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

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Last Updated: November 5, 2021. Latest version here.

Abstract

The agricultural sector is the second largest contributor to greenhouse gas emissions. How can food consumption choices reduce emissions? I estimate a model of meat demand using purchasing data of meat and other protein rich products from a European retailer. I combine the purchasing data with data on production and transport emissions. In several counterfactual exercises, I analyze the reaction of consumers to some popular, supposedly eco-friendly food consumption policies. Contrary to popular belief, I find that buying local increases emissions by around 5% compared to the status quo. While vegetarianism decreases emissions by around 17%, consuming no beef and cheese yields the highest decrease in emissions of around 34%. My results show that consumer behavior can have a large impact on the emissions of food consumption.

Introduction[1]

Climate change is considered one of the biggest threats to humanity. 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? That is the research question of this paper. The effect of food consumption on emissions depends both on the emissions 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 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

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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 (Poore and Nemecek, 2018) allows me to gauge the effect of different food consumption scenarios on the environment. My counterfactuals include popular, supposedly eco-friendly consumption behaviors like buying local and vegetarianism[2]. First, I find that buying local increases overall emissions compared to the status quo. A naive counterfactual that relies on ad-hoc assumptions results in the opposite and leads to a decrease in emissions. Second, a scenario where people can purchase all meat products except beef and cheese yields a larger decrease in emissions than vegetarianism. An extensive set of external validity exercises analyzes the effect of trade policy, the impact of emissions efficiency, and the importance of consumption patterns. Overall, this paper shows that consumers' reaction to environmental or trade policies is key for determining whether the policy will hurt or help the environment.

The first step in analyzing the effect of different food consumption policies on the environment is obtaining emissions data. Three stylized facts emerge from this data. First, transport emissions are a low share of overall emissions. 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 do not only vary across food types, but also across countries. For each food type, it would be possible to halve emissions by producing with the production technology of the country with the lowest emissions. Third, the variation in production emissions across food types is large. Meat products have six times higher production emissions than vegetarian products. More specifically, beef is the most polluting meat type and has ten times higher emissions 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?".

The second step in analyzing the effect of different food consumption policies on the environment is to determine the quantities consumed in different scenarios. To illustrate that drawing conclusions from emissions data only might lead to misguided results, I calculate a naive buy local counterfactual. Buying local or autarky means that imported products cannot be purchased anymore. In that case, transport emissions would drop to zero. But what would happen with the production emissions of the imported products? Here, the researcher needs to make an assumption. Depending on the researcher's assumptions, the results of such a naive counterfactual could be very different. Instead of relying on ad-hoc assumptions about consumer behavior, I estimate how consumers substitute between different food products if they face different prices or choice sets.

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 coop-

[2]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).

eration 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. As the emissions data varies by food type, country of origin, and transport mode, I aggregate the bar code level data to larger product groups according to these dimensions. Aggregating reduces the impact of the econometric error on the results. 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 higher 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.

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 this variable 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. I instrument the within group market share with 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 -0.07 and -2.7.

Combining the estimates of the model with emissions data, I calculate several counterfactual scenarios. These hypothetical scenarios quantify the consumers’ reaction to different policies. The buy local scenario implies moving to full autarky, so that imported products cannot be purchased anymore. The naive buy local scenario relies on the ad-hoc assumption that consumers buy the same amounts of each food type. It results in a decrease of overall emissions of around 1% compared to the status quo. Using the estimates from the model to predict consumer behavior, I find that emissions increase in autarky by around 4%. As expected, transport emissions decrease. But production emissions increase because consumers respond by increasing their overall demand for meat. As meat is more polluting than the average vegetarian product, this increase in production emissions overcompensates the decrease in transport emissions. The next set of counterfactuals addresses excluding meat products from the choice set. Vegetarianism results in a decrease of emissions of around 17%. A related counterfactual considers decreasing beef consumption while all other meat products can be purchased. Consuming no beef and no cheese, but buying all other meat types leads to a decrease of 34% 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.

To address external validity, I consider three aspects. First, the trade regime in Home might be very different than for other countries. While most developed countries place relatively high trade restrictions on the agricultural sector, Home is close to autarky. Therefore, I calculate a free trade scenario which forms the basis for less strict trade restrictions. A move to free trade would decrease prices for the most polluting meat types and lead to an increase in emissions of around 9%. Second, the results could depend on the production emissions of Home relatively to other countries. I calculate the autarky scenario under the assumption that Home has the highest average production emissions and the lowest average production emissions. As expected, autarky would yield an increase in emissions of around 8% if Home was the ecologically least efficient producer in all food types. If Home was the most efficient producer, overall emissions would barely change compared to the status quo. Thus, autarky would not lead to profound changes in emissions even for countries with high ecological efficiency. Third, 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 and conclude that a large share of countries have similar consumption patterns as Home. Based on these considerations, I conclude that my results are likely to be representative for most developed European countries.

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 the main 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. My findings for autarky are in line with those results. Comparing the status quo with the free trade scenario however, I find that emissions would increase.

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 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. Contrary to the environmental scientists, I show that buying local will 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 both important for international trade and environmental economics. While the effect of food consumption choice on a variety of topics including health has been widely analyzed in the IO literature (Briggs et al., 2013; Dubois et al., 2017; Edjabou and Smed, 2013; Griffith et al., 2019), this is the first study to discuss its effects on climate change in an open economy. Overall, this paper shows that assessing the demand side implications of a policy is important to determine its effectiveness.

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, discusses estimation and presents the regression results. The counterfactual scenarios are presented in section 5. Section 6 discusses external validity and section 7 concludes.

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 will 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. Contrary to standard scanner data sets, I obtain the country of origin and the marginal costs of all products. 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. 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.

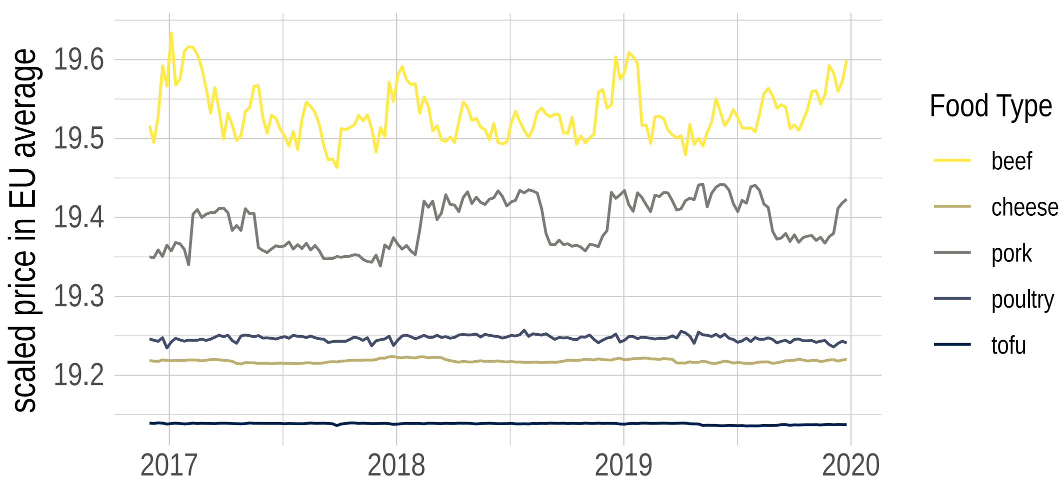
There are around 12000 bar code level products from 37 countries in the period of 2017-2019 with a weekly frequency. Product characteristics include country of origin, labels (e.g. organic), brand name (e.g. "European Retailer Premium Brand"), food type (e.g. beef or cheese), and product category (e.g. 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. Prices and quantities vary by product, week, and region. The retailer operates in all of the different geographical regions of Home. Verifying this calculation with a subset of the data for which exact prices are available shows an accuracy of over 99%.

Production emissions stem from a peer-reviewed meta data of life cycle assessments of food products (Poore and Nemecek, 2018). 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 LCA's, 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. 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 vary by food type (beef, beef dairy herd, lamb/mutton, poultry, pork, crustaceans, fish, tofu, eggs, cheese, legumes), and country. 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.

The transport emissions originate from two different sources. Emissions 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 emission 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 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. I assume that the outside good is domestic and thus, the transport emissions are zero. As for the production emissions, I use the average of all other food types (excluding drinks) in Poore and Nemecek (2018) that are not included in the food types I consider. 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). 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. The aggregate price variation for selected food types is shown in graph 1.



This graph shows the price per kg for selected food types averaged across regions, transport modes, and origins.
Due to anonymity, I scale the price to match the average price level in the EU.

Figure 1: Price Variation

The majority of price variation comes from variations in marginal costs and sales. There are three types of sales. With standard sales, the price is reduced per kg of product. Packaged sales also offer price reductions, but at the same time require the consumer to buy the product in packages (e.g. three 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. I observe revenues and quantities for packaged sales, but only revenues from standard sales and expiry sales. The price however will include all reductions from the three types of sales.

Table 19 in the Appendix gives some product characteristics by food type[3]. Overall, most food is not imported, thus imported market shares are low. Similarly to other supermarket data (Berto Villas-Boas, 2007; Nevo, 2001), Table 1 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 1: Coefficient of Variation

For the trade regime analysis, I rely on the experts at the European retailer and with their help, categorize my products according to which trade regime they belong to. There are three types of trade 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 of the World Trade Organization. This tariff represents an upper bound as the AVE tariffs are very high.

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 (Poore and Nemecek, 2018) and transport emissions, Figure 2 shows that transport emissions only account for a small fraction of overall emissions of products consumed. The three products represent median overall emissions 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 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 7 in the Appendix illustrates this for the case of beef and tofu. Therefore, the first assumption of the buy local concept is flawed.

[3]To respect the retailer’s anonymity, I am limited in the types of summary statistics I show in Table 19.

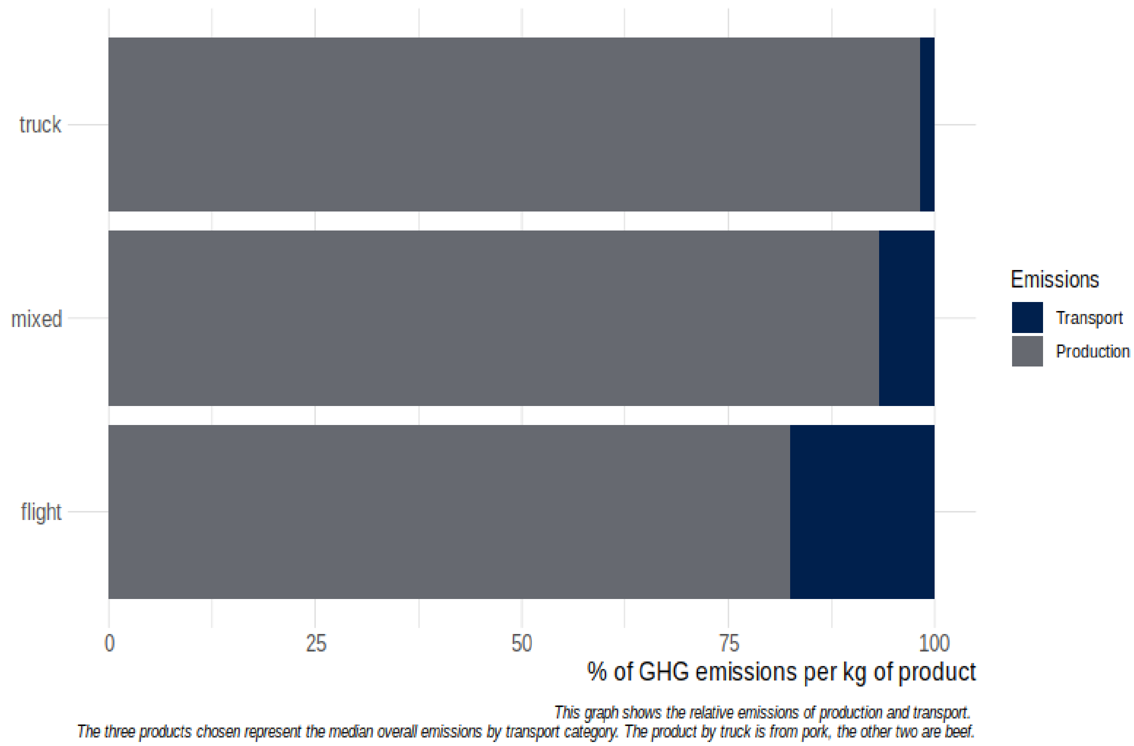


Figure 2: Total GHG Emissions of some Imported Meat Products

Figure 3 shows the distribution of emissions of producing 1 kg of food across different countries[4]. First, the emissions of vegetarian products are lower than those of meat products[5]. Therefore, a vegetarian diet yields lower emissions compared to a standard diet. Second, the production emissions vary substantially by meat type. Substituting beef by poultry or pork could reduce emissions by a factor of 10. The reason for these stark differences is a biological one: Ruminants (cattle, lamb, mutton) have higher emissions due to their enteric fermentation and because of lower efficiency when converting feed to edible meat (feed-conversion ratio). Third, the emissions of vary across countries. For each food type, production emissions could be at least halved if production took place with the technology of low-emission countries. This suggests that the second assumption of the buy local rule does not hold either.

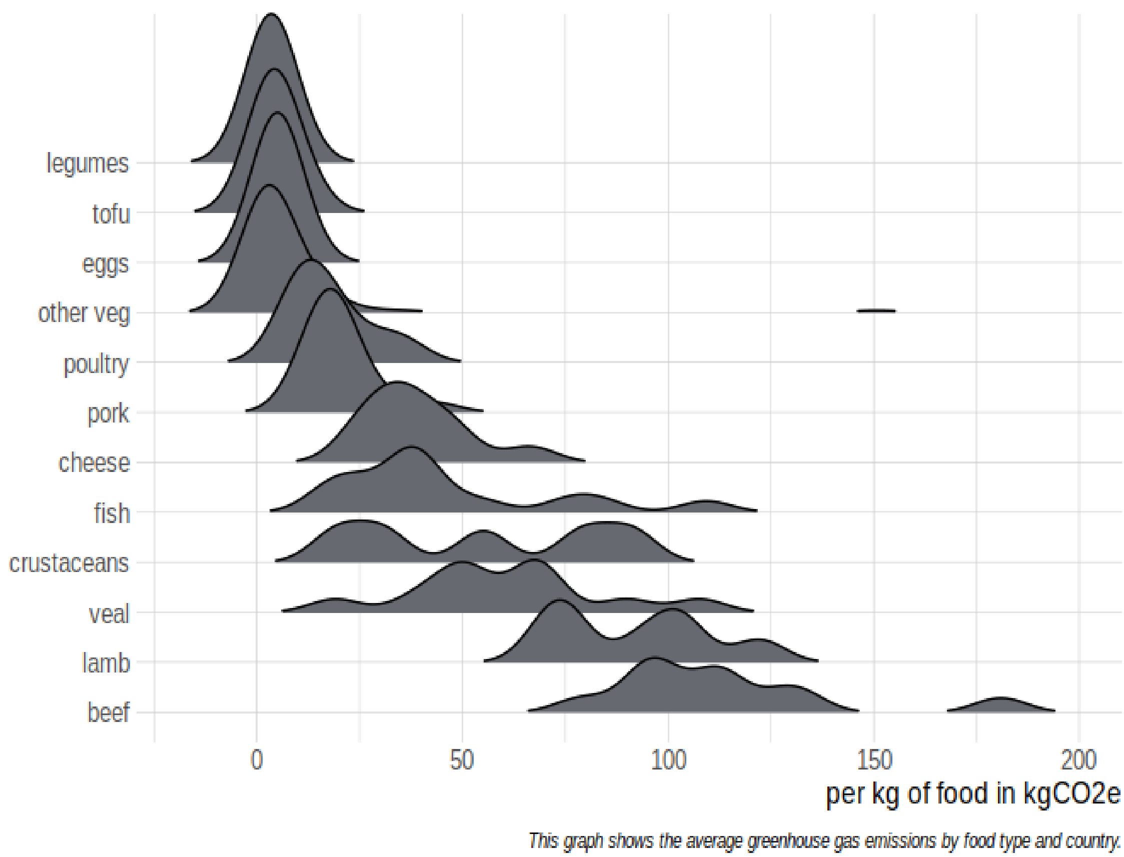


Figure 3: GHG Emissions across Countries

[4]These emissions 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 for all products, but the ordering and the spread of emissions across meat types stays the same. See graph 9 in the Appendix.

[5]The interested reader can find a graph 10 with more detailed groups of food types in the Appendix, including the beloved yet much criticized avocado. Avocados actually have a low CO2 footprint, but require a lot of water for production. Whether that is a problem depends on the water scarcity in the country of production and is out of the scope for this paper.

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".

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. The supply side that represents the pricing decision of the firm is work in progress. Second, I explain how the model is estimated and discuss identification. Third, I show the estimation results.

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 4 shows a stylized representation of the 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. This outside good captures the option not to buy any of the protein-rich products in my

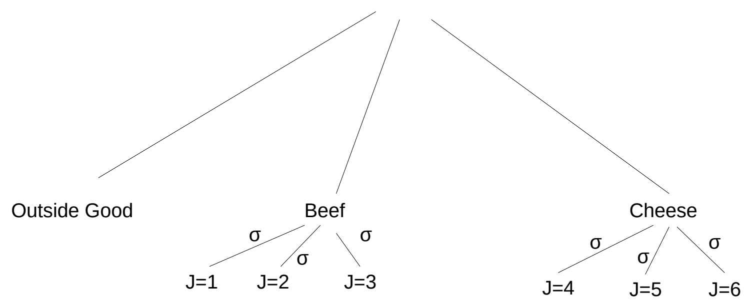


Figure 4: Nesting Structure

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 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:

$$s_{ijrw} = \frac{exp(\frac{\delta_{jrw}}{1-\sigma})}{exp(\frac{I_{igrw}}{1-\sigma})} \frac{exp\ I_{igrw}}{exp\ I_{irw}}$$

where I_{igrw} and I_{in} are inclusive values defined as:

$$I_{igrw} = (1-\sigma) ln \sum_{k \in g} exp(\delta_{krw}/(1-\sigma))$$

$$I_{irw} = ln \sum_{g=1}^{G} exp(I_{igrw})$$

Summing across consumers yields market shares for market rw: $s_{jrw} = \sum_i s_{ijrw}$.

Estimation

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):

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

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 2 shows the median market shares for the median domestic and imported food type.

				Group	Within Group
	Food Type	Imported	Market Share	Market Share	Market Share
1	beef	no	1.21	1.36	90.88
2	beef	yes	0.12	1.36	0.32
3	cheese	no	4.94	5.35	92.63
4	cheese	yes	0.40	5.35	7.37
5	eggs	no	1.53	1.93	84.73
6	eggs	yes	0.31	1.93	15.27
7	fish	no	0.43	0.61	70.76
8	fish	yes	0.19	0.61	0.76
9	lamb	no	0.08	0.20	45.79
10	lamb	yes	0.09	0.20	21.28
11	legumes	no	0.29	0.38	77.18
12	legumes	yes	0.08	0.38	22.82
13	pork	no	2.92	2.92	99.92
14	pork	yes	0.00	2.99	0.10
15	poultry	no	2.56	2.61	98.49
16	poultry	yes	0.03	2.61	1.51
17	tofu	no	0.16	0.20	81.01
18	tofu	yes	0.03	0.20	18.99
19	veal	no	0.33	0.33	100.00
20	veal	yes	0.00	0.29	1.35

Note:

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

Table 2: 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 final estimating equation is:

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

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 the internal price calculations, 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. Some argue that in grocery settings, the price is exogenous conditional on product characteristics. Depending on the specification, I do find an upward bias, so I prefer to include marginal costs as an instrumental variable.

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 in 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 11 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.

Regression Results

This section shows the regression results for the nested logit model and the corresponding elasticities. In Table 3, I show the results for the nested logit regressions. All columns include continent, food type, quarter, year, and regional fixed effects, and a set of controls. Interacting the fixed effects or including week-of-the-year fixed effects does not alter the results. The control variables include the percentage of products on sale, 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 20 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. 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 for each product could enter the utility function. As emissions vary across continents and across products, my setup does not allow to estimate a coefficient on emissions. A specification in Appendix Table 21 where instead of continent fixed effects I only control for domestic or imported products and include greenhouse gas emissions shows that the coefficients of interest do not change and that the coefficient on emissions is very low. As consumers do not observe emissions, but rather product characteristics like food type and country of origin, I do not include emissions in the main specification.

Table 3: Nested Logit Regression IV

	Relative Market Share	
	NL	NL IV
	(1)	(2)
Price	-0.002^{***}	-0.019^{***}
	(0.0001)	(0.002)
Within Group Market Share	0.960^{***}	0.531^{***}
	(0.001)	(0.062)
Sales 1	0.450^{***}	2.018^{***}
	(0.033)	(0.233)
Sales 2	0.093^{***}	0.601^{***}
	(0.010)	(0.075)
Sales 3	-0.095^{***}	-0.990^{***}
	(0.010)	(0.132)
Fidelity Points	0.012	0.442^{***}
	(0.016)	(0.068)
Label Organic	-0.043^{***}	-0.380^{***}
	(0.013)	(0.055)
F-Statistic		81
Observations	40,233	40,233
R^2	0.988	0.959

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.

	Price		Within Mkt Share	
	Estimate	Std. Error	Estimate	Std. Error
Margincal Cost	0.814***	0.004	-0.032***	0.001
Proxy for Advertisement	-1.337	1.373	-1.389***	0.181
FStat	81		111	

Note:
This table shows the first stage of a regression of the relative market share on prices, the within group market share, and other product characteristics. The instruments are the marginal costs and a proxy for advertisement.

Table 4: Nested Logit First Stage

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 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.

Table 4 shows the first stage estimates for the nested logit regression in column 2 of Table 3 including all control variables that are not reported. Increasing marginal costs by 1 € results in a consumer price increase of around 0.40 €. For the within group market share first stage, 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.

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 -0.07 and -2.7. This is comparable to other's findings in the meat market (Anders and Mőser, 2010; Eales and Unnevehr, 1988; Reed et al., 2003; Yang et al., 2018). 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. The share switched to the outside good in the fourth column is around 8%. 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).

	Group	OPE NL	CPE Within Group	CPE Across Groups	Share switched to OG
1	Beef Dom	-1.5997	0.0023	0.0092	7.5204
2	Beef Imp	-2.7678	0.0188	0.0000	7.4467
3	Cheese Dom	-0.4938	0.0027	0.0124	7.8254
4	Cheese Imp	-0.6737	0.0186	0.0013	7.6466
5	Eggs Dom	-0.1425	0.0004	0.0011	7.5421
6	Eggs Imp	-0.1353	0.0011	0.0002	7.4991
7	Fish Dom	-1.0900	0.0014	0.0022	7.4471
8	Fish Imp	-1.3109	0.0037	0.0000	7.5107
9	Lamb Dom	-1.3879	0.0008	0.0005	7.4218
10	Lamb Imp	-1.9154	0.0015	0.0002	7.4037
11	Legumes Dom	-0.0925	0.0001	0.0001	7.4394
12	Legumes Imp	-0.0804	0.0001	0.0000	7.4315
13	Pork Dom	-1.0872	0.0021	0.0157	7.8773
14	Pork Imp	-1.8367	0.0290	0.0000	7.7333
15	Poultry Dom	-0.7222	0.0013	0.0089	7.6240
16	Poultry Imp	-0.7811	0.0107	0.0001	7.5260
17	Tofu Dom	-0.1865	0.0001	0.0001	7.4249
18	Tofu Imp	-0.1628	0.0001	0.0000	7.4196
19	Veal Dom	-1.5909	0.0003	0.0020	8.3594
20	Veal Imp	-2.2938	0.0033	0.0000	8.3387

Note:

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

Table 5: Nested Logit Elasticities Ad

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 and comparing the outcome to the status quo. I analyze several scenarios which emerge as popular, supposedly eco-friendly strategies in a representative survey of food consumption and sustainability (BEUC, 2020). Usually, we think about such counterfactuals as a government-imposed policy. Alternatively, one could interpret them as a self-imposed restraint. In that case, the vegetarian scenario would correspond to all consumers self-imposing mental taxes on meat. While these counterfactuals are extreme[6], they show how popular movements would affect the environment if taken seriously. The standard economic approach to account for the externality from emissions is to impose a Pigouvian tax and is still work in progress.

Before proceeding to the counterfactuals, I would like clarify three limitations of this analysis. At this stage of the project, all counterfactuals assume that a change in choice sets has no effect on the price of other products that stay in the choice set. This will be relaxed once I implement the supply side of the model. To show in which direction implementing the supply side would go, I add some counterfactuals with ad-hoc

[6]Calculating extreme counterfactuals stretches the interpretation of the elasticities that only hold for local changes. I plan to address this problem along the lines of Ackerberg and Rysman (2005).

assumption of price increases of other products. Additionally, I make the assumption of full pass-through of costs into consumer prices, meaning that if marginal costs change by 1 percent, the corresponding consumer price also changes by 1 percent. This assumption will also be relaxed once I add the supply side[7]. A feature of the discrete choice model is to express quantities in terms of an outside good. This implies that my autarky counterfactuals will analyze a move to autarky for the protein-rich products in my data, but no change in the products of the outside good.

In general, emissions might change due to three effects: scale, composition, and technique. Decomposing a change in emissions is a widely used approach to describe the reason why emissions change (Antweiler et al., 2001; Holland et al., 2019). In this paper, the scale effect will refer to the quantities consumed of all protein-rich products as compared to the quantities of the outside good. As the outside good has lower emissions on average, consuming more of the outside good should lead to a decrease in emissions. The composition effect refers to the quantities consumed of different protein-rich products. If for example the consumption of beef increases, this will lead to an increase in emissions. The technique effect refers to improvements of both the production and the transport emissions of products. I will use this terminology to describe my results.

First, I show the status quo of food consumption and the related emissions. Second, I consider an autarky scenario. I compare a naive counterfactual where I rely on ad-hoc assumptions for consumer behavior with an autarky outcome that uses the quantities predicted by the model. Third, I assess several counterfactuals about meat reduction. I analyze vegetarianism, a scenario where no beef can be purchased but all other products can, and one where neither beef nor cheese can be bought. Fourth, I provide a naive counterfactual on a supply side policy where consumption is not changed, but production emissions are assumed to be the lowest for each food type.

Figure 5 summarizes the counterfactuals. It shows the total emissions for each counterfactual scenario as a percentage of the total emissions in the status quo. If a counterfactual yields higher emissions than the status quo, it will be to the right of the vertical black line. Autarky is the only counterfactual which would make things worse than the status quo. Calculating an autarky scenario without an economic model but making ad-hoc assumptions about consumption behavior leads to a decrease in emissions. The three meat consumption scenarios (vegetarianism, no beef, no beef and cheese) all lead to a decrease in emissions. Refraining from both no beef and no cheese consumption would yield the largest decrease of about 34%. To judge the potential of improvements of production emissions through supply side interventions, I include a naive counterfactual with the quantities from status quo but the best possible production emissions for each food type. While this does lead to a decrease in emissions, demand side policies have a larger potential to curb emissions.

[7] Genakos and Pagliero (2019) find markups between 0.44 and 1 depending on the competitive structure of the market. They observe a competitive market with a pass through of 1 with four or more competitors in one market. As this is similar to my market situation, I do not expect to find much lower pass-through than 1.

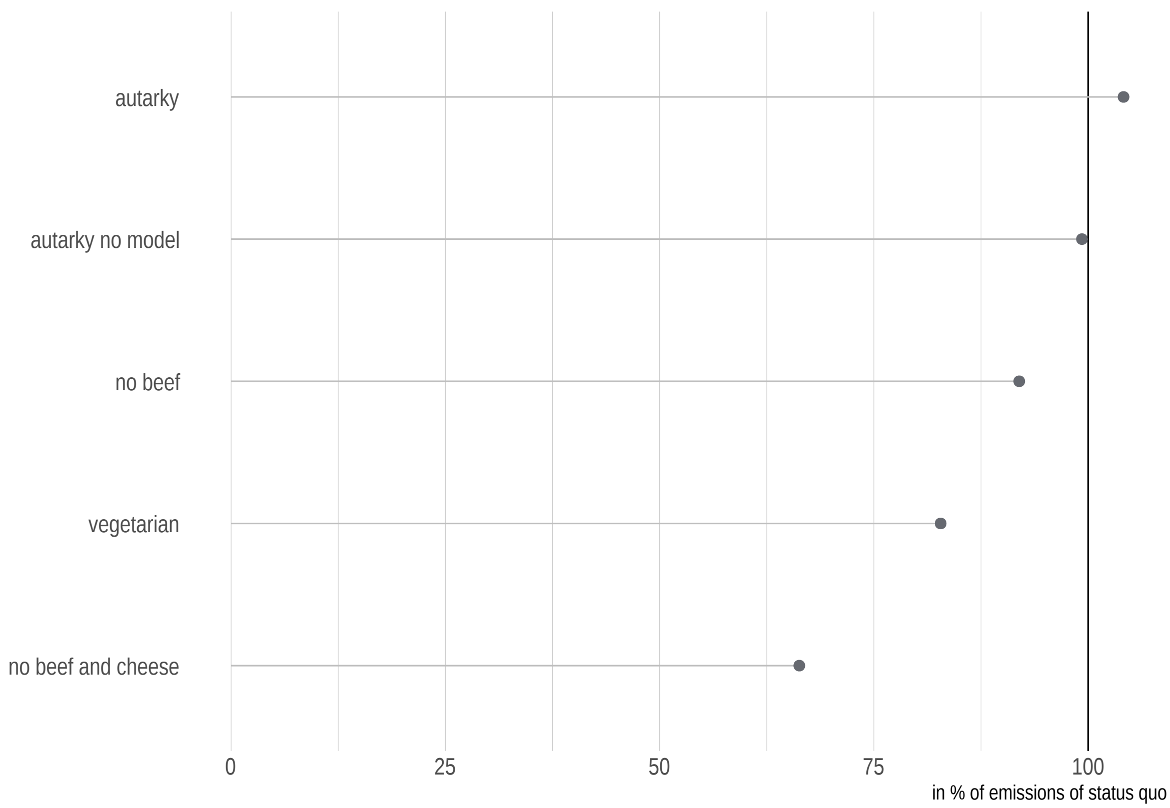


Figure 5: Summary of Counterfactuals

Status Quo

Table 6 shows the current consumption patterns in Home. The protein-rich products considered in my sample account for only 15% 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 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	5056	1.47	577927	14.83
2	cheese	19499	5.67	943576	24.21
3	eggs	6923	2.01	40515	1.04
4	fish	2220	0.65	105992	2.72
5	lamb	802	0.23	66135	1.70
6	legumes	1389	0.40	4174	0.11
7	pork	8899	2.59	166016	4.26
8	poultry	9244	2.69	95543	2.45
9	tofu	710	0.21	2770	0.07
10	veal	181	0.05	11995	0.31
11	outside good	289004	84.03	1882224	48.30
12	Total	343927	100.00	3896866	100.00

Note:

This table shows the consumption patterns in the status quo.

Table 6: Status Quo

Autarky

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

A first naive counterfactual 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. Full buy 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. This calculation would yield the expected result: Overall emissions from food consumption decrease by around 1% in Table 7. 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 those two food types, the emissions increase when produced in Home. Using the decomposition terms, scale and composition are zero here as the quantities consumed do not change. The technique effect is negative overall and leads to a decrease in emissions.

	Type	Quantity in 1000 kg			Emissions in 1000 tCO2e		
		before	after	change in %	before	after	change in %
1	beef	5056	5056	0.00	577927	573806	-0.71
2	cheese	19499	19499	0.00	943576	956467	1.37
3	eggs	6923	6923	0.00	40515	38653	-4.59
4	fish	2220	2220	0.00	105992	59458	-43.90
5	lamb	802	802	0.00	66135	79529	20.25
6	legumes	1389	1389	0.00	4174	3945	-5.48
7	pork	8899	8899	0.00	166016	166040	0.01
8	poultry	9244	9244	0.00	95543	93957	-1.66
9	tofu	710	710	0.00	2770	2707	-2.28
10	veal	181	181	0.00	11995	11995	-0.00
11	outside good	289004	289004	0.00	1882224	1882224	0.00
12	Total	343927	343927	0.00	3896866	3868779	-0.72

Note:

This table shows an autarky counterfactual in which only domestic products can be purchased. Instead of using a model of meat demand, I assume that the quantities consumed stay constant for each food type and are all produced in Home. The 'before' column refers to the status quo, the 'after' column to the counterfactual values.

Table 7: No Model Autarky Counterfactual

Contrary to the naive scenario, Table 8 reveals that overall emissions would increase in autarky by around 4%. Although emissions from transport do decrease, consumers substitute towards eating more meat overall. One reason for this increase in meat consumption might be home bias. If people prefer domestically produced meat, autarky is an opportunity to purchase more of these desirable products. As meat is more polluting than vegetarian alternatives, this overcompensates the decrease in transport emissions. Using the decomposition terms, the technique effect will be 0 now as I do not alter the production or transport emissions of products.

What changes is the quantities. The scale effect is negative and leads to an increase in emissions. The composition effect however is positive. Less polluting meat types are purchased more than the most polluting ones. Overall, this leads to a decrease in emissions.

	Type	Quantity in 1000 kg			Emissions in 1000 tCO2e		
		before	after	change in %	before	after	change in %
1	beef	5056	5535	9.46	577927	628112	8.68
2	cheese	19499	21815	11.88	943576	1070062	13.40
3	eggs	6923	6920	-0.05	40515	38635	-4.64
4	fish	2220	1831	-17.52	105992	101388	-4.34
5	lamb	802	523	-34.87	66135	41685	-36.97
6	legumes	1389	1313	-5.51	4174	3728	-10.69
7	pork	8899	10725	20.52	166016	200113	20.54
8	poultry	9244	10923	18.16	95543	111022	16.20
9	tofu	710	692	-2.47	2770	2640	-4.69
10	veal	181	218	20.76	11995	14485	20.76
11	outside good	289004	283433	-1.93	1882224	1845941	-1.93
12	Total	343927	343927	0.00	3896866	4057811	4.13

Note:

This table shows an autarky counterfactual in which only domestic products can be purchased. The 'before' column refers to the status quo, the 'after' column to the counterfactual values.

Table 8: Autarky Counterfactual

Comparing the two autarky scenarios shows that ad-hoc assumptions about consumer behavior might lead to wrong conclusions. One caveat of the current version of this paper is that without a supply side, I do not account for price changes of products as a response to changing the choice sets. In autarky, we would expect the price of domestic goods to increase, as the competition from imports decreases. Presumably, the negative effects of autarky on the environment would be dampened if domestic products were allowed to respond with a price change. To give a first idea of how the results would change, I calculate two more autarky scenarios, where I implement an increase in the price of domestic products by 10% and 20%, respectively. Tables 9 and 10 show that while the magnitude of the effect decreases, it still leads to an increase in overall emissions. In reality, we would expect the price of products that are more competitive to increase more than the price of less competitive goods. As more competitive goods are also less polluting, I do not expect the missing supply side to impact my results too much.

	Type	Quantity in 1000 kg			Emissions in 1000 tCO2e		
		before	after	change in %	before	after	change in %
1	beef	5056	5210	3.04	577927	591244	2.30
2	cheese	19499	21369	9.59	943576	1048215	11.09
3	eggs	6923	6881	-0.61	40515	38419	-5.17
4	fish	2220	1757	-20.88	105992	97259	-8.24
5	lamb	802	497	-38.10	66135	39616	-40.10
6	legumes	1389	1308	-5.83	4174	3715	-10.99
7	pork	8899	10286	15.59	166016	191930	15.61
8	poultry	9244	10627	14.96	95543	108017	13.06
9	tofu	710	688	-3.13	2770	2622	-5.34
10	veal	181	205	13.18	11995	13576	13.18
11	outside good	289004	285100	-1.35	1882224	1856795	-1.35
12	Total	343927	343927	0.00	3896866	3991408	2.43

Note:

This table shows an autarky counterfactual in which only domestic products can be purchased. Additionally, the price of domestic products increases by 10%. The 'before' column refers to the status quo, the 'after' column to the counterfactual values.

Table 9: Autarky Counterfactual 10%

	Type	Quantity in 1000 kg			Emissions in 1000 tCO2e		
		before	after	change in %	before	after	change in %
1	beef	5056	4904	-3.01	577927	556546	-3.70
2	cheese	19499	20933	7.36	943576	1026819	8.82
3	eggs	6923	6842	-1.16	40515	38204	-5.70
4	fish	2220	1685	-24.09	105992	93303	-11.97
5	lamb	802	472	-41.17	66135	37651	-43.07
6	legumes	1389	1304	-6.14	4174	3703	-11.29
7	pork	8899	9866	10.87	166016	184083	10.88
8	poultry	9244	10340	11.85	95543	105094	10.00
9	tofu	710	683	-3.80	2770	2604	-5.99
10	veal	181	192	6.09	11995	12725	6.09
11	outside good	289004	286706	-0.80	1882224	1867258	-0.80
12	Total	343927	343927	-0.00	3896866	3927990	0.80

Note:

This table shows an autarky counterfactual in which only domestic products can be purchased. Additionally, the price of domestic products increases by 20%. The 'before' column refers to the status quo, the 'after' column to the counterfactual values.

Table 10: Autarky Counterfactual 20%

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. Since a vegetarian diet includes cheese consumption, completely refraining from beef consumption is not reasonable. Ideally, one would model the cow demand for the level of cheese production in a vegetarian scenario and allow to consume the meat of the dairy cows. Additionally, veal is a by-product of the cheese industry. To approximate that scenario, I include veal consumption into all scenarios where cheese is purchased. As a dairy cow needs to give birth to a calf once per year, the true value for meat consumption of dairy cows used in cheese production would not likely to be much higher. Still, it might dampen the effects of the following counterfactuals somewhat.

The vegetarian scenario in Table 11 shows that emissions decrease by around 17%. In this scenario, the consumption of all vegetarian products increases. As the emissions of each product remain unchanged, the technique effect is 0. The scale effect is positive and leads to a decrease in emissions. The composition effect is 0 here as well. The reason for this similar increase in the consumption of other 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.

	Type	Quantity in 1000 kg			Emissions in 1000 tCO2e		
		before	after	change in %	before	after	change in %
1	beef	5056	0	-100.00	577927	0	-100.00
2	cheese	19499	23563	20.84	943576	1140306	20.85
3	eggs	6923	8364	20.82	40515	48948	20.82
4	fish	2220	0	-100.00	105992	0	-100.00
5	lamb	802	0	-100.00	66135	0	-100.00
6	legumes	1389	1675	20.57	4174	5032	20.56
7	pork	8899	0	-100.00	166016	0	-100.00
8	poultry	9244	0	-100.00	95543	0	-100.00
9	tofu	710	855	20.52	2770	3338	20.52
10	veal	181	220	21.55	11995	14580	21.55
11	outside good	289004	309250	7.01	1882224	2014076	7.01
12	Total	343927	343927	0.00	3896866	3226281	-17.21

Note:

This table shows a vegetarian counterfactual in which veal is the only meat type that can be purchased. The 'before' column refers to the status quo, the 'after' column to the counterfactual values.

Table 11: Vegetarian Counterfactual

The no beef scenario in Table 12 considers a shutdown of beef consumption. Since beef has the highest emissions of all meat types, a lot can be achieved by refraining from eating beef. The quantities consumed increase for almost food types while emissions decrease by around 8%. Here again, the technique effect will be 0. The scale effect however will be negative. If we restrict beef consumption, consumers will purchase less of the outside good overall. The composition effect is positive, since eating less of the most polluting food type will lead to a decrease in emissions. Overall, the composition effect dominates, so that we have a decrease in emissions.

	Type	Quantity in 1000 kg			Emissions in 1000 tCO2e		
		before	after	change in %	before	after	change in %
1	beef	5056	0	-100.00	577927	0	-100.00
2	cheese	19499	23563	20.84	943576	1140306	20.85
3	eggs	6923	8364	20.82	40515	48948	20.82
4	fish	2220	2679	20.66	105992	127900	20.67
5	lamb	802	971	20.99	66135	80023	21.00
6	legumes	1389	1675	20.57	4174	5032	20.56
7	pork	8899	10742	20.71	166016	200403	20.71
8	poultry	9244	11152	20.64	95543	115268	20.65
9	tofu	710	855	20.52	2770	3338	20.52
10	veal	181	220	21.55	11995	14580	21.55
11	outside good	289004	283705	-1.83	1882224	1847713	-1.83
12	Total	343927	343927	-0.00	3896866	3583512	-8.04

Note:
This table shows a no beef counterfactual in which beef cannot be purchased. The 'before' column refers to the status quo, the 'after' column to the counterfactual values.

Table 12: No Beef Counterfactual

Refraining from beef and cheese consumption in Table 13 results in the highest decrease of overall emissions with around 34%. The technique effect is 0 again. In this scenario, both the scale effect and the composition effect are positive. The consumption of the outside good increases, while the composition of the the other goods consumed shifts towards lower polluting food types. Therefore, we have the largest decrease of these counterfactuals.

	Type	Quantity in 1000 kg			Emissions in 1000 tCO2e		
		before	after	change in %	before	after	change in %
1	beef	5056	0	-100.00	577927	0	-100.00
2	cheese	19499	0	-100.00	943576	0	-100.00
3	eggs	6923	8364	20.82	40515	48948	20.82
4	fish	2220	2679	20.66	105992	127900	20.67
5	lamb	802	971	20.99	66135	80023	21.00
6	legumes	1389	1675	20.57	4174	5032	20.56
7	pork	8899	10742	20.71	166016	200403	20.71
8	poultry	9244	11152	20.64	95543	115268	20.65
9	tofu	710	855	20.52	2770	3338	20.52
10	veal	181	0	-100.00	11995	0	-100.00
11	outside good	289004	307489	6.40	1882224	2002607	6.40
12	Total	343927	343927	0.00	3896866	2583519	-33.70

Note:

This table shows a no beef and no cheese counterfactual. The 'before' column refers to the status quo, the 'after' column to the counterfactual values.

Table 13: No Beef and Cheese Counterfactual

All in all, the counterfactuals of reducing meat consumption lead to the most promising decreases in emissions. The decomposition analysis shows that the strength of the decrease depends on whether consumers respond both by decreasing overall meat demand and shifting the demand for specific foods towards the lowest emissions ones. Overall, these results imply that the question is not whether to buy local or become vegetarian. It is “To Beef or Not To Beef”.

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. To give a sense of the magnitudes of such a policy, I calculate a naive supply side 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 14% in Table 14. Using the decomposition terms, the scale and composition effects would be 0. The technique effect would be positive and lead to a decrease in emissions of around 14%.

	Type	Quantity in 1000 kg			Emissions in 1000 tCO2e		
		before	after	change in %	before	after	change in %
1	beef	5056	5056	0.00	577927	486275	-15.86
2	cheese	19499	19499	0.00	943576	586533	-37.84
3	eggs	6923	6923	0.00	40515	29271	-27.75
4	fish	2259	2259	0.00	107885	61024	-43.44
5	lamb	821	821	0.00	66951	64164	-4.16
6	legumes	1389	1389	0.00	4174	3701	-11.34
7	pork	8899	8899	0.00	166016	142710	-14.04
8	poultry	9244	9244	0.00	95543	79587	-16.70
9	tofu	710	710	0.00	2770	2069	-25.32
10	veal	181	181	0.00	11995	3452	-71.22
11	outside good	288948	288948	0.00	1881854	1881854	0.00
12	Total	343927	343927	0.00	3899206	3340640	-14.33

Note:
This table shows the consumption patterns in the status quo, but assumes that production emissions are the lowest for each food type.

Table 14: Improving Emissions

The assumption that all our food can be produced with the lowest emissions for each food type is very strong. While it is possible to improve emissions with better production practices, a part of emissions of food production is related to land characteristics and cannot be adapted easily. From an emissions perspective, 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 which might lead to a higher decrease in emissions. 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, these results hold under the assumption of perfect competition on the producer market.

Compared to this naive supply side counterfactual, the vegetarian and no beef and cheese scenarios lead to a larger decrease in emissions. This implies that changing consumer behavior is an important factor for reducing the emissions of agriculture.

External Validity

For this analysis to be externally valid, three aspects need to be considered. First, the trade regime in Home might be very different than for other countries. Second, the results could depend on the production emissions 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.

Trade Regime

While most developed countries place relatively high trade restrictions on the agricultural sector, Home is close to autarky. Therefore, I calculate a free trade scenario which forms the basis for less strict trade restrictions. In this section, I compare the status quo of Home to a free trade scenario. A future version will compare free trade and autarky, and analyze the effect of the average European country's trade restrictions.

Analyzing a free trade scenario involves determining the free trade price for each imported product. I assume that Home is a small open economy and takes prices as given. There are three types of trade regimes for my products: no restriction, tariff, and tariff-rate quotas. Figure 6 illustrates these different tariff regimes.

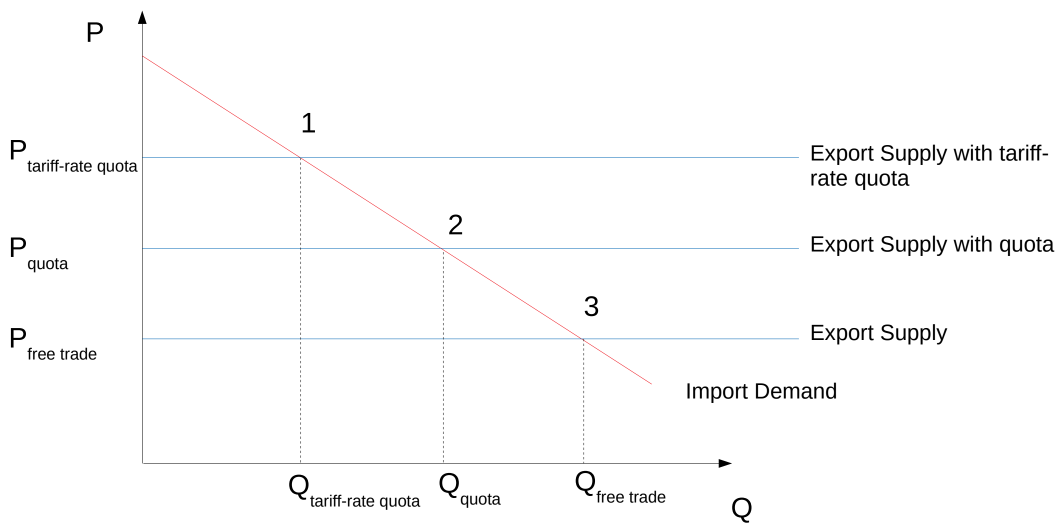


Figure 6: Prices under Different Tariff Regimes

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. Using the assumption of full pass-through of costs into prices, I subtract the tariff from the consumer price to obtain the free trade price. 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. Additionally, there is a tariff on the price. 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.

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

Tables 15 and 16 both indicate that emissions would increase under free trade by 9% and 10%, respectively. Using the decomposition terms, the technique effect would be 0. The composition effect would lead to an increase of beef and lamb, two rather polluting meat types. The scale effect would also enter negatively, as there is lower consumption of the outside good. Overall, free trade would lead to a decrease in prices and an increase in emissions. At this stage of the project, the prices of domestic goods are not allowed to vary. Adding the supply side would yield an even larger increase in meat consumption, as then the prices of domestic goods would also decrease. Therefore, free trade would lead to an increase in emissions.

	Type	Quantity in 1000 kg			Emissions in 1000 tCO2e		
		before	after	change in %	before	after	change in %
1	beef	5056	6129	21.22	577927	700703	21.24
2	cheese	19499	23568	20.87	943576	1140528	20.87
3	eggs	6923	8376	20.99	40515	49027	21.01
4	fish	2259	2726	20.70	107885	130220	20.70
5	lamb	821	995	21.22	66951	81188	21.26
6	legumes	1389	1676	20.63	4174	5035	20.63
7	pork	8899	10745	20.75	166016	200458	20.75
8	poultry	9244	11156	20.68	95543	115312	20.69
9	tofu	710	856	20.54	2770	3339	20.55
10	veal	181	220	21.76	11995	14605	21.76
11	outside good	288948	277481	-3.97	1881854	1807176	-3.97
12	Total	343927	343927	0.00	3899206	4247591	8.93

Note:

This table shows a free trade counterfactual in which the tariff is subtracted from the price of imported products. The 'before' column refers to the status quo, the 'after' column to the counterfactual values.

Table 15: Free Trade No Tariffs Counterfactual

	Type	Quantity in 1000 kg			Emissions in 1000 tCO2e		
		before	after	change in %	before	after	change in %
1	beef	5056	6301	24.61	577927	725565	25.55
2	cheese	19499	23568	20.87	943576	1140528	20.87
3	eggs	6923	8378	21.02	40515	49044	21.05
4	fish	2259	2727	20.75	107885	130255	20.74
5	lamb	821	1123	36.77	66951	93078	39.02
6	legumes	1389	1676	20.61	4174	5034	20.60
7	pork	8899	10745	20.75	166016	200463	20.75
8	poultry	9244	11163	20.75	95543	115439	20.82
9	tofu	710	856	20.54	2770	3339	20.55
10	veal	181	219	20.80	11995	14490	20.80
11	outside good	288948	277174	-4.07	1881854	1805173	-4.07
12	Total	343927	343927	0.00	3899206	4282408	9.83

Note:

This table shows a free trade counterfactual in which the MFN ad-valorem equivalent tariff is subtracted from the price of imported products. The 'before' column refers to the status quo, the 'after' column to the counterfactual values.

Table 16: Free Trade No Ad Valorem Equivalent Tariffs Counterfactual

Ecological Efficiency

My results could depend on the production emissions of Home relatively to other countries. I calculate the autarky scenario under the assumption that Home has the highest production emissions and the lowest production emissions for each food type. These scenarios are extreme and provide upper and lower bounds, respectively. There is no single country which has the highest or lowest production emissions for each food type. The ecological production efficiency is diverse and depends not only on production practices, but also on natural endowments of countries.

As expected, Table 17 shows that autarky would yield an increase in emissions of around 8% if Home was the ecologically least efficient producer in all food types.

	Type	Quantity in 1000 kg			Emissions in 1000 tCO2e		
		before	after	change in %	before	after	change in %
1	beef	5056	5535	9.46	1612637	1881550	16.68
2	cheese	19499	21815	11.88	943576	1070062	13.40
3	eggs	6923	6920	-0.05	40515	38635	-4.64
4	fish	2220	1831	-17.52	188614	200163	6.12
5	lamb	802	523	-34.87	74467	51799	-30.44
6	legumes	1389	1313	-5.51	10264	11074	7.90
7	pork	8899	10725	20.52	294776	355545	20.62
8	poultry	9244	10923	18.16	192439	227917	18.44
9	tofu	710	692	-2.47	8494	8223	-3.19
10	veal	181	218	20.76	12306	14863	20.78
11	outside good	289004	283433	-1.93	1882224	1845941	-1.93
12	Total	343927	343927	0.00	5260311	5705773	8.47

Note:

This table shows an autarky counterfactual in which only domestic products can be purchased. This scenario assumes that Home has maximum emissions for all food types concerned. The 'before' column refers to the status quo, the 'after' column to the counterfactual values.

Table 17: Autarky Maximum Emissions Counterfactual

If Home was the most efficient producer, in Table 18 overall emissions would barely change compared to the status quo. Thus, autarky would not lead to profound changes in emissions even for countries with high ecological efficiency.

	Type	Quantity in 1000 kg			Emissions in 1000 tCO2e		
		before	after	change in %	before	after	change in %
1	beef	5056	5535	9.46	539318	531164	-1.51
2	cheese	19499	21815	11.88	600234	655045	9.13
3	eggs	6923	6920	-0.05	31216	27397	-12.24
4	fish	2220	1831	-17.52	79652	49043	-38.43
5	lamb	802	523	-34.87	67794	38314	-43.48
6	legumes	1389	1313	-5.51	3921	3423	-12.71
7	pork	8899	10725	20.52	142719	171990	20.51
8	poultry	9244	10923	18.16	81422	93986	15.43
9	tofu	710	692	-2.47	2069	1956	-5.44
10	veal	181	218	20.76	3507	4169	18.86
11	outside good	289004	283433	-1.93	1882224	1845941	-1.93
12	Total	343927	343927	0.00	3434076	3422428	-0.34

Note:

This table shows an autarky counterfactual in which only domestic products can be purchased. This scenario assumes that Home has minimum emissions for all food types concerned. The 'before' column refers to the status quo, the 'after' column to the counterfactual values.

Table 18: Autarky Minimum Emissions Counterfactual

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 and conclude that a large share of European countries have similar consumption patterns as Home.

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. A naive counterfactual assesses the impact of buying local without specifying a demand model but making ad-hoc assumptions about consumer behavior. This leads to an increase in emissions compared to the status quo. Using the estimates of the model, I find that contrary to popular belief, emissions increase in autarky by 4%. Vegetarianism decreases emissions by around 17%. Consuming no beef products including meat and cheese yields the highest decrease in emissions of around 34%.

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. The current version of the analysis has some limitations. As I have not implemented a supply side yet, my counterfactuals do not fully account for a price change of products that stay in the choice set. Additionally, the analysis could be complemented by a welfare analysis to judge whether the decrease in emissions from refraining from e.g. beef and cheese are welfare improving. A Pigouvian tax would be the standard way to achieve optimal emissions and is also missing in this version. Overall, I find that estimating consumer demand is important for policy decisions. This is the first economic analysis on the effects of food consumption choice 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. I aim at exploring other ways of reducing meat consumption, e.g. through information campaigns or CO2 labels. The second avenue takes on a long-term perspective of food consumption. On a country level, meat consumption correlates with GDP. While increasing meat consumption for the least developed countries might have positive health benefits, the environmental cost suggests that there is a limit to an optimal level of meat consumption. One worry is that with increasing levels of development, meat consumption is going to increase as well and lead to skyrocketing emissions. In future work, I plan to test these hypotheses and provide an optimal level of meat consumption for each country.

Appendix

	Food Type	Imported	Transport Mode	Continents	Quantity	Sales 1	Sales 2	Sales 3	Fidelity Points	Label Organic	Label Local
1	beef	no	internal	1	4561.06	17.60	17.21	33.36	20755.07	66.81	462.28
2	beef	yes	flight	5	80.95	25.33	145.12	135.42	43135.24	0.00	0.00
3	beef	yes	mixed	4	19.25	29.23	513.55	74.55	35186.25	0.00	0.00
4	beef	yes	truck	1	376.63	10.17	103.99	36.78	15783.51	1.12	0.00
5	cheese	no	internal	1	18047.14	5.95	31.98	13.91	3111.65	41.31	283.11
6	cheese	yes	mixed	1	1451.67	5.92	15.65	8.65	9979.41	16.09	3.61
7	eggs	no	internal	1	5725.01	2.54	59.85	7.70	2945.54	104.90	478.80
8	eggs	yes	mixed	1	1197.83	1.91	31.96	7.13	2490.26	6.01	37.32
9	fish	no	internal	1	1545.08	13.92	36.88	39.39	16934.85	47.41	35.37
10	fish	yes	mixed	6	707.88	33.75	442.02	165.92	75555.56	124.05	0.00
11	lamb	no	internal	1	429.22	14.42	10.90	53.44	15353.14	3.92	358.62
12	lamb	yes	flight	2	321.56	27.62	17.93	45.97	21671.20	0.00	0.00
13	lamb	yes	mixed	2	54.98	15.31	486.11	127.84	25522.79	154.58	0.00
14	legumes	no	internal	1	1088.13	3.20	98.75	0.23	1529.55	91.12	4.69
15	legumes	yes	mixed	1	301.02	4.37	5.85	0.32	1922.58	44.18	0.00
16	pork	no	internal	1	8882.28	12.12	17.74	24.73	4962.36	23.25	353.21
17	pork	yes	mixed	1	0.93	0.48	0.00	8.03	5865.81	0.00	0.00
18	pork	yes	truck	1	13.31	9.30	3.33	41.73	12975.99	0.00	6.22
19	poultry	no	internal	1	9044.96	10.37	27.80	40.50	344.35	41.57	338.16
20	poultry	yes	mixed	1	189.34	10.57	97.19	69.91	8508.28	0.00	0.00
21	tofu	no	internal	1	574.69	1.87	40.02	20.53	8844.02	165.56	17.43
22	tofu	yes	mixed	1	134.91	1.64	0.00	15.05	8393.65	205.58	0.00
23	veal	no	internal	1	179.42	2.50	1.33	4.41	3061.55	1.59	65.23
24	veal	yes	mixed	1	1.17	2.91	0.00	6.68	4249.81	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 19: Summary Statistics

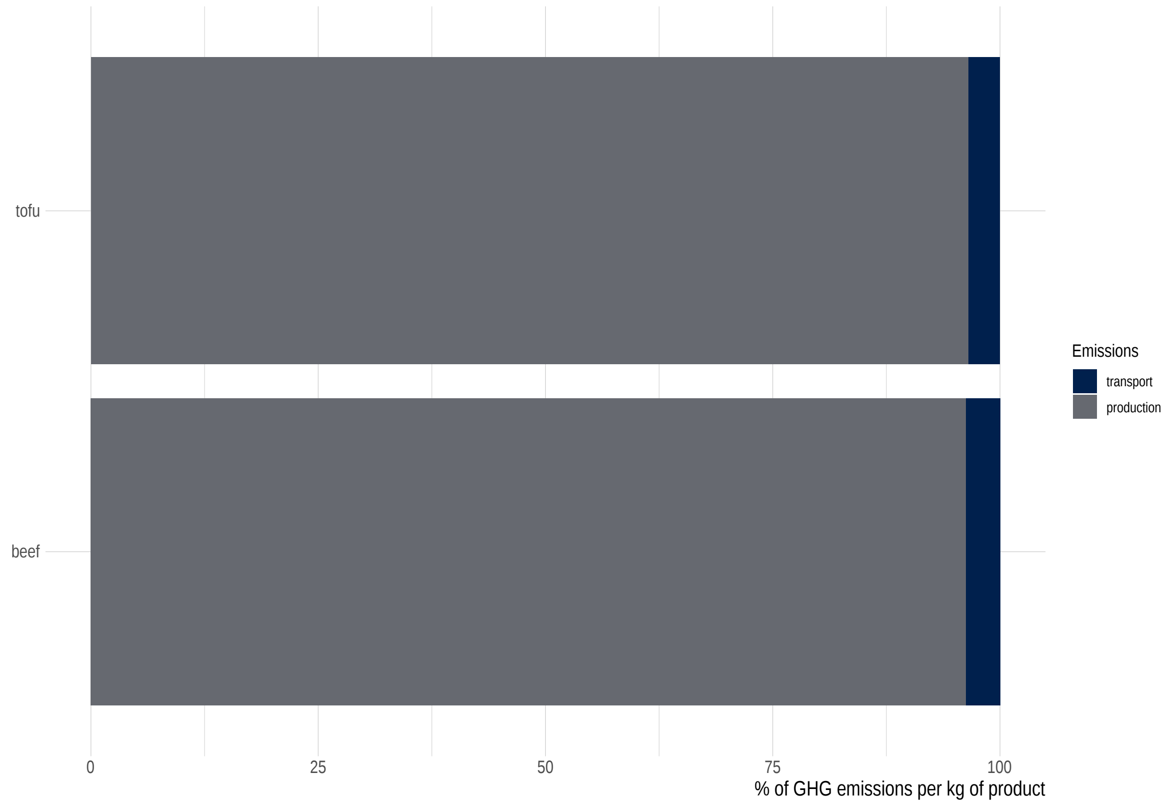


Figure 7: Total GHG Emissions of Imported Beef and Imported Tofu

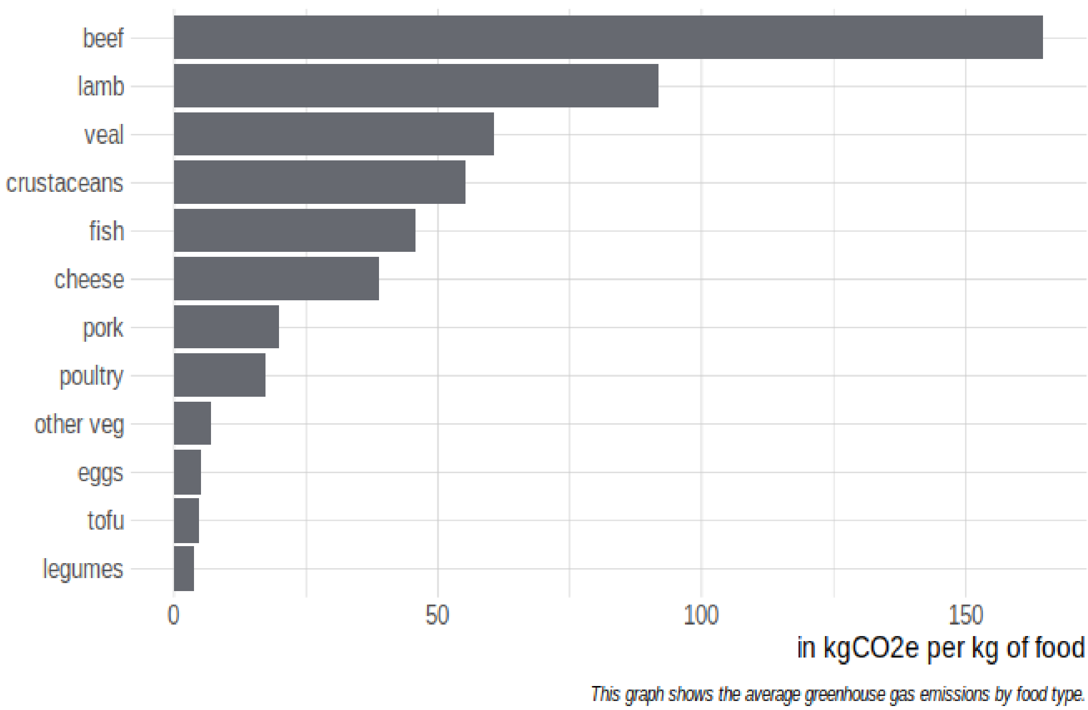


Figure 8: Average GHG Emissions of Different Food Types

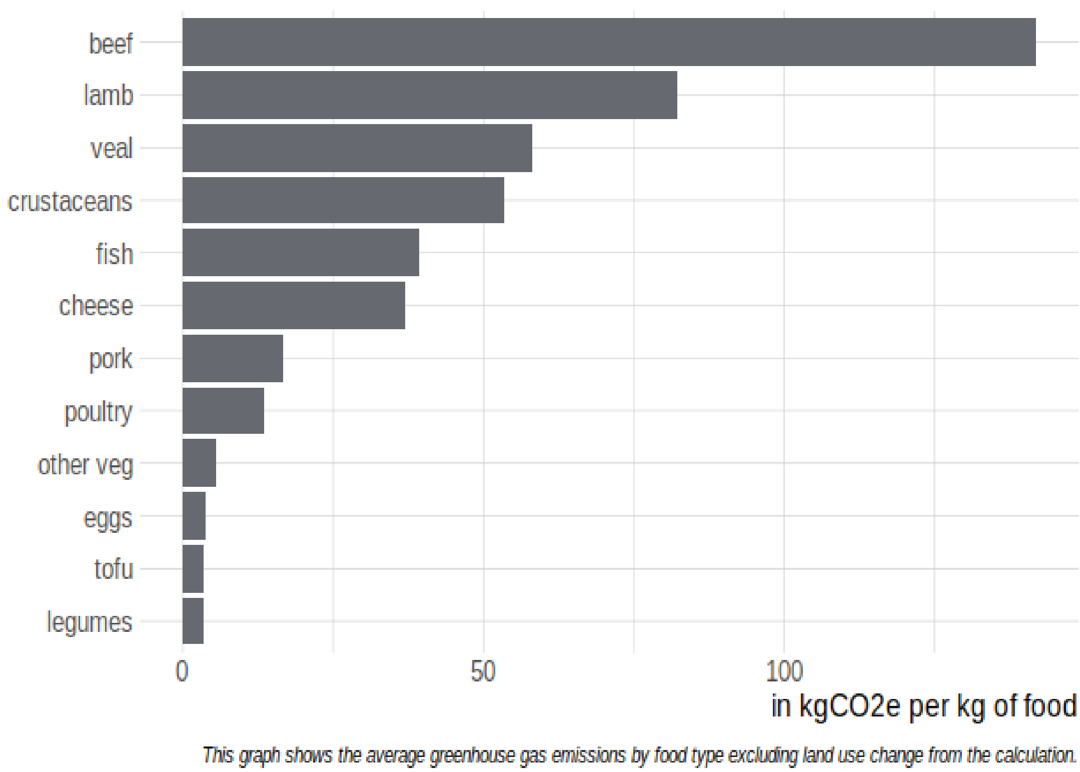


Figure 9: Average GHG Emissions of Different Food Types Excluding Land Use Change

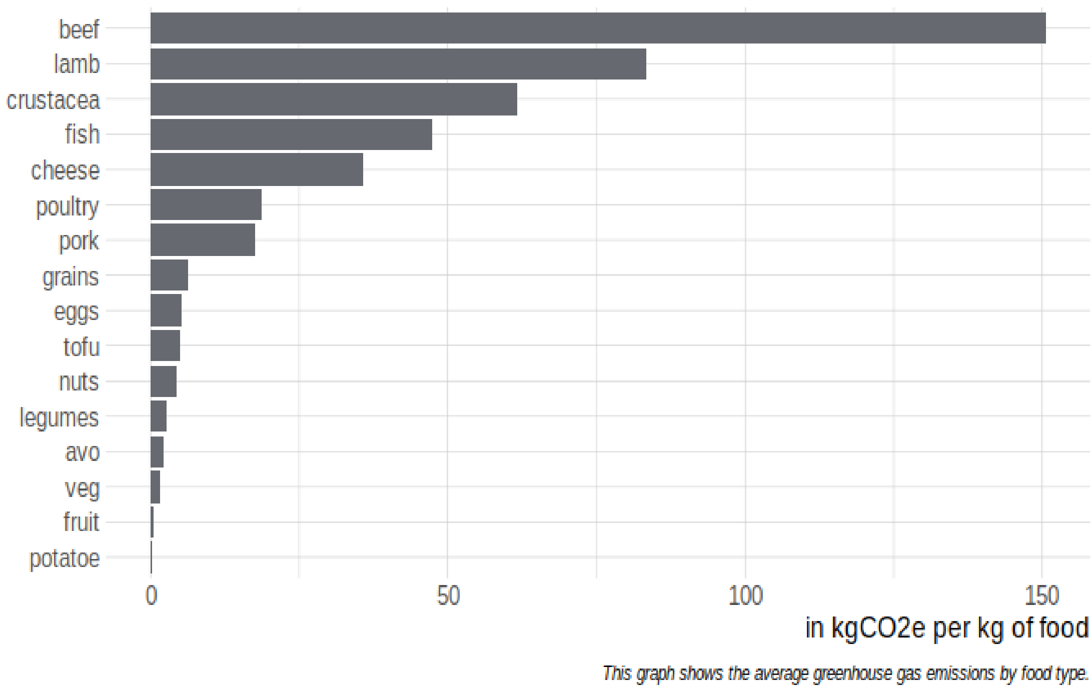


Figure 10: Average GHG Emissions of Different Food Types

Table 20: Nested Logit Regression OLS

	Relative Market Share
	NL
Price	-0.002^{***} (0.0001)
Within Group Market Share	0.960^{***} (0.001)
Sales 1	0.450^{***} (0.033)
Sales 2	0.093^{***} (0.010)
Sales 3	-0.095^{***} (0.010)
Label Organic	0.012 (0.016)
Label Local	-0.043^{***} (0.013)
Chicken Brandname	0.933^{***} (0.131)
European Retailer Brandname	-0.594^{***} (0.086)
Meat Substitute Brandname	-0.175^{***} (0.012)
No Brandname	-0.092^{***} (0.032)
Other Brandname	4.343^{***} (0.689)
Sausage Brandname	0.311^{***} (0.089)
Cheese Brandname	-0.429^{***} (0.061)
Label Fish	-0.563^{***} (0.065)
Observations	40,233
R^2	0.988

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 21: Nested Logit Regression IV with Emissions

	Relative Market Share	
	NL IV	NL IV
	(1)	(2)
Sales 1	2.018***	1.763***
	(0.233)	(0.187)
Sales 2	0.601***	0.118***
	(0.075)	(0.018)
Sales 3	−0.990***	−0.744***
	(0.132)	(0.094)
Label Organic	0.442***	1.789***
	(0.068)	(0.243)
Label Local	−0.380***	−0.625***
	(0.055)	(0.081)
GHG in CO2e		−0.007***
		(0.001)
Imported		−1.006***
		(0.125)
Price	−0.019***	−0.017***
	(0.002)	(0.002)
Within Group Market Share	0.531***	0.664***
	(0.062)	(0.042)
Observations	40,233	39,778
R^2	0.959	0.968

Note: *p<0.1; **p<0.05; ***p<0.01
Includes quarter, year, region, ad 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.

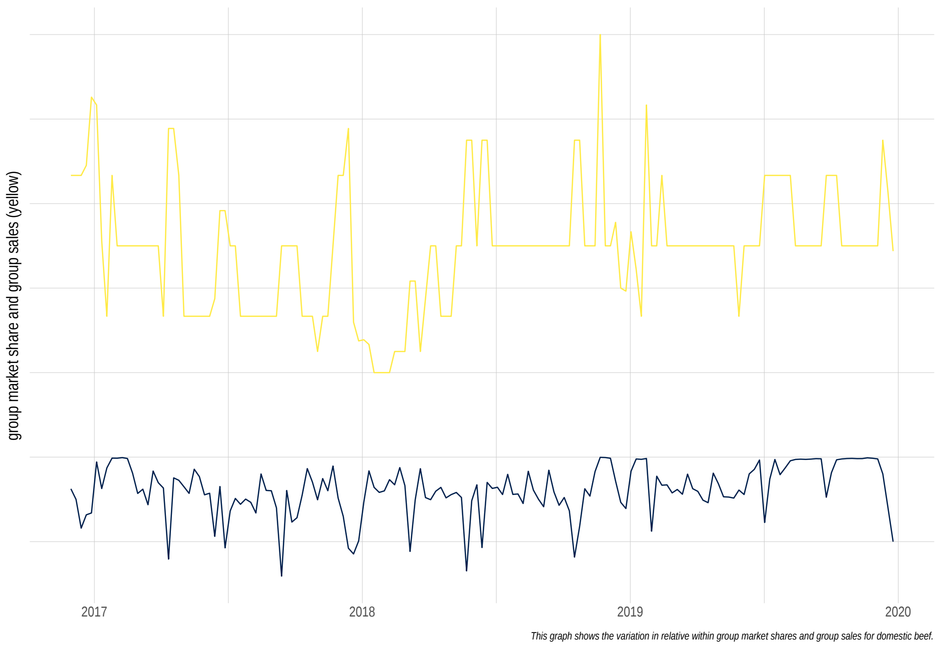


Figure 11: Variation of within group market share

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:

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

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