current tariff rates are subtracted from the product price. The values are for an average year per 1 mio. consumers. The 'before' column refers to the status quo, the 'after' column to the counterfactual values.

Figure 7: Prices in Free Trade Counterfactual



Note: This figure shows the median price for each food type. The grey bars show the price in the status quo, the yellow bars show the price in the counterfactual. The dark blue bar refers to the price without the within-quota tariff.

in favor of beef and lamb, although some products like veal also experience a decrease in prices. Veal is not subject to a tariff-rate quota and has the same price decrease as in the free trade counterfactual. Because of the large decrease in beef prices, the consumption of veal now decreases despite the veal price decreasing.

In terms of the magnitudes of these effects, the ad-valoem equivalent scenario should be seen as an upper bound. The ad-valorem tariff equivalents are very large compared to the actual tariffs, that is why they imply a doubling of the demand for both beef and lamb[12]. In the case of beef, this would imply tripling the emissions. Overall, we can conclude that free trade is likely to increase emissions, because the most polluting products have the highest tariffs. Decreasing tariffs on those products would lead to an increase in total emissions.

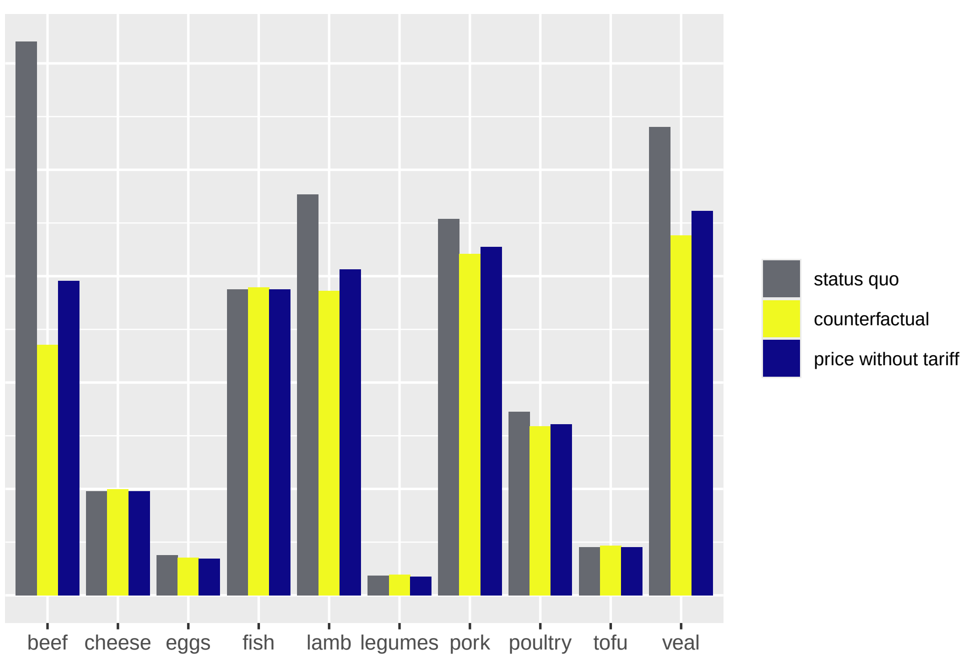
[12]Also, this counterfactual stretches the interpretaion of an elasticity which is a local measure.

Table 10: Free Trade Ad Valorem Equivalent Counterfactual

	Quantity (in mt.)			Emissions (in 1,000 mtCO2e)		
Type	Before	After	Δ%	Before	After	Δ%
Beef	2,392	7,117	197.52	272,361	1,088,151	299.53
Cheese	9,283	8,877	-4.38	450,617	430,869	-4.38
Eggs	3,301	3,179	-3.69	19,251	18,606	-3.35
Fish	1,079	1,030	-4.51	40,692	38,855	-4.51
Lamb	364	1,137	212.18	35,319	103,475	192.97
Legumes	662	635	-4.11	1,898	1,820	-4.1
Pork	4,140	3,970	-4.12	77,230	74,019	-4.16
Poultry	4,376	4,203	-3.94	45,855	44,557	-2.83
Tofu	313	299	-4.44	1,233	1,178	-4.44
Veal	82	79	-3.38	5,458	5,444	-0.26
Outside Good	137,123	132,590	-3.31	893,054	863,528	-3.31
Total	163,115	163,115	0	1,842,968	2,670,503	44.9

Note.— This table shows a free trade counterfactual in which the ad valorem equivalent of tariff rate quotas is subtracted from the product price. The values are for an average year per 1 mio. consumers. The 'before' column refers to the status quo, the 'after' column to the counterfactual values.

Figure 8: Prices in Free Trade Ad Valorem Equivalent Counterfactual



Note: This figure shows the median price for each food type. The grey bars show the price in the status quo, the yellow bars show the price in the counterfactual. The dark blue bar refers to the price without the ad-valorem equivalent tariff.

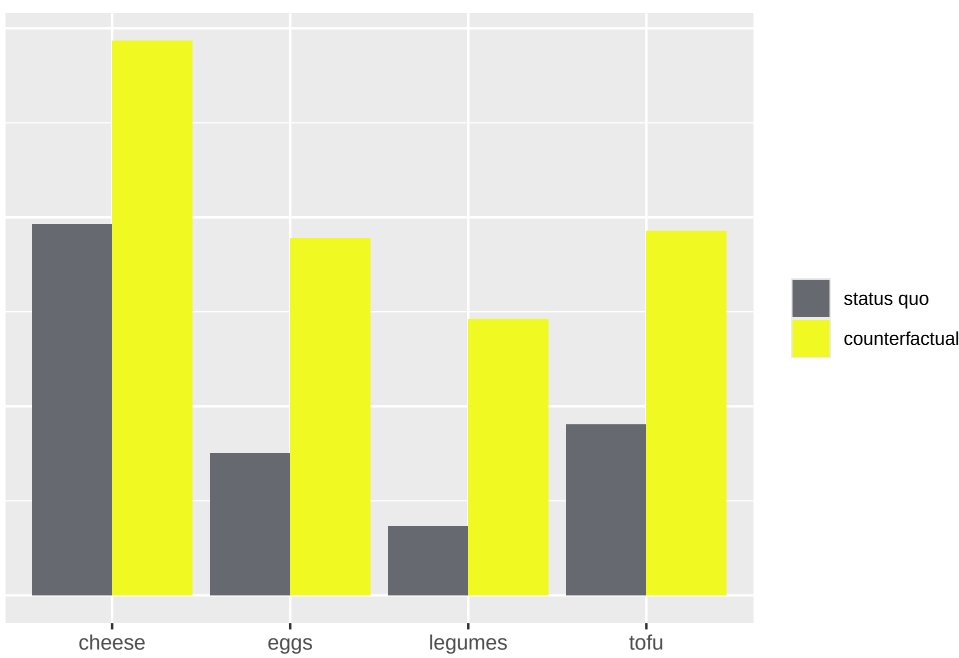
6.4 Reducing meat consumption

The next set of counterfactuals considers a reduction in meat consumption. As meat is a large contributor to emissions, reducing meat consumption might lead to high savings in emissions.

6.4.1 Vegetarianism

The vegetarian scenario is displayed in Table 11[13]. It shows that emissions decrease by around 23%. Interestingly, the consumption of all other products decreases as well. In this scenario, people would consume more of the outside good - meaning the food products not in the dataset like potatoes. The reason for this is the supply side and thus the pricing behavior of the retailer. Figure 9 reveals that the counterfactual prices in the vegetarian scenario increase for all vegetarian products. The reason is that there are no other products to compete with, so that there is more concentration in the market. Thus, the quantities purchased decrease. A vegetarian scenario with only the demand model (see Appendix Table 25) would yield a decrease in emissions of around 19%, with a roughly equal increase of consumption of products that remain in the choice set. Similarly to the buy local scenario, accounting for the pricing behavior of the firm leads to a larger decrease in emissions.

Figure 9: Prices in Vegetarian Counterfactual



Note: This figure shows the median price for each food type. The grey bars show the price in the status quo, the yellow bars show the price in the counterfactual.

[13]A vegetarian diet includes cheese consumption, for which holding cattle is necessary. Ideally, one would model the cattle demand for the level of cheese production in a vegetarian scenario and allow to consume the meat of the dairy cows. This is outside of the scope of this paper.

Table 11: Vegetarian Counterfactual

	Quantity (in mt.)			Emissions (in 1,000 mtCO2e)		
Type	Before	After	Δ%	Before	After	Δ%
Beef	2,392	0	-100	272,361	0	-100
Cheese	9,283	8,546	-7.94	450,617	413,561	-8.22
Eggs	3,301	2,890	-12.46	19,251	16,900	-12.21
Fish	1,079	0	-100	40,692	0	-100
Lamb	364	0	-100	35,319	0	-100
Legumes	662	571	-13.8	1,898	1,637	-13.76
Pork	4,140	0	-100	77,230	0	-100
Poultry	4,376	0	-100	45,855	0	-100
Tofu	313	276	-11.75	1,233	1,093	-11.39
Veal	82	0	-100	5,458	0	-100
Outside Good	137,123	150,833	10	893,054	982,340	10
Total	163,115	163,115	0	1,842,968	1,415,531	-23.19

Note.— This table shows a vegetarian counterfactual in which no meat products can be purchased. The values are for an average year per 1 mio. consumers. The 'before' column refers to the status quo, the 'after' column to the counterfactual values.

6.4.2 No beef

The no beef scenario in Table 12 considers a shutdown of beef consumption. Since beef has the highest emissions intensity of all meat types, a lot can be achieved by just refraining from eating beef. The total emissions decrease by around 15%. Figure 10 shows how the prices change in the no beef counterfactual. For cheese, eggs, legumes, poultry, and tofu, the prices increase. Here, we see a similar competition effect like in the vegetarian counterfactual. For the other products, the own-price elasticity effect dominates: As beef becomes unavailable, the other products experience an increase in their consumption and a decrease in the price. The only exception is poultry: Its price increases, but so does the quantity consumed. Poultry has a relatively low own-price elasticity. Therefore, increasing the poultry price would lead to a small decline in poultry consumption. On the other hand, the cross-price elasticity of beef would yield an increase in poultry consumption. Here, this last effect dominates over the own-price elasticity effect.

6.4.3 No beef no cheese

Refraining from beef and cheese consumption in Table 13 results in the highest decrease of overall emissions with around 33%. Similarly to the no beef scenario, prices for some products increase in Figure 11 (eggs, legumes, poultry, tofu). For these products, the quantity consumed decreases. Thus, the competition effect dominates. For the other products, the cross-price elasticity effect dominates: These products experience an increase in the quantity consumed. Poultry is again a special case: The price increases, but the quantity consumed as well. This scenario yields the largest decrease in emissions, although only two food types are excluded.

Table 12: No Beef Counterfactual

	Quantity (in mt.)			Emissions (in 1,000 mtCO2e)		
Type	Before	After	Δ%	Before	After	Δ%
Beef	2,392	0	-100	272,361	0	-100
Cheese	9,283	7,773	-16.27	450,617	375,964	-16.57
Eggs	3,301	2,682	-18.75	19,251	15,676	-18.57
Fish	1,079	1,447	34.13	40,692	58,003	42.54
Lamb	364	509	39.67	35,319	47,777	35.27
Legumes	662	522	-21.19	1,898	1,497	-21.15
Pork	4,140	4,694	13.39	77,230	87,456	13.24
Poultry	4,376	4,469	2.14	45,855	47,267	3.08
Tofu	313	257	-17.65	1,233	1,018	-17.45
Veal	82	124	51.85	5,458	8,476	55.3
Outside Good	137,123	140,637	2.56	893,054	915,939	2.56
Total	163,115	163,115	0	1,842,968	1,559,074	-15.4

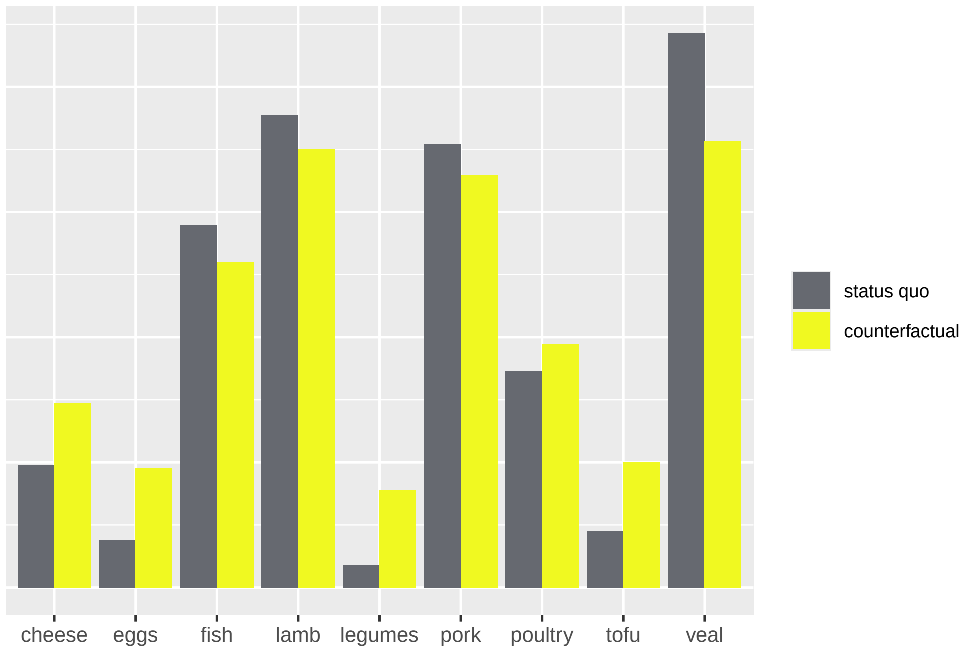
Note.— This table shows a no beef counterfactual in which all other products can be purchased, except for beef. The values are for an average year per 1 mio. consumers. The 'before' column refers to the status quo, the 'after' column to the counterfactual values.

Table 13: No Beef No Cheese Counterfactual

	Quantity (in mt.)			Emissions (in 1,000 mtCO2e)		
Type	Before	After	Δ%	Before	After	Δ%
Beef	2,392	0	-100	272,361	0	-100
Cheese	9,283	0	-100	450,617	0	-100
Eggs	3,301	2,772	-16.03	19,251	16,235	-15.67
Fish	1,079	1,538	42.54	40,692	61,411	50.92
Lamb	364	526	44.44	35,319	49,359	39.75
Legumes	662	535	-19.22	1,898	1,534	-19.16
Pork	4,140	5,087	22.87	77,230	94,771	22.71
Poultry	4,376	4,737	8.26	45,855	50,208	9.49
Tofu	313	271	-13.22	1,233	1,074	-12.91
Veal	82	127	55.52	5,458	8,733	60.01
Outside Good	137,123	147,522	7.58	893,054	960,779	7.58
Total	163,115	163,115	0	1,842,968	1,244,103	-32.49

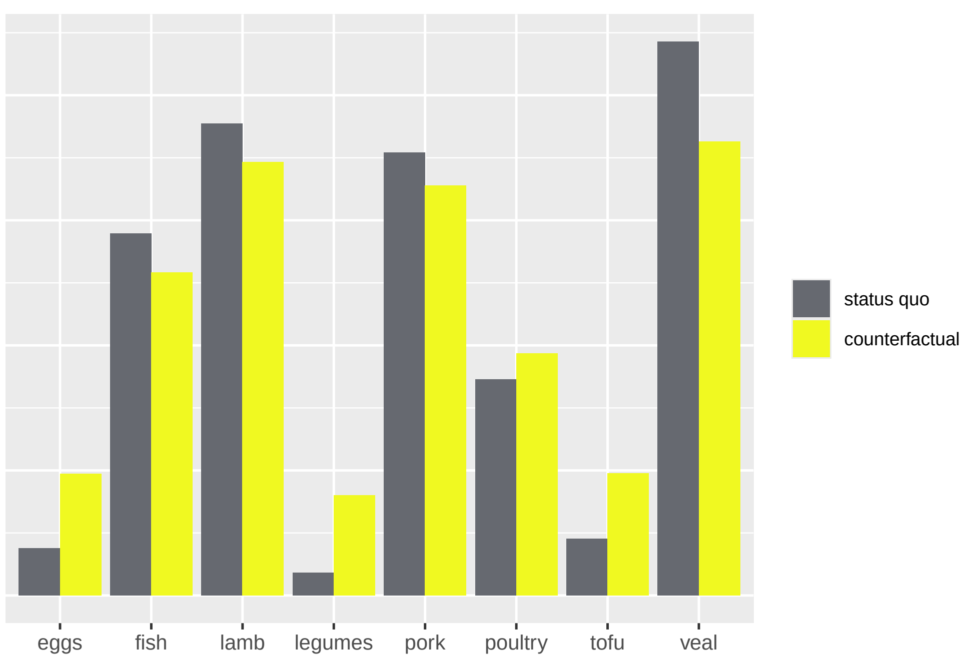
Note.— This table shows a no beef no cheese counterfactual in which all other products can be purchased, except for beef and cheese. The values are for an average year per 1 mio. consumers. The 'before' column refers to the status quo, the 'after' column to the counterfactual values.

Figure 10: Prices in No Beef Counterfactual



Note: This figure shows the median price for each food type. The grey bars show the price in the status quo, the yellow bars show the price in the counterfactual.

Figure 11: Prices in a No Beef No Cheese Counterfactual



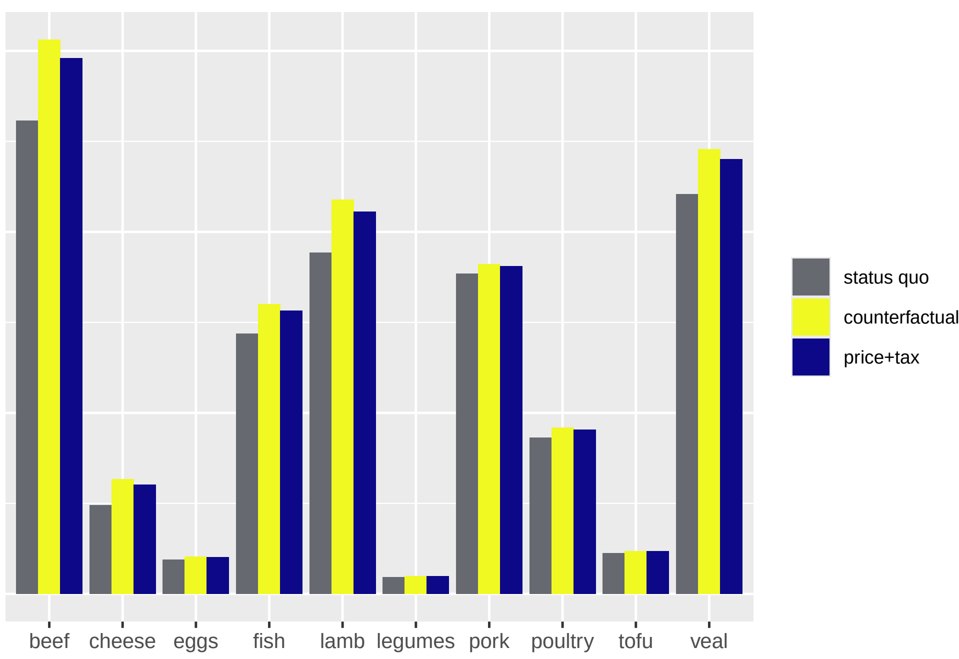
Note: This figure shows the median price for each food type. The grey bars show the price in the status quo, the yellow bars show the price in the counterfactual.

6.5 Pigouvian taxes

The following set of counterfactuals explores Pigouvian taxes, that is taxes that are proportional to the emissions intensity of a product. Pigouvian taxation is the most common policy tool when externalities are present. In the context of this discrete choice model, all prices increase with Pigouvian taxes as all products have a certain level of emissions intensity[14].

Table 14 shows the results for a 50 EUR/tCO_2e counterfactual. Overall, emissions decrease by 9%. The composition across food types is as expected: Polluting products are consumed less, while greener products are consumed more. Thus, the consumption of eggs, legumes, and tofu increases. Figure 12 shows how the tax impacts the counterfactual prices. As expected, most prices increase. The three products which will be consumed more in this scenario exhibit a very small increase in prices. Their own-price elasticities should yield a decrease in the consumption of these products. However, the cross-price elasticities of the other products dominate and thus, the quantities increase for eggs, legumes, and tofu. Comparing the counterfactual prices to the status-quo price plus the tax, we can observe that the counterfactual price is higher. This is inline with the pass-through estimates being larger than 1.

Figure 12: Prices in a 50EUR/tCO_2e Pigouvian Tax Counterfactual



Note: This figure shows the median price for each food type. The grey bars show the price in the status quo, the yellow bars show the price in the counterfactual. The blue bars show the price in the status quo adding the tax, assuming full pass-through.

Table 15 shows a counterfactual with a 100EUR/tCO_2e tax. The price changes in Figure 13 are similar as before, just slightly more pronounced. The total emissions decrease by around 16%. In terms of quantities, the results are also similar as before: The most polluting products see the largest decrease in consumption,

[14] In a general equilibrium model, the tax revenues would be rebated lump-sum to the households. This mechanism is not modeled in this setup.

Table 14: 50EUR/tCO2 Pigouvian Tax Counterfactual

	Quantity (in mt.)			Emissions (in 1,000 mtCO2e)		
Type	Before	After	Δ%	Before	After	Δ%
Beef	2,392	1,574	-34.19	272,361	177,831	-34.71
Cheese	9,283	7,886	-15.05	450,617	382,577	-15.1
Eggs	3,301	3,306	0.15	19,251	19,270	0.1
Fish	1,079	954	-11.58	40,692	35,616	-12.47
Lamb	364	255	-30.11	35,319	24,595	-30.36
Legumes	662	671	1.3	1,898	1,923	1.29
Pork	4,140	3,946	-4.7	77,230	73,600	-4.7
Poultry	4,376	4,303	-1.66	45,855	44,940	-1.99
Tofu	313	315	0.86	1,233	1,243	0.85
Veal	82	65	-21.08	5,458	4,302	-21.17
Outside Good	137,123	139,841	1.98	893,054	910,758	1.98
Total	163,115	163,115	0	1,842,968	1,676,656	-9.02

Note.— This table shows a Pigouvian tax counterfactual with a 50EUR/tCO2e tax on all products. The values are for an average year per 1 mio. consumers. The 'before' column refers to the status quo, the 'after' column to the counterfactual values.

while cleaner products (legumes and tofu) are consumed more. This time, the own-price elasticity effect dominates for eggs, so that the quantity consumed decreases.

Table 16 shows a 150EUR/tCO_2e Pigouvian tax counterfactual. The total decrease in emissions is around 21%, and thus lower than the vegetarian and the no beef no cheese scenarios. Qualitatively, the effects on both quantities and prices in Figure 14 are more pronounced but go in the same direction as before. Again, more polluting products are consumed less, while greener products (legumes and tofu) are consumed more.

In all Pigouvian tax counterfactuals, the decrease in consumption is proportional to the emissions intensity per kilogram of product. Thus, the order of the percentage decrease in consumption is the same as the order of the most polluting products in Figure 2.

Table 15: 100EUR/tCO2 Pigouvian Tax Counterfactual

	Quantity (in mt.)			Emissions (in 1,000 mtCO2e)		
Type	Before	After	Δ%	Before	After	Δ%
Beef	2,392	1,032	-56.86	272,361	116,058	-57.39
Cheese	9,283	6,665	-28.21	450,617	323,144	-28.29
Eggs	3,301	3,296	-0.15	19,251	19,204	-0.24
Fish	1,079	841	-22.07	40,692	31,122	-23.52
Lamb	364	177	-51.31	35,319	17,069	-51.67
Legumes	662	677	2.15	1,898	1,939	2.15
Pork	4,140	3,743	-9.59	77,230	69,824	-9.59
Poultry	4,376	4,213	-3.72	45,855	43,869	-4.33
Tofu	313	317	1.28	1,233	1,248	1.25
Veal	82	51	-38	5,458	3,377	-38.13
Outside Good	137,123	142,105	3.63	893,054	925,496	3.63
Total	163,115	163,115	0	1,842,968	1,552,351	-15.77

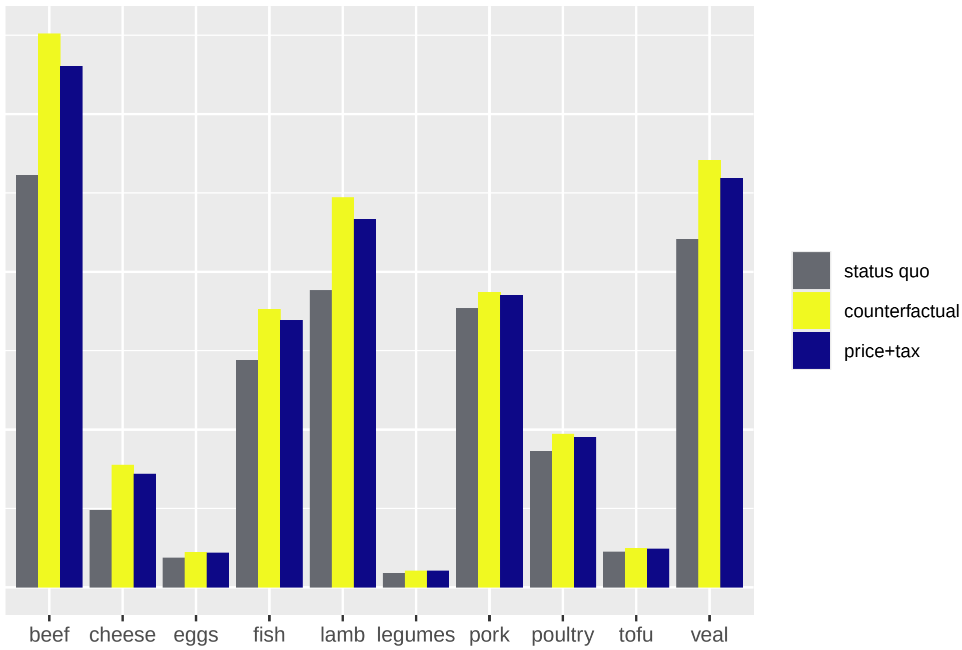
Note.— This table shows a Pigouvian tax counterfactual with a 100EUR/tCO2e tax on all products. The values are for an average year per 1 mio. consumers. The 'before' column refers to the status quo, the 'after' column to the counterfactual values.

Table 16: 150EUR/tCO2 Pigouvian Tax Counterfactual

	Quantity (in mt.)			Emissions (in 1,000 mtCO2e)		
Type	Before	After	Δ%	Before	After	Δ%
Beef	2,392	674	-71.82	272,361	75,613	-72.24
Cheese	9,283	5,610	-39.57	450,617	271,854	-39.67
Eggs	3,301	3,275	-0.79	19,251	19,073	-0.92
Fish	1,079	739	-31.49	40,692	27,159	-33.26
Lamb	364	123	-66.16	35,319	11,818	-66.54
Legumes	662	680	2.67	1,898	1,948	2.66
Pork	4,140	3,539	-14.52	77,230	66,012	-14.53
Poultry	4,376	4,111	-6.04	45,855	42,697	-6.89
Tofu	313	317	1.35	1,233	1,249	1.31
Veal	82	40	-51.47	5,458	2,642	-51.6
Outside Good	137,123	144,007	5.02	893,054	937,885	5.02
Total	163,115	163,115	0	1,842,968	1,457,950	-20.89

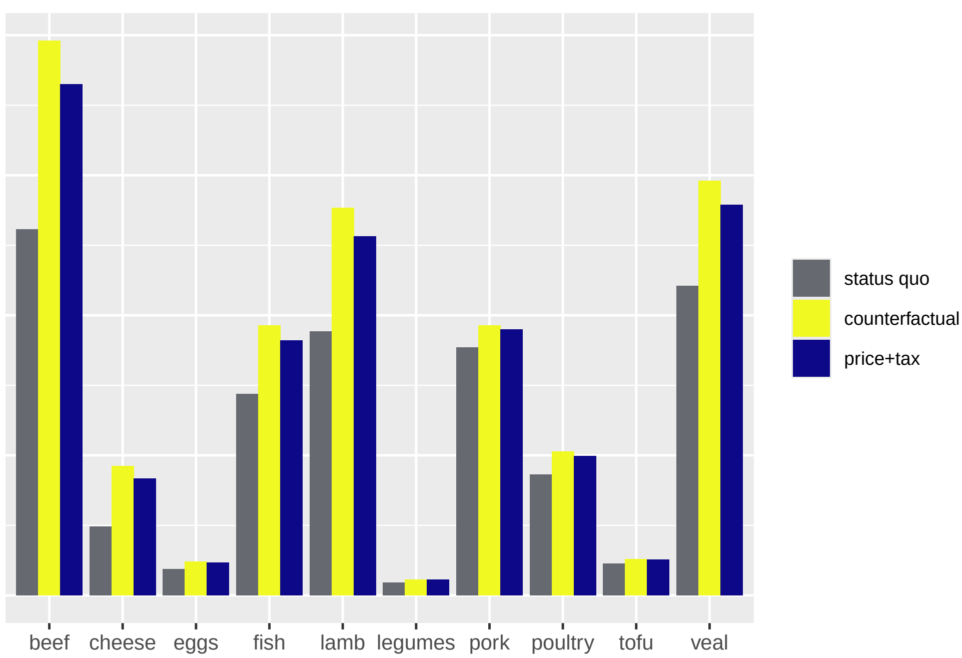
Note.— This table shows a Pigouvian tax counterfactual with a 150EUR/tCO2e tax on all products. The values are for an average year per 1 mio. consumers. The 'before' column refers to the status quo, the 'after' column to the counterfactual values.

Figure 13: Prices in a 100EUR/tCO_2e Pigouvian Tax Counterfactual



Note: This figure shows the median price for each food type. The grey bars show the price in the status quo, the yellow bars show the price in the counterfactual. The blue bars show the price in the status quo adding the tax, assuming full pass-through.

Figure 14: Prices in a 150EUR/tCO_2e Pigouvian Tax Counterfactual



Note: This figure shows the median price for each food type. The grey bars show the price in the status quo, the yellow bars show the price in the counterfactual. The blue bars show the price in the status quo adding the tax, assuming full pass-through.

7 Relevance and external validity

For this analysis to be relevant externally valid, three aspects need to be considered. First, the results might be irrelevant if reducing the production emissions intensities would yield larger benefits than changing food consumption patterns. Second, the results could depend on the production emissions intensity of Home relatively to other countries. Third, the consumption patterns of Home could be different from other countries. I discuss each of these aspects in turn.

7.1 Status quo with better production

Most of the trade and environment literature has focused on the supply side (Cherniwchan et al., 2017). In that spirit, the emissions of the agricultural sector could be reduced by improving production technologies in terms of their ecological efficiency. Gauging the effect of improved production would require a model of meat production and the corresponding emissions intensities. To give a sense of the magnitudes of such a policy, I calculate a naive improved production counterfactual. Keeping consumption shares of different food types constant and assuming that production emissions are the lowest for each food type, I find that overall emissions decrease by around 9% in Table 17.

The assumption that all our food can be produced with the lowest emissions intensity for each food type is very strong. While it is possible to improve emissions intensities with better production practices, a part of emissions intensity of food production is related to land characteristics and cannot be adapted easily. These estimates on reducing agriculture's impact from the supply side represent an upper bound. Still, the question remains whether it would be possible to produce the same quantities with simply changing the production emissions. If the best possible emissions technology would imply lower yields, we might produce lower quantities on the same fields. Thus, we would need more land to produce the same amount of food which leads to higher emissions intensities. From a pricing perspective, it is unclear how ecologically efficient production maps into prices. Price changes depend on the competitiveness of the market. If the best production technology implies moving to a monopoly, prices might increase. Therefore, the true impact of improving production emissions intensities remains unclear.

Compared to this naive supply side counterfactual, all scenarios that imply reducing meat consumption and all Pigouvian tax scenarios yield a larger decrease in emissions. This implies that changing consumer behavior is an important factor for reducing the emissions of agriculture.

7.2 Ecological efficiency

My results could depend on the production emissions intensity of Home relatively to other countries. I calculate the buy local scenario under the assumption that Home has the highest production emissions intensity and the lowest production emissions intensity for each food type. These scenarios are extreme and

Table 17: Status Quo with Best Production Counterfactual

	Quantity (in mt.)			Emissions (in 1,000 mtCO2e)		
Type	Before	After	Δ%	Before	After	Δ%
Beef	2,392	2,392	0	272,361	227,504	-16.47
Cheese	9,283	9,283	0	450,617	375,756	-16.61
Eggs	3,301	3,301	0	19,251	19,106	-0.75
Fish	1,079	1,079	0	40,692	21,497	-47.17
Lamb	364	364	0	35,319	28,654	-18.87
Legumes	662	662	0	1,898	1,560	-17.78
Pork	4,140	4,140	0	77,230	60,522	-21.63
Poultry	4,376	4,376	0	45,855	44,493	-2.97
Tofu	313	313	0	1,233	1,233	0
Veal	82	82	0	5,458	4,432	-18.8
Outside Good	137,123	137,123	0	893,054	893,054	0
Total	163,115	163,115	0	1,842,968	1,677,812	-8.96

Note.— This table shows a counterfactual in which I only change the production emissions to the best emissions for each food type. The values are for an average year per 1 mio. consumers. The 'before' column refers to the status quo, the 'after' column to the counterfactual values.

provide upper and lower bounds, respectively. There is no single country which has the highest or lowest production emissions intensity for each food type. The ecological production efficiency is diverse and depends not only on production practices, but also on natural endowments of countries.

If Home was the most efficient producer, in Table 18 overall emissions would decrease by around 11%. This number is larger than the actual buy local scenario, but still smaller than all vegetarian scenarios. The lowest Piouvian tax of 50 EUR/tCO_2e would yield a similar decrease in emissions of around 9%. Table 19 shows that autarky would yield an increase in emissions of around 38% if Home was the ecologically least efficient producer in all food types. This suggests that buying local might lead to a small decrease in emissions for greener countries, and a large increase in emissions for dirtier countries. Thus, vegetarianism and Pigouvian taxes seem like more effective policies for decreasing greenhouse gas emissions from food consumption.

7.3 Consumption patterns across countries

The consumption patterns of Home could be different from other countries. Most of the literature attributes differences in consumption patterns to different prices and product characteristics. One exception is Dubois et al. (2014) who do find evidence for different preferences between consumers from the US, the UK, and France in terms of caloric intake. Still, their estimates for the preferences of meat and dairy in those countries are similar. To gauge how representative Home is for Europe, I compare the average meat consumption patterns of different European countries using the quantity of domestic food supply data from the Food and Agricultural Organization. Figure 15 shows that Home is close to the mean for all available food types. Thus, a large share of European countries have similar consumption patterns as Home.

Table 18: Buy Local with Best Production Counterfactual

	Quantity (in mt.)			Emissions (in 1,000 mtCO2e)		
Type	Before	After	Δ%	Before	After	Δ%
Beef	2,392	2,650	10.78	272,361	251,567	-7.63
Cheese	9,283	7,473	-19.5	450,617	302,137	-32.95
Eggs	3,301	2,306	-30.13	19,251	12,731	-33.87
Fish	1,079	1,110	2.86	40,692	21,740	-46.58
Lamb	364	276	-24.21	35,319	19,405	-45.06
Legumes	662	426	-35.72	1,898	979	-48.42
Pork	4,140	4,744	14.58	77,230	69,345	-10.21
Poultry	4,376	4,474	2.25	45,855	45,472	-0.83
Tofu	313	224	-28.2	1,233	856	-30.6
Veal	82	119	45.23	5,458	6,436	17.92
Outside Good	137,123	139,312	1.6	893,054	907,313	1.6
Total	163,115	163,115	0	1,842,968	1,637,981	-11.12

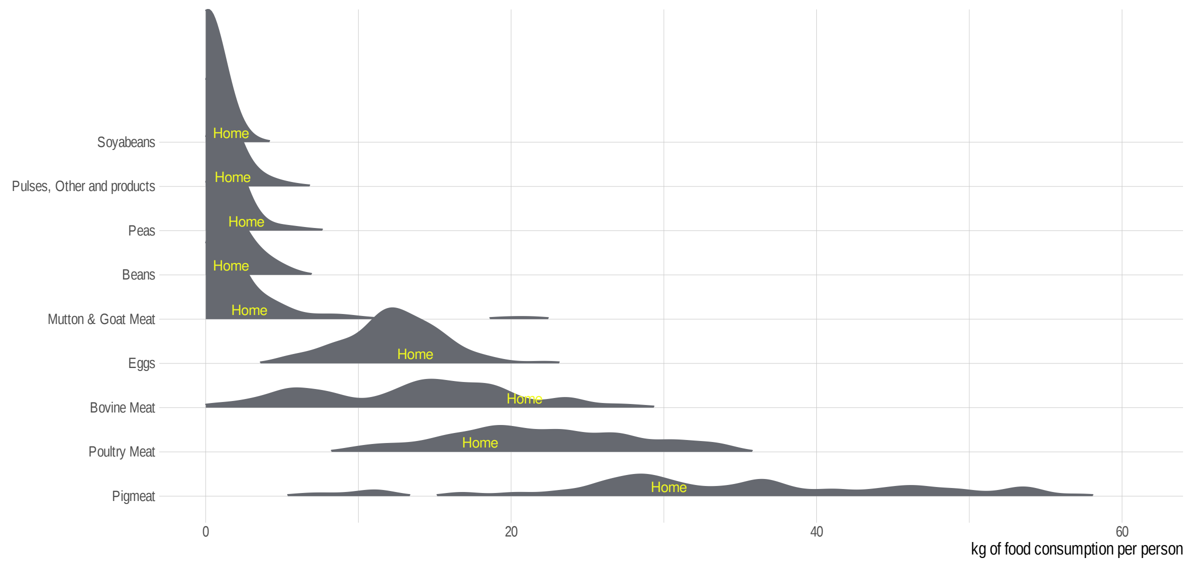
Note.— This table shows how the buy local scenario would change if Home was the country with the best production emissions. The values are for an average year per 1 mio. consumers. The 'before' column refers to the buy local scenario, the 'after' column to the counterfactual values.

Table 19: Buy Local with Worst Production Counterfactual

	Quantity (in mt.)			Emissions (in 1,000 mtCO2e)		
Type	Before	After	Δ%	Before	After	Δ%
Beef	2,392	2,650	10.78	272,361	900,847	230.75
Cheese	9,283	7,473	-19.5	450,617	366,595	-18.65
Eggs	3,301	2,306	-30.13	19,251	12,853	-33.23
Fish	1,079	1,110	2.86	40,692	101,176	148.64
Lamb	364	276	-24.21	35,319	28,408	-19.57
Legumes	662	426	-35.72	1,898	1,319	-30.51
Pork	4,140	4,744	14.58	77,230	91,468	18.43
Poultry	4,376	4,474	2.25	45,855	115,839	152.62
Tofu	313	224	-28.2	1,233	856	-30.6
Veal	82	119	45.23	5,458	12,823	134.94
Outside Good	137,123	139,312	1.6	893,054	907,313	1.6
Total	163,115	163,115	0	1,842,968	2,539,495	37.79

Note.— This table shows how the buy local scenario would change if Home was the country with the worst production emissions. The values are for an average year per 1 mio. consumers. The 'before' column refers to the buy local scenario, the 'after' column to the counterfactual values.

Figure 15: Food Consumption across Europe



Note: This figure shows the per capita food consumption of different food types across different countries.

8 Conclusion

This paper gauges how food consumption choice affects greenhouse gas emissions. Through a unique cooperation with a European retailer, I obtain confidential data on prices and quantities. I estimate a discrete choice model for meat demand using country-wide purchasing data for meat and other protein-rich products to assess the effect of alternative consumption patterns on the environment. With the estimated own- and cross-price elasticities, I calculate the counterfactual scenarios of popular consumption behaviors. Contrary to popular belief, I find that buying local only decreases emissions by around 2% compared to the status quo. Free trade might increase emissions, while vegetarianism decreases emissions by more than 20%. Consuming no beef and cheese yields the highest decrease in emissions of around 33%. Pigouvian taxes lead to emissions reductions of 8-21%.

This paper lies at the intersection of international and environmental economics. The trade and environment literature has focused on supply side considerations. I contribute to this literature by gauging the effect of consumer demand for traded goods on the emissions of the agricultural sector. While much of the environmental economics literature has focused on energy consumption, I analyze the effect of food consumption on emissions. These findings underscore the role of consumer choices in shaping food-related emissions. To my best knowledge, this is the first analysis of food consumption behavior on the environment.

There are two avenues for future work. The first avenue considers alternative policies that are easy to implement. In this paper, I propose changes in choice sets or prices as the mechanism for decreasing the emissions of the agricultural sector. It would be interesting to compare the effect of other ways of reducing meat consumption, e.g. through information campaigns or CO2 labels. The second avenue considers the microfoundation of production emissions intensities. In this paper, I take production emission intensities as given. A part of these emissions is due to geography like soil, sunshine and rain, and thus fixed. But some part of the emissions relates to management practices like manure management. It would be interesting to explore how food producers would react to environmental policy on the consumer side and how this would impact the results.

9 References

Anders, S., Mőser, A., 2010. Consumer choice and health: The importance of health attributes for retail meat demand in canada. Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie 58, 249–271.

Antweiler, W., Gulati, S., 2016. Frugal cars or frugal drivers? How carbon and fuel taxes influence the choice and use of cars. SSRN Electronic Journal.

Berry, S., Levinsohn, J., Pakes, A., 1995. Automobile prices in market equilibrium. Econometrica 63, 841–890.

Berry, S.T., 1994. Estimating discrete-choice models of product differentiation. The RAND Journal of Economics 25, 242–262.

Berto Villas-Boas, S., 2007. Vertical Relationships between Manufacturers and Retailers: Inference with Limited Data. The Review of Economic Studies 74, 625–652.

BEUC, 2020. One bite at a time: Consumers and the transition to sustainable food. The European Consumer Organisation/Bureau Européen des Unions de Consommateurs.

Bonnet, C., Réquillart, V., 2013. Tax incidence with strategic firms in the soft drink market. Journal of Public Economics 106, 77–88.

Bresnahan, T., 1997. The apple-cinnamon cheerios war: Valuing new goods, identifying market power, and economic measurement.

Briggs, A.D.M., Kehlbacher, A., Tiffin, R., Garnett, T., Rayner, M., Scarborough, P., 2013. Assessing the impact on chronic disease of incorporating the societal cost of greenhouse gases into the price of food: An econometric and comparative risk assessment modelling study. BMJ open 3, e003543.

Cherniwchan, J., Copeland, B.R., Taylor, M.S., 2017. Trade and the environment: New methods, measurements, and results. Annual Review of Economics 9, 59–85.

Copeland, B.R., Taylor, M.S., 1995. Trade and the environment: A partial synthesis. American Journal of Agricultural Economics 77, 765–771.

Davis, L.W., Kahn, M.E., 2010. International trade in used vehicles: The environmental consequences of NAFTA. American Economic Journal: Economic Policy 2, 58–82.

Dominguez-Iino, T., 2021. Efficiency and redistribution in environmental policy: An equilibrium analysis of agricultural supply chains. Working Paper.

Dubé, J.-P., 2004. Multiple discreteness and product differentiation: Demand for carbonated soft drinks. Marketing Science 23, 66–81.

Dubois, P., Griffith, R., Nevo, A., 2014. Do prices and attributes explain international differences in food purchases? American Economic Review 104, 832–67.

Dubois, P., Griffith, R., O'Connell, M., 2017. The Effects of Banning Advertising in Junk Food Markets. The Review of Economic Studies 85, 396–436.

Eales, J.S., Unnevehr, L.J., 1988. Demand for Beef and Chicken Products: Separability and Structural Change. American Journal of Agricultural Economics 70, 521–532.

Edjabou, L.D., Smed, S., 2013. The effect of using consumption taxes on foods to promote climate friendly diets – the case of denmark. Food Policy 39, 84–96.

Genakos, C., Pagliero, M., 2022. Competition and pass-through: Evidence from isolated markets. American Economic Journal: Applied Economics 14, 35–57.

Gerber, P.J., Steinfeld, H., Henderson, B., Mottet, A., Opio, C., Dijkman, J., Falcucci, A., Tempio, G., 2013. Tackling climate change through livestock: A global assessment of emissions and mitigation opportunities. Food; Agriculture Organization of the United Nations (FAO), Rome, Italy.

Griffith, R., O'Connell, M., Smith, K., 2019. Tax design in the alcohol market. Journal of Public Economics 172, 20–35.

Hanson, A., Sullivan, R., 2009. The incidence of tobacco taxation: Evidence from geographic micro-level data. National Tax Journal 62, 677–698.

Hendel, I., 1999. Estimating multiple-discrete choice models: An application to computerization returns. The Review of Economic Studies 66, 423–446.

IPCC, 2014. Summary for policymakers. In: Climate change 2014: Impacts, adaptation, and vulnerability. Part a: Global and sectoral aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, [Field, C.B., V.R. Barros, D.J. Dokken, K.J. Mach, M.D. Mastrandrea, T.E. Bilir, M. Chatterjee, K.L. Ebi, Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel, A.N. Levy, S. MacCracken, P.R. Mastrandrea,; L.L. White (eds.)]; Cambridge University Press, Cambridge, United Kingdom; New York, NY, USA, pp. 1–23.

ITC, I.T.C., 2020. Market access map.

Mayer, T., Zignago, S., 2006. GeoDist: The CEPII's distances and geographical database.

McAusland, C., 2008. Trade, politics, and the environment: Tailpipe vs. smokestack. Journal of Environmental Economics and Management 55, 52–71.

McFadden, D., 1974. The measurement of urban travel demand. Journal of Public Economics 3, 303–328.

Miller, N.H., Osborne, M., Sheu, G., 2017. Pass-through in a concentrated industry: Empirical evidence and regulatory implications. The RAND Journal of Economics 48, 69–93.

Nevo, A., 2001. Measuring market power in the ready-to-eat cereal industry. Econometrica 69, 307–342.

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

Reed, A.J., Levedahl, J.W., Clark, J.S., 2003. Commercial disappearance and composite demand for food with an application to u.s. meats. Journal of Agricultural and Resource Economics 28, 53–70.

Shapiro, J.S., 2016. Trade costs, CO2, and the environment. American Economic Journal: Economic Policy 8, 220–54.

Shapiro, J.S., 2020. The Environmental Bias of Trade Policy*. The Quarterly Journal of Economics 136, 831–886.

Weber, C.L., Matthews, H.S., 2008. Food-miles and the relative climate impacts of food choices in the united states. Environmental Science & Technology 42, 3508–3513.

Yang, Q., Honda, K., Otsuki, T., 2018. Structure Demand Estimation of the Response to Food Safety Regulations in the Japanese Poultry Market (OSIPP Discussion Paper No. 18E003). Osaka School of International Public Policy, Osaka University.

A Appendix

A.1 Data treatment

This section gives details on how to combine the production emissions from Poore and Nemecek (2018) with the supermarket data from the European retailer. Life cycle assessments (LCA) are a common method to analyze the environmental impact of a product. Typically, environmental scientists measure the emissions related to every part of a production process of a single product. As there exist many methodologies for LCAs, independent studies are typically not comparable. Poore and Nemecek (2018) combine data from 38,700 individual farms in a methodologically consistent manner and provide a worldwide overview of production emissions. I do not observe whether a beef product stems from a dairy herd or a standard beef herd, so I use the standard beef herd emissions for all beef products. Meat from a dairy herd is rare, as most beef products originate from beef herds. Additionally, the consumption data contains veal products for which I do not observe emissions separately. Since calves are a by-product of milk production, I use the emissions from beef from the dairy herds for veal products. Finally, I include crustaceans in the fish category.

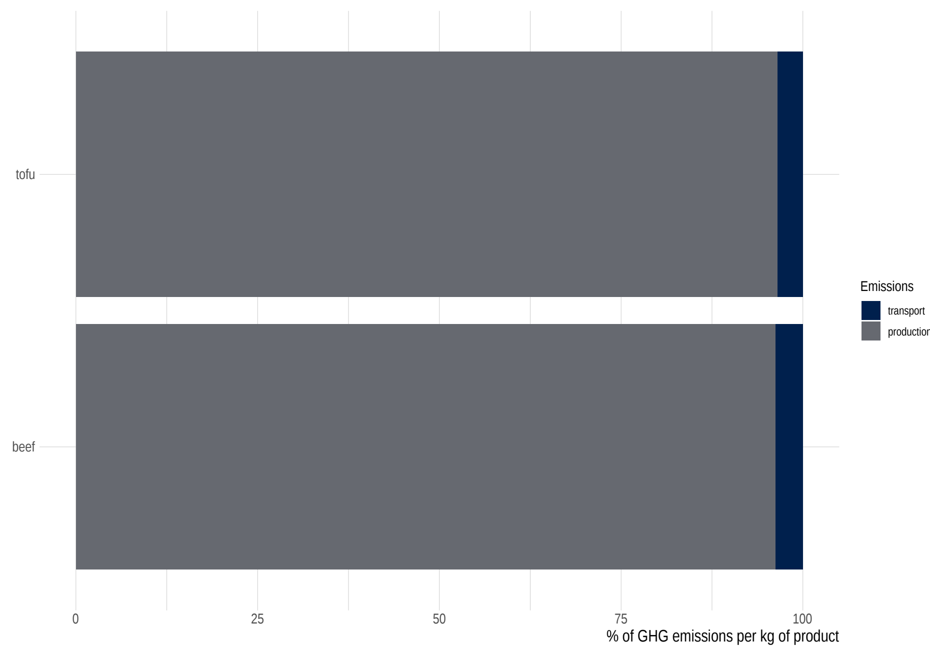


Figure 16: Total GHG emissions of imported beef and imported tofu

A.2 Intuition example

This section gives a numerical example for the intuition of the own- and cross-price elasticities when several prices change. Here, we consider a simplified version of the model with a logit specification for two goods, as in section 4.3.

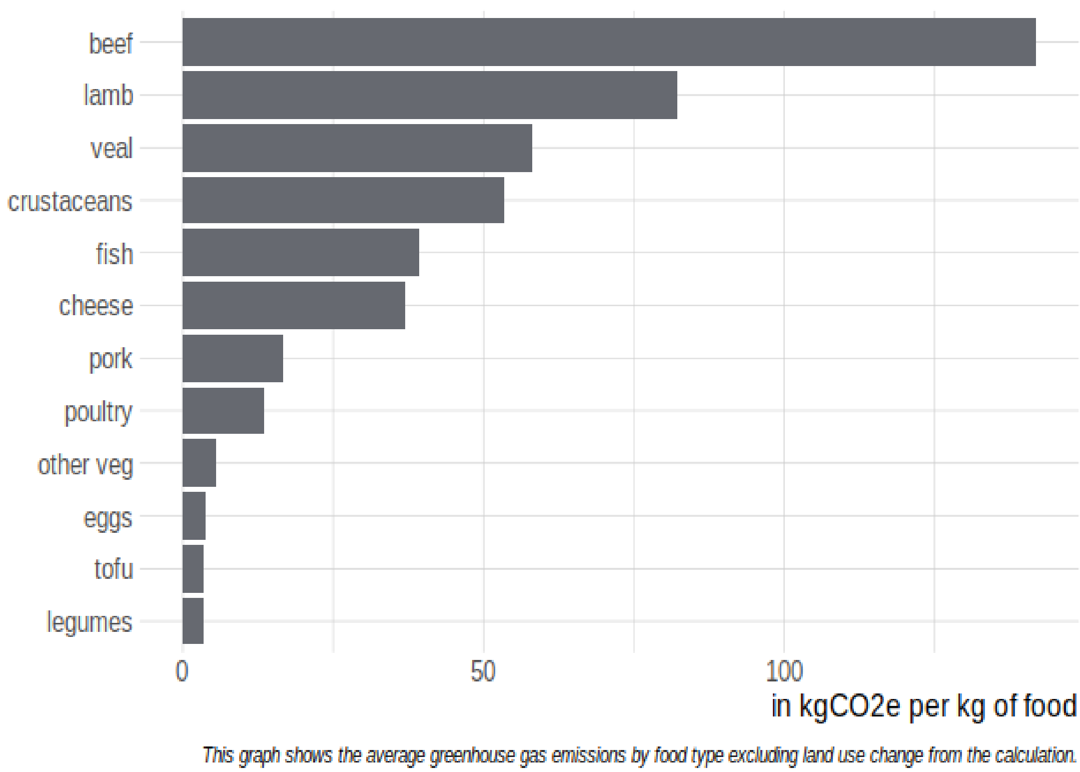


Figure 17: Average GHG emissions of different food types excluding land use change

	p_j	p_l	s_j	s_l
1	10.0	10.0	0.00665	0.00665
2	8.0	10.0	0.01787	0.00657
3	8.0	3.0	0.01475	0.17973
4	9.9	3.0	0.00576	0.18138

Table 20: Dummy Model Example

Table 20 illustrates several scenarios with α=-0.5. In row 1, products j and l have the same price and thus the same market shares. Decreasing the price of product j in row 2 yields an increase in the market share of product j, and a decrease in the market share of product l. This is the expected result form the own- and cross-price elasticities. In rows 3 and 4, I decrease the price of both goods compared to row 1. Product l experiences a much larger decrease than product j in both scenarios. In row 4, the market shares of both products increase through what I call the own-price effect. Note that s_j increases less than in row 2, because now also the price of product l decreased. This leads to a cross-price effect from the effect of the cross-price elasticity on the market share. In row 4, the price of product j only decreases a little, while the price of l decreases a lot. As a result, the market share of l increases, while the market share of good j *decreases*.

For both products, we have an own- and a cross-price effect that go in opposite directions. In row 4, product j had a small decrease in the price, and thus we would expect an increase in the market share from the own-price effect. However, product l had a large price decrease, from which we expect an increase in the market share of product l. The cross-price effect dominated over the own-price effect for product j, and thus its market share decreases.

A.3 Additionall regression tables

Table 21: Nested Logit IV

	Relative Market Share
	NL IV
Sales 1	2.133*** (0.066)
Sales 2	−1.999*** (0.074)
Sales 3	0.674*** (0.021)
European Retailer Brandname	3.152* (1.654)
Chicken Brandname	4.069** (1.653)
Sausage Brandname	6.811*** (1.660)
Other Brandname	2.634 (1.658)
No Brandname	2.896* (1.655)
Cheese Brandname	2.384 (1.740)
Meat Substitute Brandname	1.776 (1.661)
Label Organic	−0.132*** (0.024)
Label Local	0.394*** (0.023)
Label Fish	−0.560*** (0.022)
Label Animal Welfare	0.164*** (0.046)
Label Allergy	8.948*** (0.693)
Label Grassfed	−0.060 (0.149)
Label Vegan	−0.828*** (0.077)
Label Vegetarian	0.238*** (0.079)
Price	−0.016*** (0.001)
Within Group MS	0.621*** (0.014)
Observations	39,262
Note:	*p<0.1; **p<0.05; ***p<0.01 Includes quarter, year, region, continent, and food type fixed effects, labels, and brands. This table shows a regression of the relative market share on prices, the within group market share, and other product characteristics.

Table 22: Nested Logit IV Barcode Level

	Relative Market Share			
	NL	NL IV	NL	NL IV
	(1)	(2)	(3)	(4)
Price	−0.001*** (0.00001)	−0.013*** (0.0002)	−0.001*** (0.00005)	−0.176*** (0.003)
Within Group MS	0.985*** (0.0001)	0.386*** (0.007)	0.977*** (0.0001)	0.403*** (0.020)
Sales 1	0.177*** (0.002)	2.589*** (0.028)		
Sales 2	−0.038*** (0.001)	−0.879*** (0.010)		
Sales 3	0.006*** (0.001)	−0.177*** (0.003)		
European Retailer Brand	0.015*** (0.002)	0.318*** (0.009)		
Chicken Brand	0.007*** (0.002)	0.177*** (0.010)		
Sausage Brand	0.013*** (0.002)	−0.204*** (0.010)		
Other Brand	0.020*** (0.002)	−0.271*** (0.009)		
No Brand	0.011*** (0.002)	−0.428*** (0.010)		
Cheese Brand	0.002 (0.002)	−0.052*** (0.009)		
Meat Substitute Brand	0.009*** (0.003)	0.128*** (0.012)		
Label Organic	−0.007*** (0.001)	0.134*** (0.003)		
Label Local	0.009*** (0.0004)	0.236*** (0.003)		
Label Fish	−0.037*** (0.001)	0.134*** (0.004)		
Label Animal Welfare	0.012*** (0.001)	0.153*** (0.005)		
Label Allergy	−0.010*** (0.002)	0.221*** (0.007)		
Label Grassfed	0.023*** (0.002)	−0.135*** (0.007)		
Label Vegan	−0.015*** (0.002)	−0.110*** (0.008)		
Label Vegetarian	−0.021*** (0.003)	0.038*** (0.010)		
Product FE	No	No	Yes	Yes
IV	None	Both	None	Both
Observations	2,597,846	2,597,846	2,597,846	2,597,846

Note: *p<0.1; **p<0.05; ***p<0.01
Includes quarter, year, region, continent, and food type fixed effects, labels, and brands. This table shows a regression of the relative market share on prices, the within group market share, and other product characteristics.

Table 23: Nested Logit Regression IV with Emissions

	Relative Market Share	
	NL	NL IV
	(1)	(2)
Sales 1	2.133***	2.231***
	(0.066)	(0.066)
Sales 2	−1.999***	−1.840***
	(0.074)	(0.067)
Sales 3	0.674***	0.406***
	(0.021)	(0.013)
Label Organic	−0.132***	0.465***
	(0.024)	(0.031)
Label Local	0.394***	−0.033*
	(0.023)	(0.017)
Imported		−0.742***
		(0.028)
Emissions		−0.006***
		(0.0002)
Price	−0.016***	−0.015***
	(0.001)	(0.001)
Within Group MS	0.621***	0.692***
	(0.014)	(0.011)
Observations	39,262	39,262

Note: *p<0.1; **p<0.05; ***p<0.01
Includes quarter, year, region, and food type fixed effects, labels, and brands.
This table shows a regression of the relative market share on prices, the within group market share, and other product characteristics.
The first column includes continent fixed effects.
The second column includes an imported dummy, and the greenhouse gas emissions related to each product.

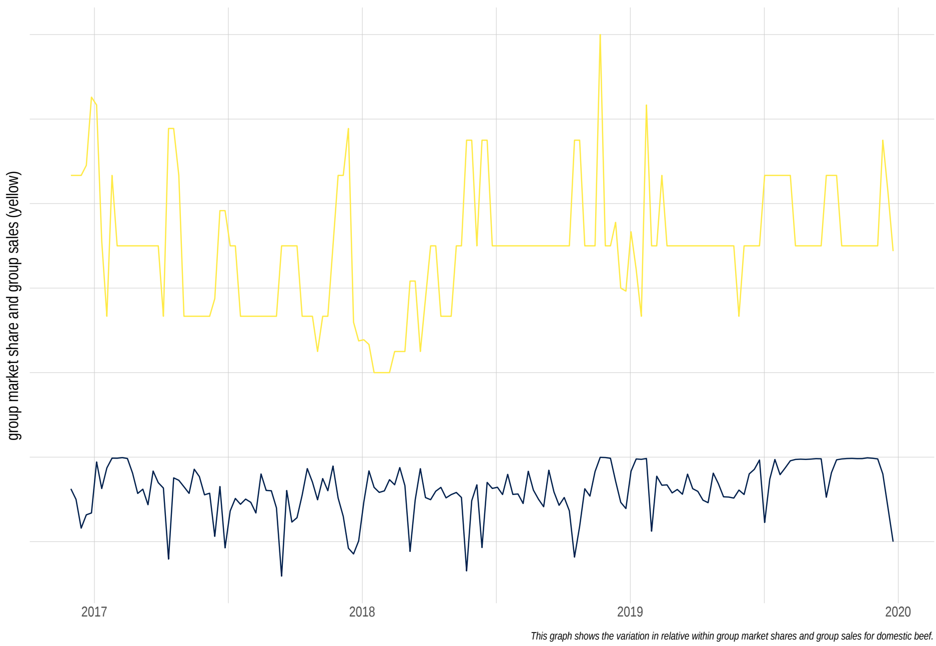


Figure 18: Variation of within group market share

A.4 Elasticity formulas

The nested logit formula for calculating the own-price elasticity is given by:

$$\frac{\alpha p_{jrw}}{1-\sigma}(1-\sigma s_{j|g,rw}-(1-\sigma)s_{jrw}),$$

where α is the price coefficient, σ is the coefficient on the within group market share , p_{jrw} is the price of good j in market n, s_{jrw} is the market share of good j in market n, and $s_{j|g,rw}$ is the within group market share of product j in group g in market rw. Similarly, the cross-price elasticity for products in the same nest is given by

$$\frac{\alpha p_{krw}}{1-\sigma}(s_{k|g,rw}-(1-\sigma)s_{krw})$$

and the cross-price elasticity for products in different nests is the same as the simple logit cross-price elasticity:

$$-\alpha p_{krw} s_{krw}$$

Table 24: Buy Local Demand Only Counterfactual

	Quantity (in mt.)			Emissions (in 1,000 mtCO2e)		
Type	Before	After	Δ%	Before	After	Δ%
Beef	2,392	2,316	-3.19	272,361	262,809	-3.51
Cheese	9,283	9,068	-2.32	450,617	444,794	-1.29
Eggs	3,301	3,087	-6.47	19,251	17,206	-10.62
Fish	1,079	925	-14.22	40,692	35,685	-12.3
Lamb	364	288	-21.03	35,319	29,598	-16.2
Legumes	662	607	-8.37	1,898	1,723	-9.2
Pork	4,140	4,162	0.53	77,230	77,660	0.56
Poultry	4,376	4,367	-0.19	45,855	44,390	-3.2
Tofu	313	288	-7.9	1,233	1,098	-10.97
Veal	82	82	0.47	5,458	5,461	0.05
Outside Good	137,123	137,925	0.58	893,054	898,273	0.58
Total	163,115	163,115	0	1,842,968	1,818,697	-1.32

Note.— This table shows a buy local counterfactual which is calculated using only the demand side. This implies that the price of domestic products is not allowed to change as a response to the disappearance of the imported products from the choice set. The values are for an average year per 1 mio. consumers. The 'before' column refers to the status quo, the 'after' column to the counterfactual values.

A.5 Additional counterfactuals

Table 24 shows a buy local scenario where only the demand side is used, without the supply side. This means that the quantities are predicted by the demand equation, and the domestic prices are not allowed to react to the exclusion of the imported products from the choice set.

Table 25 shows a vegetarian scenario where only the demand side is used, without the supply side. This means that the quantities are predicted by the demand equation, and the prices of the vegetarian products are not allowed to react to the exclusion of the meat products from the choice set. The reason for this similar increase in the consumption of the vegetarian food types lies in the nesting structure of the demand model. As food types are nests, the cross-price elasticities across different food types will be the same. Therefore, the model predicts the same increase in the consumption of each food type.

Table 25: Vegetarian Demand Only Counterfactual

	Quantity (in mt.)			Emissions (in 1,000 mtCO2e)		
Type	Before	After	Δ%	Before	After	Δ%
Beef	2,392	0	-100	272,361	0	-100
Cheese	9,283	10,062	8.39	450,617	488,416	8.39
Eggs	3,301	3,578	8.4	19,251	20,870	8.41
Fish	1,079	0	-100	40,692	0	-100
Lamb	364	0	-100	35,319	0	-100
Legumes	662	718	8.38	1,898	2,057	8.37
Pork	4,140	0	-100	77,230	0	-100
Poultry	4,376	0	-100	45,855	0	-100
Tofu	313	339	8.32	1,233	1,336	8.31
Veal	82	0	-100	5,458	0	-100
Outside Good	137,123	148,419	8.24	893,054	966,618	8.24
Total	163,115	163,115	0	1,842,968	1,479,296	-19.73

Note.— This table shows a vegetarian counterfactual which is calculated using only the demand side. This implies that the price of domestic products is not allowed to change as a response to the disappearance of the imported products from the choice set. The values are for an average year per 1 mio. consumers. The 'before' column refers to the status quo, the 'after' column to the counterfactual values.