Title

Mundane Choices with Substantial Impacts: Factors Affecting Demand and Supply in the Animal-based Food Industry

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Mundane Choices with Substantial Impacts: Factors Affecting Demand and Supply in the Animal-based Food Industry

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Economics

by

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2023

TABLE OF CONTENTS

LIST OF FIGURES

Page

LIST OF TABLES

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I would like to acknowledge the Chicago Booth NeilsenIQ because their database forms the foundation of this research project. It is important to note that the researcher's own analyses were calculated based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researcher and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

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VITA

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ABSTRACT OF THE DISSERTATION

Mundane Choices with Substantial Impacts: Factors Affecting Demand and Supply in the Animal-based Food Industry

By

Erin M. Costigliolo

Doctor of Philosophy in Economics

University of California, Irvine, 2023

Associate Professor Jiawei Chen, Chair

Plant-based alternatives have been gaining attention due to their health and environmental benefits, as well as their technological improvements that make the taste, texture, and appearance more similar to animal-based meats and milk. Demand estimates from this study's nested logit model show that people are much more flexible in their milk choice than their meat choice, which is likely due to the fact that milk has a much wider array of applications than meat. The results show that consumers care about the health effects of their choice, but still have a higher willingness to pay for products that best satisfy their taste preferences. With an understanding of which characteristics consumers value in animal-based meats, research and development efforts in the plant-based protein industry can be more focused in trying to develop those attributes. Decreasing the environmental footprint associated with agriculture requires not only adopting plant-based products but also analyzing the marginal costs of the beef industry with more scrutiny. Through a random-coefficient logit model, including supply-side estimation, federal meat crop subsidies incentivize beef production because they are shown to have a small, but negative impact on marginal cost.

Chapter 1

Evolution of plant-based protein adoption into the meat market

1.1 Introduction

In the United States, the possibility of substituting meat with a plant-based alternative would not have seemed feasible before the advent of convincing plant-based meat alternatives. However, new entrants into the meat market, including Beyond Meat, Impossible Foods, and Gardein, have given consumers new options to choose from. The health benefits of plant-based alternatives may be valuable to consumers because attributes like fat and cholesterol are easily visible when consumers are deciding what to purchase. Of people who are already eating plant-based proteins, the majority of them are doing so to be healthier [21]. It seems that consumers are now paying more attention to these issues, but meat is still a central part of diet in many cultures. Now that plant-based products, especially meat, are becoming much more familiar in taste to their traditional counterparts, people could be more likely to switch between them to address their health concerns.

Additional benefits from adopting plant-based meats include the lower environmental impacts associated with their production. In fact, in a cradle-to-grave lifecycle analysis conducted by the Center for Sustainable Systems at the University of Michigan a quarter pound of Beyond Burger is estimated only to generate 0.4kg of carbon-equivalent emissions. In comparison, a traditional beef patty is responsible for 3.7kg of carbon-equivalent emissions. Other environmental benefits of a Beyond Burger compared to an animal-based US beef patty are a 46% decrease in energy use, a 99% lower impact on water scarcity – based on water use that will not be returned to the system, and a 93% less impact on land use [30]. To make animal-based protein, three of the most serious greenhouse gasses (GHGs), carbon dioxide, methane, and nitrous oxide, are emitted [25]. Of the three GHGs, methane has the greatest heating potential, and animal agriculture is its most significant source [25]. Once all the carbon-equivalent emissions are taken into account, animal agriculture is responsible for about 15 percent of the world's anthropogenic emissions [25]. Compared to legumes, beef production emits 250 times more [60], but it is more reasonable to estimate the carbon savings associated with products like Beyond Burger because they are a more suitable substitute. In addition to the carbon-equivalent emissions issue, traditional meat will not be sustainable in the long term, because its production requires 70% of all agricultural land in the globe to produce feed and raise livestock [57]. Plant-based meats do not require feed, so their water and land use footprint is significantly smaller than their animal-based counterparts.

There have been attempts to gauge consumer preferences for plant-based meats through consumer surveys [21], but this is the first paper to estimate demand in the aggregate meat market through a nested logit model. Here the aggregate meat market is modeled with nests to allow for the correlation between products purchased in each group to differ. All products are nested by whether they are plant-based or not. The sample used to conduct this research comes from the Nielsen IQ Consumer Panel, which tracks the purchases of 40,000 to 60,000 households every year from 2004-2020. With the number of purchases for each product by week and DMA code, which are the regions specified in the database, I can estimate the market share captured by each product. The time period of interest is from 2016-2019 because these are the first few years where convincing meat substitutes, like Beyond Meat, were available in the market. The COVID-19 pandemic is not included in order to avoid any confounding factors that may have altered demand for meat. Then the product characteristics of interest are the nutritional composition of each product, as well as their meat type.

Some key findings of this paper are that while plant-based alternatives are growing in popularity, their uptake in grocery stores is still in the nascent stages between 2016 and 2019. Currently, people are not likely to switch between plant-based and animal-based proteins and the fact that a product is plant-based decreases an individual's demand for that meat type. However, the demand estimates, resulting from the nested logit model, demonstrate that consumers care about the health effects of their protein choice, given that their taste preferences are satisfied. Secondly, this study estimates which meat types people are most willing to pay for. Namely, I find that agents have stronger preferences toward beef than poultry, pork, or fish. Understanding which characteristics of animal-based meats are most important to consumers will help focus research and development efforts in the plant-based protein industry; investments in mimicking these aspects of their animal-based counterparts could therefore aid plant-based adoption.

Among other contributions, this study helps flesh out the study of plant-based meats in a budding field. While Van loo et al., (2020) is believed to be one of the first papers that try to gauge consumer preferences for plant-based and lab-grown meats. Through a discrete choice experiment, they found that people had a higher willingness to pay for plant-based and lab-grown meats when they asked participants to choose a product after bringing sustainability issues to their attention [66]. However, agents still preferred animal-based meats according to their random parameter logit models [66]. One of the primary contributions of this paper includes developing a structural nested logit model for demand estimation where animal- and plant-based meats are part of the same market and agents are allowed to switch between nests, rather than rely on consumer surveys or experiments. Literature has shown that plant-based meats have yet to be fully accepted by the consumer [29]. However, this paper uniquely contributes to the field, because nested logit demand estimation allows for the direct comparison of consumer purchasing preferences between the different meat sources.

Another contribution of this study is using nutritional characteristics as well as meat type to estimate demand. It is important because consumer willingness to pay for the nutrients can be inferred from the results. Previously, using the Van loo et al., (2020) own- and cross-price elasticity of demand estimates, Lusk et al., (2022) studies the impact of plant-based meat adoption on traditional ground beef demand. Similar to my findings, they see that a 10% reduction in the price of plant-based meats would only lead to a 0.15% decrease in cattle production [36]. However, they do not use the same approach and do not incorporate the nutritional characteristics of each meat type. In combination with the results of this study, the Lusk et al., (2020) finding is not surprising because it means that consumers have not started using plant-based alternatives as a true substitute for traditional meat.

Lastly, this study provides a compilation of plant-based UPCs from the top ten revenue-generating plant-based protein companies in 2019. The list, which can be found in the Appendix, also includes the products from two other popular brands in 2019 that did not yet make the list as most revenue-generating. Please see the Appendix to see the complete list of UPCs, product names, and their labeled meat type.

Throughout the rest of the article, Section 1.2 describes the relevant literature in the field and outlines how this study contributes to other work already done in the field. Section 1.3 highlights the data used to conduct the analysis. Section 1.4 outlines the empirical model for the nested logit, which is based on foundational demand estimation models in the Industrial Organization field. Section 1.5 reports the nested logit results on each agent's willingness to switch between nests and the effect of various nutrition and meat type characteristics on the agents' choice probabilities. Section 1.6 concludes the study and highlights opportunities for future research.

1.2 Literature Review

1.2.1 Demand for Traditional vs Plant-Based Meats

For the purpose of this study, meat is defined as a major source of protein with the texture of, or mimicking, animal flesh. Therefore, both animal- and plant-protein with the appearance of beef, chicken, pork, and fish will be included in the market of interest, while other sources of protein, like legumes, would be excluded as an outside option. Studying discrete choice is particularly interesting in the market for meat, because of these different possibilities for consumption. There are a variety of dishes, flavor profiles, and nutritional characteristics that may make consumers partial to some meat types over others. Since meat alternatives are relatively new products, their addition to the marketplace will necessarily increase the variety of protein available to consumers. The technology behind plant-based meats has made them very similar to traditional meat in taste, texture, or appearance, so consumers are less likely to avoid these alternatives for those reasons. The model, described below, treats traditional meat and their plant-based alternatives as substitutes because their taste, texture, and appearance are similar. By treating these goods as substitutes, it is possible to determine how different health attributes and lack of cruelty affect aggregate demand. Just as in standard differentiated product demand estimation, this model assumes that people all evaluate products in the same way and therefore the only thing that changes between agents is their willingness to pay for different product characteristics [24]. In the meat market, this assumption is interesting, because all people value taste and their health outcomes, but these values are opposing forces in food products much of the time. For example, an animal-based beef hamburger is high in cholesterol and saturated fats, but is considered to be delicious by a majority of the US population. Therefore, it is understandable that some people will be willing to pay more for taste, even though the overall health of the product will come into question.

1.2.2 New Product Entrance and Discrete Choice

In a related line of research, Hausman (1996) studies the ready-to-eat cereal oligopoly market, where new products are introduced regularly. While most new cereals get discontinued, they are important because new brands accounted for 25 percent of all cereal consumption and significantly added to consumer welfare [28]. This study is especially relevant to estimating demand in the meat market because of the nature of the cereal market. As a commonly consumed food item, the frequency at which buyers make their decisions is quite high. The meat market acts in the same way and can be considered a discrete choice as well. There are limits to considering the meat market a discrete choice because consumers do not necessarily need to be limited to one meat type in the week. Instead, it would be more optimal to estimate demand with food bundles, but that is outside of the scope of this study because it would be too technically complicated.

Similarly to the ready-to-eat cereal market, new goods in the automobile market, like the introduction of the Dodge Caravan minivan, are very beneficial to consumers because they have a larger variety of products to choose from and the quality of such products rises over time [47]. These improvements stem from competition between firms, since they want to benefit from a temporary increase in market share which later leads to lower overall profit for all firms [47]. In the meat industry, a similar effect will likely take place. However, since plant-based proteins are still more expensive than their animal alternatives [21], it is expected that competition between plant-based proteins will first have the effect of lowering prices within their own sector of the meat industry.

1.2.3 BLP Foundations and the Nested Logit Model

A fundamental model needed to study demand and supply in differentiated product markets was developed by Steven Berry, James Levinsohn, and Ariel Pakes (BLP), (1995). They analyzed the US automobile industry to estimate the demand for differentiated goods, with flexible substitution patterns, at an aggregate level. This model was revolutionary because it allowed the researcher to obtain some insight into the consumer decision-making process without having access to micro data, while still accounting for the endogeneity of prices. Endogenizing prices is appropriate because producers can observe product characteristics that are not available to the researcher and factor that knowledge into the price they set for the good [4]. In this model, a nested logit model is used. The Berry et al., (1995) characterization of consumer utility will also be employed in this model because it accounts for both individual and product characteristics, which allows for a more intuitive grasp of what makes a consumer happy to make a purchase.

A nested logit approach makes sense because there are clearly defined groups between which to make a decision. The agent must decide whether they want to have plant- or animal-based meat and then they must decide on their variety of choice. The benefit of a discrete choice structural model is that the economic impacts of a policy can be measured more explicitly [7]. The entrance of plant-based proteins to the aggregate meat market is the factor being measured in terms of its relationship to consumers' willingness-to-pay for product health characteristics like fat and cholesterol. Here, the type of protein that they choose in the plant-based or traditional nests are treated as regressors, because revealing consumer preferences for each meat type is of interest to better understand their taste preferences. A similar example is the decision of whether to purchase an electric vehicle. First, the consumer decides on the "Smart Way" versus "Non-Smart Way" models and then they choose the make and model of their car [51]. Siriwardnea et al., (2012) used the nested logit approach to analyze the effect of marketing on a consumer's decision to buy an electric car. Since there are many car models, it can be used as an example for this model. The corresponding make and models here would be meat type.

1.3 Data

Estimating the demand for meat is achievable, because of the Nielsen Data sets from The University of Chicago Booth School of Business.[1] The author has obtained access to both the Consumer Panel data set and the Retail Scanner data set, even though the Retail Scanner data set was not employed in the end. Since the data are so expansive, it is difficult to work with them without the proper tools. The Consumer Panel data set has information on 40,000 to 60,000 participating households weekly grocery store purchases from 2004 to 2020. The number of households included varies by year. Characteristics of the head of the household, such as age, income, education, and ethnicity are included in the data but are not included in this study due to homogeneous agent assumptions. These data include store zip code, price, and quantity of each product, as well as the total amount spent on the shopping trip and any discounts available for the goods purchased. Therefore, the necessary TSV files are exceptionally large and difficult to manage. To solve this issue, an account has been set up in the UCI Library's Campus Research Storage Pool (CRSP). Consequently, the nested logit results will depict demand in the meat market from 2016 to 2019.

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

The organization of the Consumer Panel is efficient, but not intuitive. It provides information on consumer purchases of meat and plant-based alternatives, as well as gives some indication of what kind of consumer will be more willing to try plant-based proteins and incorporate some into their diet. When household characteristics are incorporated into the model, this information will give insight into where a transition to plant protein is coming from. Within the massive data set, there are four main sections divided by year. They are the Purchases, Trips, Panelists, and Retailers files. In this paper, demand estimation is approached from the demand side, which made the Retailers file unnecessary. Future research on this topic could incorporate Panelists files to understand which agent characteristics lead to greater adoption of plant-based meats. For the current version, information on specific departments and the universal product codes (UPCs) of plant-based proteins are essential. The Purchases and Trips files can be joined on UPC, while the Panelist file can then be joined by household ID from the Trips file if appropriate. With this combination of files, it is then relatively easy to filter data by the UPC, given that the computer's RAM can handle loading each subset of data into Python's pandas. Lastly, to find specific departments, the Products File, which can be found in the Master Files of the overall Consumer Panel, is extremely useful.

Unfortunately, Nielsen does not clearly categorize products by animal- or plant- sources. This paper contributes to the field by creating a comprehensive list of plant-based meat alternatives that are available in the Consumer Panel data set. To do this, the top ten plant-based companies, determined by total revenue measured by The Good Food Institute's 2019 U.S. State of the Industry Report for Plant-based Meat, Eggs and Dairy, are used to determine the sample space for the market of plant-based alternatives for meat or meat-centered prepared foods. It is important to note that there are various vegan companies that are too small to be in commonly shopped-in stores, so it does not make sense to include such products. Then, Impossible Foods and Alpha were also included, because they are growing companies that will most likely be at the top of the industry soon, even though their sales were not at the level of the other top ten firms in 2019. Using these companies, the data set for plant-based products was created by listing all of the products made by these companies that have a meat-alternative component. For example, there are some prepared meals produced that are simply made from vegetables or tofu and are not reminiscent of meat and were therefore not included. Once the list of all products was compiled, all the UPC codes were found by hand, meaning that each code had to be looked up individually. As one can imagine, the animal-based meat data was much easier to locate. It was simply a matter of choosing the appropriate grocery departments in the Products file. From there, the plant-based meat UPCs were filtered out, because they were mixed into the animal-based meat departments. Lastly, the final data, which were the purchases of these products across all years, were found by filtering the purchases by the animal-based and plant-based meat UPCs.

A separate data set, put together by the USDA, was also vital to conducting this study. The FoodData Central database has nutritional characteristics for thousands of food products at the UPC level. It was possible to join the data set to the information obtained through Nielsen. This data set was essential in providing valuable information on non-price product characteristics.

1.4 Empirical Model

This nested logit model will solely explore the demand side of the meat market because there is no accessible information on the costs that the various firms in the meat industry face. As a result, the functional forms of marginal costs are not known. Assuming a marginal cost function would not make sense, because the model would be misspecified if incorrect. The PyBLP program is prepared for this issue and can still compute the GMM estimator by only using demand moments [10].

In the context of this empirical model, meat is defined as a commonly consumed good with many types and brands. Since most people consume some sort of protein more than once a week, it is easy to imagine that when one goes to the grocery store they have to make both a decision of what type of protein to get as well as how much of each type. Meats are perishable and commonly consumed foods, so agents are expected to make decisions on their meat type and quantity very often. The frequency of the purchasing decisions gives agents a lot of freedom between meals, which may make the case of a continuous choice model seem appealing. An example to support this point of view is that agents could easily have animal-based beef for one meal and plant-based poultry at another. As mentioned above, estimating demand with food bundles could lead to less biased results, because it would better actually model a consumer's choice if they want more than one meat type per week. However, purchasing meat should still be considered a discrete choice rather than a continuous choice, because people are still limited by the distinct meat types and the discrete packages that their purchase comes in. Hausman, (1996) provides the perfect example of a market where purchases are made very often with highly differentiated products in the ready-to-eat cereal market. It is reasonable to make the assumption that if the purchases are looked at in a small enough time frame, the discrete choice model makes sense. To account for that, in this study, products are chosen and aggregated on at the weekly level.

Meat types can have many attributes in common, but differ in some key ways that agents may have strong preferences for, namely taste and texture, so they should not be considered perfect substitutes. However, in a large part of discrete choice literature, goods are treated as perfect substitutes to simplify the problem, which allows consumers to choose only one product per period [13]. To avoid that restriction, the model will treat proteins as substitute goods rather than perfect substitutes. This minor point allows consumers to have variety in their protein choices, instead of simply choosing one meat in all time periods. Another important aspect of this study is to see whether agents are likely to switch between plant-based and animal-based proteins across different weeks. The likelihood of switching between plant-based and traditional nests will be based on the estimates of the correlation within each nest.

Within the nested logit model, which this paper follows, a distinction can be made between products in different groups. As in Hausman, (1996), products within the same group, like children's cereal, are going to have the greatest substitutability. Here, correlation between products purchased within a group can be used to determine how likely agents are to substitute between goods. The correlation can be measured using, ρ, which lies between 0 and 1. When ρ is 0 there is no correlation within a group, which makes the model the same as a standard logit model [26]. If this were the case in the aggregate meat market, where the nests are plant-based and animal-based proteins, then there would be a great degree of movement between nests, and people who bought an animal-based good one week would not necessarily choose another animal-based protein in the next week. On the other hand, when ρ gets to 1, that means that the goods within the group are closer to perfect substitutes [26]. If ρ is exactly one, then agents would never leave their group [10]. In this case, we would expect ρ to be relatively high between plant-based and animal-based meats, because most Americans are still not very familiar with plant-based alternatives even though they are growing in popularity. The lack of exposure to plant-based meats makes them a relatively foreign alternative that many may not be willing to try, or may be unaware that it is an option for them.

Before getting an estimate for demand, this model defines the utility function very similarly to the model formulated by Berry et al. (1995) and specifies it to apply to the meat industry. Here, agent utility depends on both individual characteristics such as age, education, and income, as well as the product's characteristics. In this case, the product characteristics will be price, protein, fat, and whether it is beef or not. Other product characteristics, including animal treatment, taste, and cultural importance may be difficult to quantify or totally unobservable to the researcher. As a result, an agent's utility function can be characterized by (1), because it can capture the observable and unobservable product characteristics that would factor into the agent's utility.

$$U(p_j, x_j, \xi_j; \theta) = x_j \beta^{ex} + \alpha p_j + \xi_j + \epsilon_j \tag{1.1}$$

Following the BLP model, p_j is the price of each good, indexed by j, while x_j and ξ_j are vectors of the observable and unobservable characteristics of each product, respectively. While the original BLP model had a vector, ζ_i, that represented all individual characteristics of interest for agent i, this model does not include that specification, because individual characteristics are beyond the scope of this paper. Instead, the model assumes homogeneous agents, but it would be interesting to see how demand for different proteins varies by household factors, like income or education level. Lastly, θ is a vector of the parameters that need to be estimated. To estimate total market demand, an outside option must be available to normalize the distribution of the unobserved error term, ϵ_j [4]. With this term normalized to zero, the model for aggregate demand of meat can be a function of their prices and characteristics [4]. Since people need to include protein in their diets, the outside option should still be a protein. However, the proteins considered to be outside options will be those that are plant-based and do not try to mimic the taste or texture of traditional meats. These proteins include beans, nuts, and any other type of legume that has a high protein content. Similarly to the approach taken in Berry et al., (1995), to estimate the market share of the outside option, the number of meat products, where the protein is evidently the aspect of the good, is totaled to some number, J. Then, the total number of households, n, is used on a weekly basis to determine what share of those households purchased meat-tasting protein. The fraction of households that are not observed to have consumed meat in that week will represent the market share of the outside option.

As mentioned before, estimating the vast number of parameters necessary in the large meat market is computationally taxing. This paper will use a nested logit model to generate the parameters with the PyBLP python package, which can be used to obtain the final demand estimates. With (2), the model allows for substitution patterns to change depending on the nest that each product is in. The level of substitutability is captured by the term ρ, as explained above.

$$U(p_j, x_j, \xi_j; \theta) = \alpha p_{jt} + x_{jt}\beta^{ex} + \xi_{jt} + \bar{\epsilon}_{h(j)t} + (1-\rho)\bar{\epsilon}_{jt} \tag{1.2}$$

To apply this discrete model, it is assumed that the error term $\epsilon_{jt} = \bar{\epsilon}_{h(j)t} + (1-\rho)\bar{\epsilon}_{jt}$ are IID and have the Type I Extreme Value Distribution [10]. Even though there are differences in the utility each person may receive from a product, it is still possible to compute the mean utility associated with each good, as depicted in (3). With the mean utilities of each good, it is possible to allow for the homogeneous agent assumption.

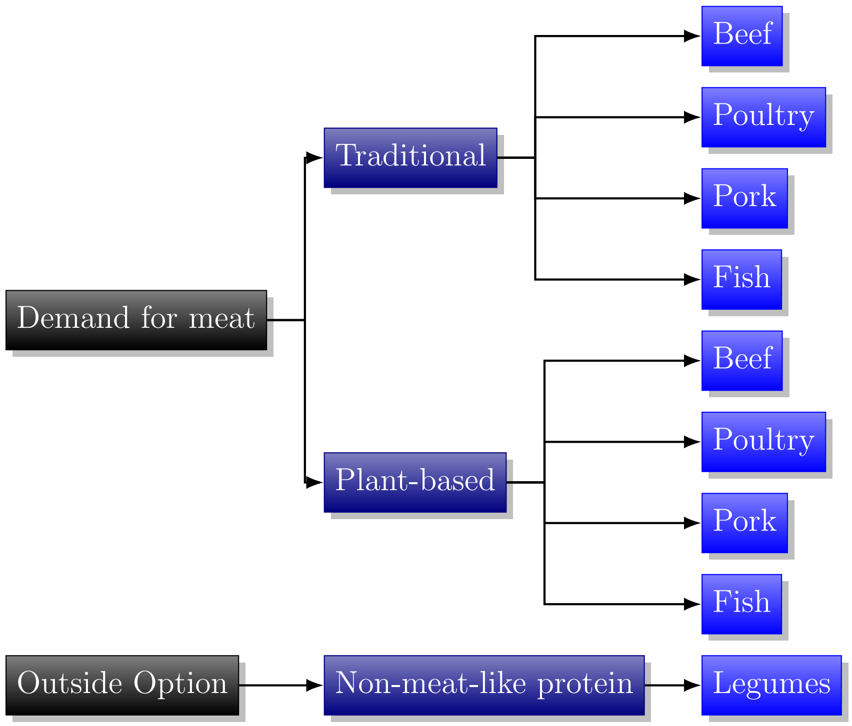
$$\delta_j = x_j\overline{\beta} - \alpha p_j + \xi_j \tag{1.3}$$

Just as the aggregate demand of the ready-to-eat cereal industry can be broken into three levels, where products are then broken up into adult, child and family cereal segments [28], the meat industry can also be broken up. Figure 1 demonstrates that the most logical way to segment demand for meat would be to have the aggregate demand for meat at the highest level, followed by the decision of whether to consume traditional meat or plant-based protein, and the last decision lies in which type of protein to consume. Therefore, the bottom segments will be organized by protein type in the broader animal- or plant-based protein category. While there are more protein types than the ones listed in the figure, the model has been restricted to only those meats for which there are viable plant-based alternatives that are widely consumed. Individuals may decide to change their main protein source for a variety of reasons, including taste, cholesterol levels, or other nutritional considerations. In fact, one may want to substantially lower their cholesterol and saturated fat intake while still getting their meat from animal sources. In that case, traditional fish may be a suitable substitute for beef, since beef has high levels of both. This scenario is very likely and will be considered in the model. It is still reasonable to track changing demand within the traditional meat category due to the entrance of plant-based proteins. The model should help identify how the presence of a plant-based alternative affects the demand for each meat type as well as the aggregate demand for traditional meat.

The Nielsen database makes identifying products by meat type difficult because there is no good way of knowing the category of each product. As was discussed above, the files in the Consumer Panel data can be organized at the UPC level. All data on prices and quantities are associated with a specific UPC along with other characteristics like product description, variety description, UPC description, etc., which can be found in the Products file of the Consumer Panel. While those descriptions are useful for finding very specific information, such as the name of the product in the UPC description column, they are all strings and do not have a uniform indicator of meat type. As a result, a contribution of this paper to the current body of literature is adding Boolean columns identifying whether or not each product was in the meat type of interest. This solution is interesting because it allows for products to have multiple meat types like beef and pork sausages, which would have a 1 indicator on both the beef and pork columns. These points were dropped from the data set, to maintain products that fit into strictly one category.

It is possible that agents first choose which type of meat they want and then decide to consume an animal- or plant-based option, because a noteworthy part of the demand for meat alternatives comes from omnivores or flexitarians, who still eat some animal-based meats [21]. While the current segment divisions seem to reflect the most likely thought

Figure 1.1: Nests in Aggregate Meat Market and Breakdown of Meat Types



process, this paper will also test the alternative solution for completeness in the future. To run the nested logit model, market shares must be accounted for. As demonstrated in [5], the well-known formula for obtaining market share with aggregate data is:

$$s_{jtg}(\delta, \rho) = \frac{[e^{\delta_j/(1-\rho)}]}{\sum\limits_{j \in G_g} e^{\delta_j/(1-\rho)}} \tag{1.4}$$

From (4), we see that the market share of product j, in market t, depends on their group g, the mean utility δ, and the measure of group substitutability ρ. This goes back to the nested logit model assumption that there are different substitution patterns between nests, which is captured by ρ. Then the probability of choosing a product from a specific group, g, is:

$$s_g(\delta, \rho) = \frac{\sum\limits_{j \in G_g} (e^{\delta_j/(1-\rho)})^{(1-\rho)}}{\sum\limits_{g} (\sum\limits_{j \in G_g} e^{(\delta_j/1-\rho})^{(1-\rho)}} \tag{1.5}$$

To get the total market share from there, the market shares in each group times the probability of being in each group need to be multiplied. The resulting expression is:

$$s_{jt}(\delta,\rho) = s_g(\delta,\rho)s_{jtg}(\delta,\rho) = \frac{e^{\delta_j/(1-\rho)}}{(\sum\limits_{j\in G_g})^{\rho}(\sum\limits_{j\in G_g} e^{\delta_j/(1-\rho)})^{(1-\rho)}} \tag{1.6}$$

The last thing to consider when calculating market shares is how the outside option would fit in with the market. Since the mean utility is normalized to zero, the resulting expression for its market share is:

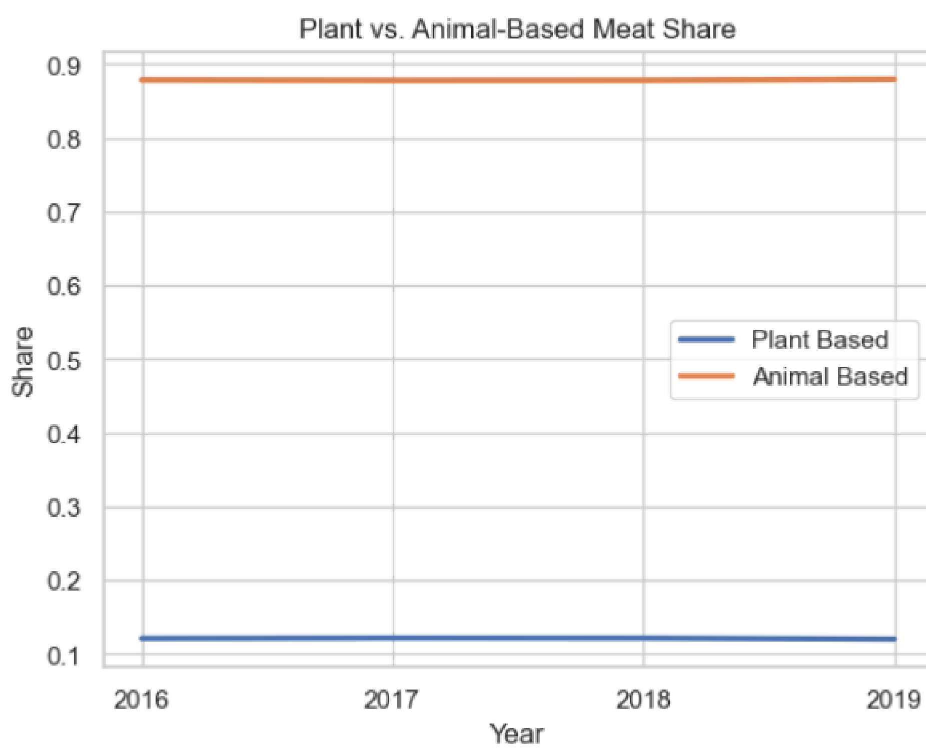
$$s_{0t}(\delta,\rho) = \frac{1}{\sum\limits_{g}(\sum\limits_{j\in G_g} e^{\delta_j/(1-\rho)})^{(1-\rho)}} \tag{1.7}$$

With these aggregate market shares, it is then possible to get the linear estimating equation in (8). Since δ_j is the mean utility attributed to purchasing product j and it is linear, we can use the linear IV GMM estimator to estimate this model.

$$ln(s_{jt}) - ln(s_{0t}) = \alpha p_{jt} + x_{jt}\beta^{ex} + \rho ln s_{jgt} + \xi_{jt} \tag{1.8}$$

In this paper, shares were calculated directly and then used in the estimation process. Since all the products purchased in the sample are recorded, the quantities of each product purchased were added and then divided by the quantity of all products purchased in the year. As a result, there are measures of market share for every UPC. With these calculations, it is easy to see that while the plant-based sector is growing in market share over the years, it is still an almost negligible part of the meat industry as a whole. Figure (1.2) illustrates the market shares of all plant-based and animal-based products. By looking at the scale of the shares on the y-axis, the difference in overall market share in each section is huge. This difference makes sense because there are many households in the US that have not heard of plant-based meats, let alone have bought them to prepare at home. There seems to be a significant uptick in the proportion of the total market share that is plant-based between 2019 and 2020. However, 2020 data are not included in the analysis to avoid picking up the effects of the COVID-19 pandemic on plant-based meat adoption. Future papers should examine the demand for plant-based meats before and after the COVID-19 shock to determine whether the increased adoption persists after the effects of the pandemic fade.

Figure 1.2: Animal-based vs Plant-based Products Market Share



Since price is endogenous to our demand estimation from (8), demand instruments must be used to obtain final estimates for demand. In this paper, a variety of nutrient characteristics is used as regressors, because they will directly affect the agent's purchasing choice. In Berry et al., (1995), the demand instruments were the characteristics themselves, the sum of characteristics of other goods within the same brand, and the sum of characteristics of goods from other brands, as demonstrated in (9).

$$z_{jk}, \sum_{r \neq j, r \in F_f} z_{rk}, \sum_{r \neq j, r \notin F_f} z_{rk} \tag{1.9}$$

Demand instruments are necessary because the unobserved demand-side characteristics (ξ_j) are expected to be correlated with price, which would cause an endogeneity issue [48]. However, in this model, these demand instruments do not work, because the number of products available is so large that they become too weak. This can happen when there is a weak correlation between the residual function and instruments that are away from the true parameter value [23]. Consequently, the local difference instruments, developed in Gandhi and Houde, (2019), are used, as seen in (10).

$$A_j(x_t) = \{x_{jt}, \sum_{j'} 1(|d^1_{jtj'} < sd_1), ..., \sum_{j'} 1(|d^1_{jtj'} < sd_K)\} \tag{1.10}$$

With instrumental variables, the price effects can be captured without actually using price. As a result, the nested logit model can be run with these instruments to prevent price from being correlated with the unobserved demand-side characteristics.

Given that the appropriate demand instruments have been selected, they now have to be calculated by choosing specific characteristics of interest. Here, the characteristics of interest are those that may be important to consumers as they make their purchases. When choosing which meats to buy, an agent may be concerned about the total fat and protein content of the product, as well as its size. Using the USDA nutrition data set, all characteristics of interest were joined to the Nielsen data set on UPC.

1.5 Nested Logit Results and Interpretation

To find the demand estimates with nested logit, prices, market IDs, product IDs, shares, nutritional characteristics, and the local demand instruments had to be included. Demand estimates are found from 2016 to 2019 because the overall market share of plant-based meats did not change significantly and consumer preferences for plant-based meats are unlikely to have changed. Instead, it is more interesting to use these years as a baseline estimate for demand in the meat market. That way, these results can be used as a benchmark to see how a consumer's willingness-to-pay for plant-based proteins grows in the future. The ρ estimate will represent how likely people are to switch nests, namely whether agents currently buying animal-based protein are going to try buying the plant-based alternatives. The final formulation for the linear demand model used while running PyBLP is:

$$Pyblp.Formulation(0 + prices + protein + fat + totalOunces + beef) \tag{1.11}$$

Below, in Tables (1) and (2) are the results from the 2016-2019 nested logit model, based on weekly aggregations of market shares from the purchases in that week. From Table (1), the correlation within the animal-based and plant-based nests is indicated to be 0.75, which means that some consumers are switching between nests, but not most. This result makes sense because most households that eat animal-based meats have not tried buying the plant-based alternatives at grocery stores yet. As previously stated, most Americans have still not gotten enough exposure to plant-based proteins to be willing to try them. In fact, plant-based protein adoption in grocery store data will most likely be seen after its adoption in other food markets such as restaurants. The reason for this distinction is that people may be more willing to try the new products at restaurants for the first time because they can avoid other barriers like learning how to cook them. One of the upcoming major players in the plant-based protein market, Impossible Foods, decided to focus its entry approach through restaurants, celebrity endorsements, and social media [8].

In future papers, it may be interesting to take an in-depth look at the difference between the marketing strategies of Beyond Meat and Impossible Foods, because Beyond took the alternative approach of beginning in grocery stores [8]. One piece of insight that can already be obtained from recognizing the different strategies is that the data set for this study has a much larger market share for Beyond Meat than Impossible Foods even though they started their companies around the same time.

Based on the beta coefficients for each variable and their robust SE, it is evident that all estimates are statistically significant, even though the magnitude of some seem small. The significance of every variable can be seen by their t-statistic because they are all greater than 1.96 in magnitude. The effect on demand estimates for protein, which is a positive health characteristic, is positive. Then the coefficient for fat goes against the assumption that people want to avoid unhealthy food items since it also has a positive coefficient. However, this is due to the fact that fat adds a lot of flavor to protein products across all meat types, including plant-based meat types. Therefore, consumers still purchase meat products that are high in fat due to the taste benefits.

The coefficients for the various meat types are another important element of these results. As previously stated, each meat type is identified through a column of Boolean markers for each meat type. These markers were made by manually going through the UPC descriptions from the Products file in the Consumer Panel and identifying what meat type the highly abbreviated strings were referring to. Based on the meat type results, it is evident that beef is a sought-after meat type. The fact that beef has a relatively high willingness-to-pay is concerning from a sustainability point-of-view, because it is a ruminant meat, which is the most highly polluting meat type [60]. From a food policy perspective, it will be very valuable to invest in the research and development of plant-based meats, because they should be able to satisfy people's taste preferences in the future with a much lower environmental footprint, as the life-cycle assessment of a Beyond burger versus a traditional burger demonstrates [30].

Table 1.1: Correlation within nests 2016-2019

Rho	Robust SE	t-statistic
0.75	0.0038	197.4*

Table 1.2: Demand Estimates for 2016-2019

Variables	Betas	Robust SE	t-statistic
prices	-0.078	0.012	-6.5*
protein	0.0038	0.00042	9.05*
fat	0.00084	0.00029	2.9*
total ounces	-0.0095	0.0016	5.9*
beef	0.079	0.012	6.6*

Another food policy implication that can be taken from this paper is that consumers generally want to purchase products that are healthy as long as their taste preferences are met. With that in mind, people would benefit from more in-depth knowledge about the benefits of various foods. To do this, the US government could put greater emphasis on giving people information on how much protein they truly need in a day and how they can achieve that through plant- and animal-based sources as suggested by Lonnie and Johnstone, (2020) for the UK. The fact that being a plant-based protein currently contributes to low demand is a problem because the UN sustainable food guidelines indicate that people should only be consuming moderate levels of animal-based meats and dairies [35] and the current rate of their consumption is too high to be sustainable in the long run. Investing in further research, development, and outreach of plant-based proteins will be a key component of promoting more sustainable diets in the long term because people will not want to switch to healthier and more environmentally conscious alternatives without maintaining tastes, textures, and dishes that they are accustomed to.

1.6 Conclusions and Future Research

The ultimate goal of this project is to gain insight into the growth of plant-based meat alternatives in the market share of protein because an increasing market share for plant-based meats would mean a decrease in traditional meat consumption. Since the production and consumption of animal-based meat leads to externalities, including the release of carbon-equivalent emissions, and excess water and land use, information on the best ways to reduce traditional meat consumption would be of primary interest to policymakers. Estimating demand in this differentiated good industry helps illuminate how consumer preferences may not yet be changing toward healthier and more sustainable foods. With the introduction of more plant-based alternatives, consumers might become more exposed to plant-based proteins. The growing popularity of these goods may make agents more aware of the environmental and health impacts of their diets. As a result, there may also be a transition away from more resource-intensive foods like traditional beef, to other animal-based proteins that have less of an impact on the environment. If the introduction of these more meat-like substitutes reduces demand for all traditional meat options, like beef, pork, and chicken there will be more noticeable positive effects on anthropogenic greenhouse gas emissions, and water and land use. The ultimate role of this paper will be to explore how demand in the industry may change over time. While the industry seems to be relatively stagnant at this time, it should continue to be monitored. Current practices in traditional meat consumption will not be sustainable in the long run, so other solutions must be sought.

Some counterfactuals that would be interesting to analyze are those that would increase the price of traditional meat. For example, since there are huge externalities associated with animal agriculture, if a tax were imposed on animal-based proteins that made producers and consumers face externality costs including carbon-equivalent emissions, excess water and land use, and increased healthcare costs it may be expected that the demand for animal-based protein would decrease. In this case, one might expect that there will be a much larger investment into plant-based meats. Perhaps the companies currently in control of the meat industry would put more resources toward not only the development of these new products but also a marketing campaign to inform and convince consumers of the benefits these meat alternatives have over traditional meat. Alternatively, a counterfactual where subsidies on animal-based meats are removed should also be analyzed.

Meat alternatives are an exciting and new technology in the food sector, so studying their market share growth and effect on animal agriculture is extremely interesting even at this small market share. In later iterations and extensions on this study some subsequent questions to address would be, “How will the market share of meat-like plant-based proteins grow?” and “Will their rate of growth in market share mainly be driven by smaller start-up companies, like Beyond Meat and Impossible Foods, or huge meat corporations that add a new vegan product?” However, understanding that the demand for plant-based proteins has not yet truly taken off in the meat industry is essential, because it can help guide new policies that may ease their adoption in the future.

Chapter 2

A Flexible Choice: Demand in the highly developed plant-based milk market

2.1 Introduction

Plant-based milk alternatives have greatly risen in popularity in recent years. In fact, they are the most commonly adopted plant-based product currently available, when compared against cheese and meat alternatives [69]. Demand in the milk industry depends on the consumer's milk-base choice, which can be affected by their taste preferences or their environmental and health concerns. Cow's milk has been part of the American psyche for many decades. The USDA still includes cow's dairy, albeit now encouraging low-fat options for most or fortified soy milk for those who want dairy alternatives, in its dietary guidelines for Americans because it is an easily accessible source of calcium, vitamin A, and vitamin D [62]. However, other sources can easily provide the same nutritional benefits without the negative environmental effects of cow's milk that the consumer may not be internalizing [20]. To avoid these environmental externalities, households should have a suitable substitute, because milk and dairy are a central part of the American diet. Plant-based milks seem to be a reasonable substitute in terms of taste and use. While their differences have been studied through surveys [27], there has not been any work done to estimate demand in the aggregate milk market through a nested-logit analysis.

This study estimates how likely consumers are to switch between animal-based and plant-based milk products. Similarly to the first chapter, the aggregate milk market is modeled with nests to allow for the correlation between animal-based and plant-based products purchased in each group to differ. This chapter of the study also uses the Nielsen IQ Consumer Panel database to build the weekly markets used in demand estimation. In addition, the model provides insight into which milk types people prefer the most by estimating how various product characteristics affect an agent's willingness to pay. Lastly, incorporating environmental impact data is important, because there are many other alternatives to cow's milk that people can use if they are concerned about the water use and carbon equivalent emission associated with their product choice. The time period of interest is from 2016-2020, because plant-based milks have a much more established market and the pandemic shock did not seem to have a significant effect on the trend of their market share growth. Then the product characteristics of interest are the nutritional composition of each product, as well as their milk types, and environmental impact by milk type.

The primary finding of this study is that agents freely switch between animal-based and plant-based milk nests, which is much different from what I found in the aggregate meat market. These results make sense because plant-based milk is a more mature market, there are various uses for the different milk types, and there are many common animal-based milk allergies. Another interesting result from this study is that water use required in each milk type production influences demand more than the associated carbon equivalent emissions.

One reason for this may be that water is a more tangible and publicized issue in the milk market.

This is not the only study to question the infallibility of cow's milk. In previous studies, many have pointed out the environmental drawback of relying on cow's milk as society's main source of dairy. This study contributes to the literature by analyzing the correlation within plant-based and animal-based milk nests. Since consumers seem to freely switch between plant-based and animal-based nests, the next step would be to understand what may dissuade people from consuming animal-based milk, which is more resource-intensive. We already see that plant-based milk companies tend to frame their products in a positive light while highlighting the negative environmental effects of cow's milk [9]. In fact, Clay et al., (2022) explores the political thought around plant-based milks and claim that companies are encouraging people to think about the environment when purchasing their product as a way to further promote market solutions to societal problems. In reality, there are substantial benefits to consuming plant-based milks instead of cow's milk. For example, soy milk emits significantly fewer kilograms of carbon-equivalent emissions per liter than cow's milk does [49]. As this study demonstrates, market solutions, like purchasing plant-based milks, should not be disregarded, because they can help make sustainable change easier for the consumer. By satisfying the taste preferences and uses of milk, consumer welfare would be less affected than if they had to give up a cherished product completely.

The rest of this chapter also follows a similar format to Chapter 1, Section 2.2 describes the relevant papers in the field and helps outline where this study fits in. Section 2.3 highlights the data used to conduct the analysis. Section 2.4 outlines the empirical model for nested logit, which is also based on the foundational demand estimation models in the Industrial Organization field. Section 2.5 reports the nested logit results on the effect of nutritional and environmental product characteristics on an agent's willingness to pay. Section 2.6 concludes the study and highlights opportunities for future research.

2.2 Literature Review

2.2.1 Substitutability of animal- vs plant-based milk

In regard to public perception, Haas et al, (2019) surveys Austrian consumers to identify cow milk's popular image in comparison to plant-based milks. While cow's milk still has a better overall image across the consumers surveyed, plant-based milk drinkers rated their milk more highly [27]. While this study does not directly address how people rate each milk type, the results indicate that people must be more accepting of plant-based milk than plant-based meat. There is much more research done comparing plant- and animal-based milk demand than what can be found for the aggregate meat market. In fact, through a hedonic pricing model with Barten's synthetic demand system, Yang et al., (2020) estimate demand elasticities for plant-based milk. The results here are interesting, because they look at the linear hedonic distance of seven products, including the difference between soy milk, almond milk, rice milk, and cow's 1%, 2%, fat-free and whole milk [70]. They find that plant-based milks have inelastic demand. It would be interesting to estimate demand elasticities with a nested logit model in future research. The overall trend in milk sales is also important to monitor. From 2013-2017 overall household purchases for cow's milk were decreasing, but the decline was not all due to an increase in plant-based milk because their sales did not rise at the same rate [56]. This result is consistent with the conclusions of this paper, because people may be willing to switch nests, but that does not mean that they are definitely going to substitute one for the other.

2.2.2 Agent learning effect on demand estimation

Consumers can often make purchasing decisions without knowing everything about the particular product. In this study, consumers do not have labels that clearly state the environmental impact of each milk type. As a result, part of their decision depends on an unobservable. From the data available, there is no way to measure whether or not a consumer has the background to understand the ordinal ranking of the carbon equivalent emissions and water use associated with each milk type. Clear labels could help solidify whether an agent cares about the environmental impact of the product. For example, Expedia has recently started labeling whether the carbon emissions of each flight are better or worse than the average [18]. Future studies could set up an experimental design to estimate demand after agents learn about the environmental effects of various products. With more information on an agent's level of familiarity with the environmental impact of their product choice, the study could more directly estimate how the environmental footprint of each product affects the agent's demand.

This study does not estimate demand with agent heterogeneity in environmental impact knowledge. However, consumers would likely change their demand for milk as they learn more about the impact of the product. Other studies have found that agents update their purchasing decisions based on new information. For example, consumers may change their purchasing decision after trying a product for the first time based on whether or not they found it to be a good fit, the total market share of the firm, and the strategic pricing of the competing firm [67]. There are also product uncertainty considerations to deal with when a new plant-based milk brand enters the market. The recipe each firm uses is more likely to change the flavor profile more than cow's milk flavor could potentially change across brands. Price ramifications result from the way consumers learn. For example, product reviews generally give consumers more information about any product of interest, which Papanastasiou and Savva, (2017) describe as social learning. They show that the presence of social learning changes a firm's pricing decision and they are more likely to pre-announce a high price [45]. Since consumer reactions to new information can easily change a firm's strategic pricing and overall demand for various products, it would be interesting to see how the demand estimates change when agents are able to update their beliefs. While this paper does not measure whether people change their opinion of plant-based milks as they learn about the environmental ramifications of their decision, it is likely to have an effect and future papers should determine to what extent demand changes when agent learning can be controlled for.

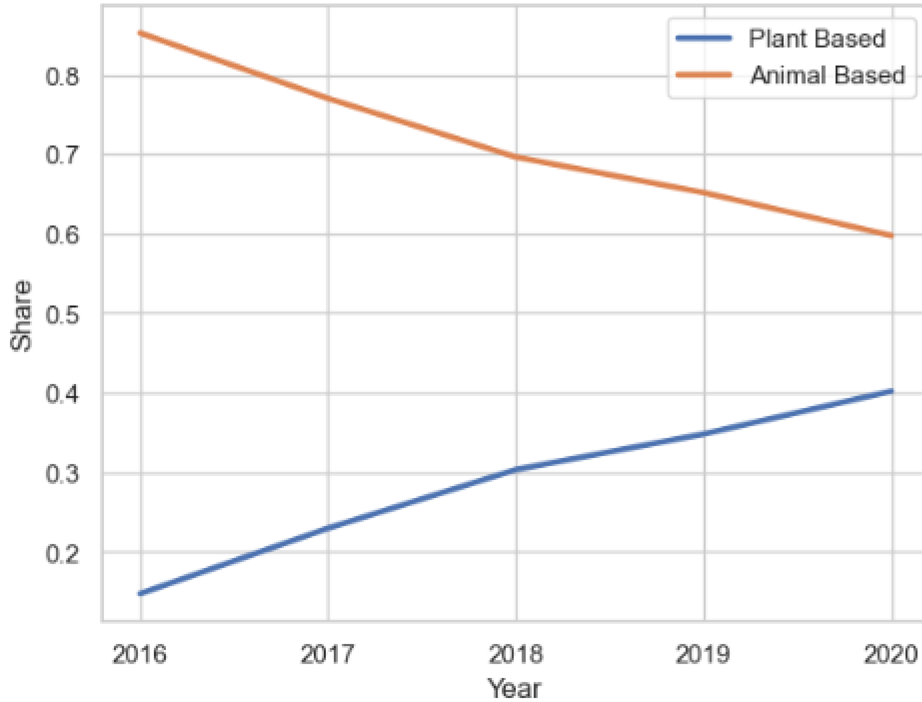
2.3 Data

The data for this study is provided by the Nielsen Data sets from The University of Chicago Booth School of Business.[1] While both the Consumer Panel data set and the Retail Scanner data set are accessible, the Retail Scanner data set is not employed here. To track the most current sentiment toward cow's milk and plant-based alternatives, the period of analysis in this study is from 2016-2020. The Consumer Panel data set has information on 40,000 to 60,000 participating households' weekly grocery store purchases, depending on the year, from 2004 to 2020, so demand is estimated through the most recent year available. While the COVID-19 pandemic may have affected demand for milk in 2020, the growth in the market share between cow's milk and the plant-based alternatives has seemed to grow at a relatively steady pace, as seen in Figure 3.1, so the effects of the pandemic do not seem to be too concerning.

Within the Consumer Panel database, there are four main sections, each broken up by year. They are the Purchases, Trips, Panelists, and Retailers files. In this paper, demand estimation is done solely with the demand side, which made the Retailers file unnecessary. The most important files for estimating demand in the milk market were the Purchases and Trips files, but in future iterations of this paper, the Panelists files can be included to estimate

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

Figure 2.1: Plant-based vs Animal-based Product Market Share



how various agent characteristics may influence whether people are more or less likely to adopt plant-based milks. For example, Generation Z, the youngest generation entering the workforce, is showing signs of increased concern for healthier and more sustainable options than traditional milk [2]. The Purchases and Trips files can be joined on UPC, while the Panelist file can then be joined by household ID from the Trips file if appropriate. Lastly, to find specific departments, the Products File, which can be found in the Master Files of the overall Consumer Panel, is extremely useful. The pertinent information from the Purchases and Trips data set includes DMA code, price, and quantity of each product, date of purchase, and total amount spent on the shopping trip. Due to data management considerations, an account has been set up in the UCI Library's Campus Research Storage Pool (CRSP).

While Nielsen does not specifically categorize products by whether they are animal- or plant-based, there is a product group in the dairy sector labeled, "Remaining Drinks & Shakes-Refrigerated." This product group had all of the cow's milk alternatives as well as other dairy-like beverages, including milkshakes. To filter down to only the plant-based options, I collected the subset of data where the products had zero cholesterol. Since dietary cholesterol is only found in animal-based products, this was an effective way of mostly isolating the plant-based options. From there, I went through the list of remaining products and pulled out the animal-based products with zero cholesterol, such as a probiotic drink called Yakult. From there, I labeled the various sources of the plant-based milks according to their UPC descriptions. There were some products whose bases were unidentifiable, so they were dropped from the sample.

A separate data set, put together by the USDA, was also vital to conducting this study. The FoodData Central database has nutritional characteristics for thousands of food products at the UPC level. It was possible to join the data set to the information obtained through Nielsen. This data set was essential in providing valuable information on non-price product characteristics. Finally, to quantify the water use and carbon equivalent emissions associated with producing each milk type, the data summary processed by Our World in Data is employed [50]. The original data comes from the Poore and Nemereck, (2018) meta-analysis, which incorporates data from 38,700 farms across 119 countries and explores five different environmental indicators including greenhouse gas emissions, land use, acidification, eutrophication and freshwater withdrawals weighted by water scarcity in the region [49]. These impact data help give insight into whether agents care about the environmental consequences of their milk choice.

2.4 Empirical Model

The milk market is an interesting subject because there are now various bases that can be used for similar purposes. While cow's milk was the only widely used milk in the United States for many decades, the trend has recently changed. There is already a small, but significant effect on dairy sales since people are switching to plant-based alternatives [55].

In this empirical model, each milk market is defined by DMA code and week, to present milk purchases as a discrete choice. Milk is a perishable and commonly consumed food, so agents are expected to make decisions on their milk type and quantity very often. A benefit of plant-based milks is that they tend to have a longer shelf life than cow's milk, which is usually only good for seven days. However, defining the market on a weekly scale makes sense because people can mix and match different milk types. Hausman, (1996) provides the perfect example of a market where purchases are made very often with highly differentiated products in the ready-to-eat cereal market. It is reasonable to make the assumption that if the purchases are looked at in a small enough time frame, the discrete choice model makes sense.

While a significant proportion of discrete choice literature presents goods as perfect substitutes to simplify the demand estimation problem, which allows consumers to choose only one product per period [13], the model will treat different milk types as substitute goods instead. In the milk market, this qualification makes much more sense, because the different milk types have noticeably different health and use qualities. For example, oat milk has less of an aftertaste when compared to alternatives, like soy milk. However, they are both much better for one's health and the environment than cow's milk. As a result, households may want to switch their milk type depending on the application. Another important aspect of this study is to see whether agents are likely to switch between plant-based and animal-based milks across different weeks. The likelihood of switching between plant-based and traditional nests will be based on the estimates of the correlation within each nest.

This nested logit model will solely explore the demand side of the milk market because there is no accessible information on the costs that the various firms in the milk industry face. As a result, the functional forms of marginal costs are not known. The PyBLP program is prepared for this issue and can still estimate the GMM estimator by only using demand moments [10]. As in Hausman, (1996), products within the same group, like children's cereal, are going to have the greatest substitutability. Here, correlation between products purchased within a group can be used to determine how likely agents are to substitute between goods. The correlation can be measured using, ρ, which lies between 0 and 1. When ρ is 0 there is no correlation within a group, which means that people are equally likely to buy each good regardless of the nest, as could be seen with a standard logit model [26]. On the other hand, when ρ gets to 1, that means that the goods within the group are closer to perfect substitutes [26]. If ρ is exactly one, then agents would never leave their group [10]. When compared to the aggregate meat market, as analyzed in the first chapter of this dissertation, we would expect ρ to be much smaller between plant-based and animal-based milks, because most Americans have a lot of exposure to plant-based alternatives.

This model defines the utility function very similarly to the model formulated by Berry et al. (1995), and specifies it to the milk industry. Here, agent utility depends on both individual characteristics such as age, education, and income, as well as the product's characteristics. The agent characteristics are assumed to be homogeneous by the model because actual panelist data is not employed. In this case, the product characteristics will be price, cholesterol, fat, calories, sugars, water use, and carbon equivalent emissions associated with each milk base, and whether it is cow's milk, almond milk, or not. While the environmental effects of the various milk types are not labeled on the box, and are therefore not easily observable to the consumer, discourse around the environmental effects of our food choices is becoming more common. Sustainability considerations are largely gaining importance, which means that many people are already aware or will become aware of the environmental differences between milk types at an ordinal level and that may affect their demand. Other product characteristics, including animal treatment, aftertaste, or premium product characteristics, like whether or not the product is organic, are either difficult to quantify or totally unobservable. As a result, an agent's utility function can be characterized by (1), because it can capture the observable and unobservable product characteristics that would factor into the agent's utility.

$$U(p_j, x_j, \xi_j; \theta) = x_j \beta^{ex} + \alpha p_j + \xi_j + \epsilon_j \tag{2.1}$$

Following the BLP model, p_j is the price of each good, indexed by j, while x_j and ξ_j are vectors of the observable and unobservable characteristics of each product, respectively. As previously discussed, individual characteristics are beyond the scope of this paper, so this model does not include the original vector representing all individual characteristics of interest for agent i, ζ_i, from the BLP specification. Instead, the model assumes homogeneous agents, but it would be interesting to see how demand for different milk type varies by household factors, like income or education level. Lastly, θ is a vector of the parameters that need to be estimated. To estimate total market demand, an outside option must be available to normalize the distribution of the unobserved error term, ϵ_j [4]. With this term normalized to zero, the model for aggregate demand of milk can be a function of their prices and characteristics [4]. Milk has a variety of functions in everyday life, so outside options could include those to replace milk as a breakfast drink, like juice or tea. However, those options do not serve the same purpose as milk in every sense. Other outside options could include less common milk types, both animal- and plant-based, that can serve the same functions. The less common milk bases, including goat milk, coconut milk, and cashew milk can all be used similarly to the base set of milk types in this analysis but were not included because their environmental effects were not quantified in Poore and Nemececk, (2018). They also have a much smaller segment of the market share, so they function nicely as an outside option.

This paper will use a nested logit model to generate the parameters with the PyBLP python package, which can be used to obtain the final demand estimates. With (2), the model allows for substitution patterns to change depending on the nest. The level of substitutability is captured by the term ρ, as explained above.

$$U(p_j, x_j, \xi_j; \theta) = \alpha p_{jt} + x_{jt}\beta^{ex} + \xi_{jt} + \overline{\epsilon}_{h(j)t} + (1-\rho)\overline{\epsilon}_{jt} \tag{2.2}$$

To apply this discrete model, it is assumed that the error term $\epsilon_{jt} = \overline{\epsilon}_{h(j)t} + (1-\rho)\overline{\epsilon}_{jt}$ are IID and have the Type I Extreme Value Distribution [10]. Even though there are differences in the utility each person may receive from a product, it is still possible to compute the mean utility associated with each good, as depicted in (3). With the mean utilities of each good, it is possible to allow for the homogeneous agent assumption.

$$\delta_j = x_j\overline{\beta} - \alpha p_j + \xi_j \tag{2.3}$$

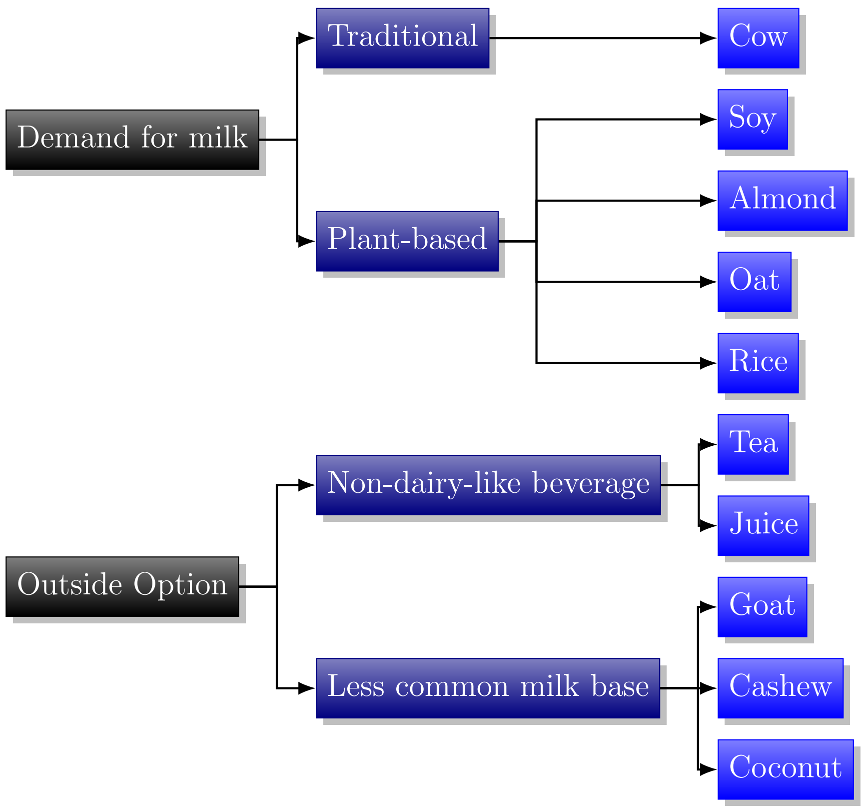
Figure 3.2 demonstrates that the most logical way to segment demand for milk would be to have the aggregate demand for milk at the highest level, followed by the decision of whether to consume traditional milk or plant-based milk, and the last decision lies in which type of milk to consume. The model will help identify how the presence of a plant-based alternative affects the demand of each milk type as well as the aggregate demand for traditional milk.

To run the nested logit model, market shares must be accounted for. As demonstrated in Berry, (1994), the well-known formula for obtaining markets share with aggregate data is:

$$s_{jtg}(\delta, \rho) = \frac{[e^{\delta_j/(1-\rho)}]}{\sum\limits_{j \in G_g} e^{\delta_j/(1-\rho)}} \tag{2.4}$$

From (4), we see that the market share of product j, in market t, depends on their group g, the mean utility δ, and the measure of group substitutability ρ. This goes back to the

Figure 2.2: Nests in Aggregate Milk Market and Breakdown of Milk Bases



nested logit model assumption that there are different substitution patterns between nests, which is captured by ρ. Then the probability of choosing a product from a specific group, g, is:

$$s_g(\delta, \rho) = \frac{\sum\limits_{j \in G_g} \big(e^{\delta_j/(1-\rho)}\big)^{(1-\rho)}}{\sum\limits_{g} \big(\sum\limits_{j \in G_g} e^{(\delta_j/1-\rho}\big)^{(1-\rho)}} \tag{2.5}$$

To get the total market share from there, the market shares in each group times the probability of being in each group need to be multiplied. The resulting expression is:

$$s_{jt}(\delta, \rho) = s_g(\delta, \rho) s_{jtg}(\delta, \rho) = \frac{e^{\delta_j/(1-\rho)}}{\big(\sum\limits_{j \in G_g}\big)^{\rho} \big(\sum\limits_{j \in G_g} e^{\delta_j/(1-\rho)}\big)^{(1-\rho)}} \tag{2.6}$$

The last thing to consider when calculating market shares is how the outside option would fit in with the market. Since the mean utility is normalized to zero, the resulting expression for its market share is:

$$s_{0t}(\delta, \rho) = \frac{1}{\sum_{g}(\sum_{j \in G_g} e^{\delta_j/(1-\rho)})^{(1-\rho)}} \tag{2.7}$$

With these aggregate market shares, it is then possible to get the linear estimating equation in (8). Since δ_j is the mean utility attributed to purchasing product j and it is linear, we can use the linear IV GMM estimator to estimate this model.

$$ln(s_{jt}) - ln(s_{0t}) = \alpha p_{jt} + x_{jt}\beta^{ex} + \rho ln s_{jgt} + \xi_{jt} \tag{2.8}$$

In this paper, shares were calculated directly from observable data. First, the units of each product sold were tallied and then divided by the overall number of products present in each market plus one. The one is added to account for the outside option. As a result, there are measures of market share for every UPC in the defined market.

Since price is endogenous to our demand estimation from (8), demand instruments must be used to obtain final estimates for demand. In this paper, a variety of nutrient characteristics are used as regressors, because they will directly affect the agent's purchasing choice. In Berry et al., (1995), the demand instruments were the characteristics themselves, the sum of characteristics of other goods within the same brand, and the sum of characteristics of goods from other brands, as demonstrated in (9).

$$z_{jk}, \sum_{r \neq j, r \in F_f} z_{rk}, \sum_{r \neq j, r \notin F_f} z_{rk} \tag{2.9}$$

Demand instruments are necessary because the unobserved demand side characteristics (ξ_j) are expected to be correlated with price, which would cause an endogeneity issue [**?**]. However, in this model, these demand instruments do not work, because they become too weak. This can happen when there is a weak correlation between the residual function and instruments that are away from the true parameter value [23]. Consequently, the local difference instruments, developed in Gandhi and Houde, (2019), are used, as seen in (10).

$$A_j(x_t) = \{x_{jt}, \sum_{j'} 1(|d^1_{jtj'} < sd_1), ..., \sum_{j'} 1(|d^1_{jtj'} < sd_K)\} \tag{2.10}$$

With instrumental variables, the price effects can be captured without actually using price. As a result, the nested logit model can be run with these instruments to prevent price from being correlated with the unobserved demand-side characteristics.

2.5 Nested Logit Results and Interpretation

Similarly to Chapter 1, the demand estimates with nested logit, prices, market IDs, product id, shares, nutritional characteristics, and the local demand instruments had to be included. Once again, the ρ estimate will represent how likely people are to switch nests, meaning whether agents currently buying animal-based milk are willing to buy plant-based alternatives. The final formulation for the linear demand model used while running a nested logit through PyBLP is:

$$Pyblp.Formulation(0 + prices + totalOunces + fat + cholesterol + sugars \\ + calories + cowMilk + almondMilk + waterUse + carboneq, absorb = `C(year)') \tag{2.11}$$

Below, in Tables (1) and (2) are the results from the 2016-2020 nested logit model, based on aggregations of market shares from the purchases in each week. In Table (1), we see that the correlation within the animal-based and plant-based milk nests is 0, which means that the plant-based versus animal-based nest does not make a significant difference to the consumer. They are very likely to switch between nests. This makes sense because plant-based milks have a very high penetration in the market and each milk type can have a very specific use. For example, people may enjoy the taste of cow's milk in their cereal but use plant-based milks while baking because they do not notice any taste difference and they want to benefit from the health benefits of the lack of cholesterol.

From Table (2), we see that once the milk-base is controlled for, households care about most health outcomes and water use consequences. Based on the beta coefficients for each variable and their robust SE, it is evident that all estimates are statistically significant, even though the magnitudes are small. The significance of every variable can be seen by their t-statistic because they are all greater than 1.96 in magnitude. The effect on demand estimates for negative health characteristics, including cholesterol, fat, and calories are negative. The only coefficient that goes against the assumption that people want to avoid unhealthy food items is that calories has a positive coefficient. Younger people are more likely to consider the environmental effects of their milk purchases according to McKinsey's 2022 US Dairy Consumer Survey. In fact, of all surveyed consumers, those solely buying plant-based milks were more likely to be younger and vegetarian or vegan [1]. Comparing the base of the various milks as demand characteristics within the plant-based nest gives insight into whether consumers value the environmental impact of their purchase. Since water use has a negative beta coefficient, people appear to be concerned about the water use needed to produce their favorite milks once the cow milk and almond milk fixed effects are controlled for. That may be because water use is a more tangible issue to them than carbon emissions. Future work can be geared toward getting people to better understand the climate consequences associated with their purchases.

Table 2.1: Correlation within nests 2016-2020

Rho	Robust SE	t-statistic
0	0.018	0*

Table 2.2: Demand Estimates for 2016-2020

Variables	Betas	Robust SE	t-statistic
prices	-0.023	0.01	-2.3*
total ounces	0.0032	0.00044	7.27*
fat	-0.058	0.0043	-4.47*
cholesterol	-0.00031	0.000045	-6.89*
sugars	-0.075	0.0021	-35.7*
calories	0.013	0.00046	28.26*
cow milk	0.15	0.068	2.21*
almond milk	2.0	0.021	95.24*
water use	-0.0015	0.000033	45.45*
carbon eq	0.32	0.0029	110.34*

2.6 Conclusions and Future Research

Studying the milk market is an enlightening extension to the nested logit in the aggregate meat market estimation because it gives more insight into how demand estimation may change as the plant-based sector of a market grows. With consumers buying from both animal- and plant-based milk nests, we can infer that people are adopting plant-based milks in significant proportions. This result is also supported by the aggregate market shares of the different milk types across time, as previously seen in Figure 2.1. Ultimately, from a climate-centered perspective, it would be ideal to see the same flexibility between nests in the aggregate meat market. It would mean that people have taken the first step in reducing their animal-based meat consumption. Further research in this field should more precisely explore the differences between the aggregate meat and milk markets to determine what some potential obstacles may be preventing consumers in the meat market from buying both animal- and plant-based meats.

The environmental indicators in the nested logit demand estimation demonstrate that people may not be familiar with the carbon equivalent emissions associated with various milk types. It appears that they may know more about the water withdrawals necessary to produce the various milk types. However, more research should be done on estimating people's background knowledge of the environmental impacts of their milk choice. It would be interesting to learn more about whether labeling the products with their respective carbon equivalent emissions and water use may change people's willingness to pay for a product. Educational campaigns can also be used in conjunction with product labeling schemes to ensure that consumers are making informed choices. Based on the results of this study, it is likely that people are considering some environmental consequences in their purchasing decisions. As seen in the comparison between the aggregate meat and milk markets, when taste and applicability traits are satisfied, people would be more likely to substitute between products. Delving into the reasons behind people's motivation for buying either milk type should be the next focus of future research because it will help expand the plant-based milk market share as well as share the success in other environmentally-friendly industries.

Chapter 3

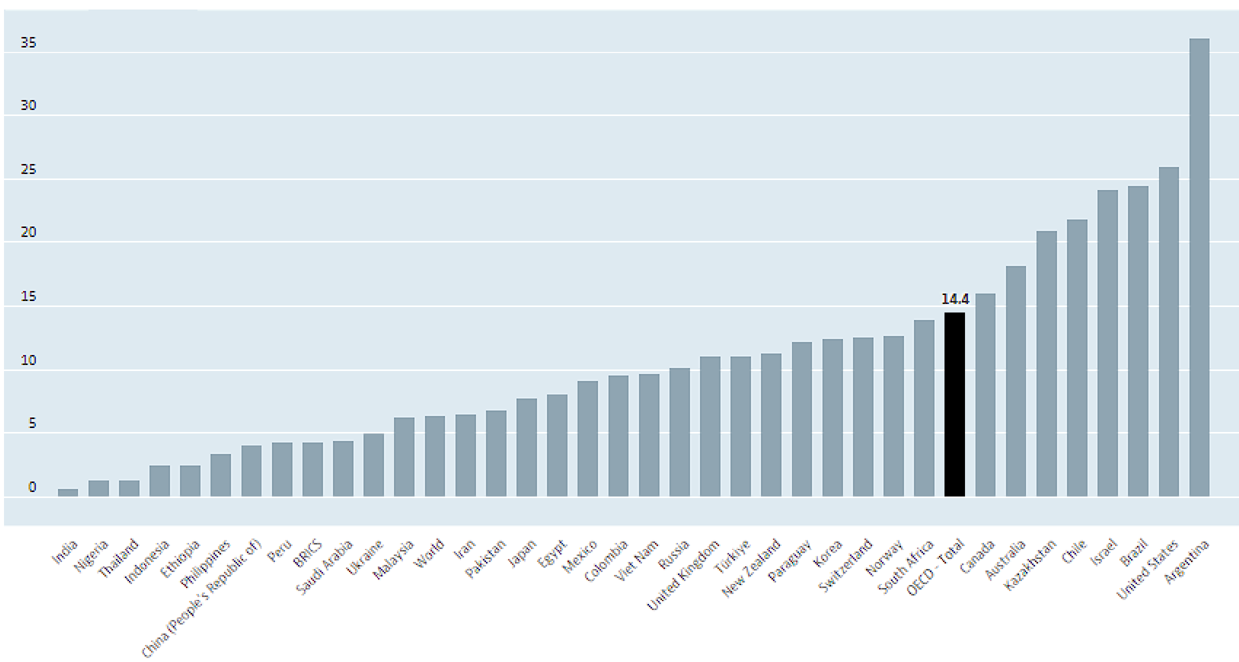
Crop Subsidies: The Inconspicuous Accomplice in the Environmental Toll of Beef

3.1 Introduction

At the dinner table, on most occasions, it might seem odd to discuss the origins or production process of the food on the plate. However, to reach climate and sustainability goals, beef on the dinner plate may soon spark discussion. President Biden's National Climate Task Force has put together a climate action plan, which involves lowering carbon emissions 50-52% below 2005 levels [59]. However, as of 2020, agriculture accounts for 11% of the country's carbon equivalent emissions [65]. Globally, livestock emissions account for about 20% of all anthropogenic emissions [15]. Within the agricultural sector, beef production requires the greatest resource allocation of land, water, and fertilizer [16]; it is also responsible for the greatest amount of carbon-equivalent emissions [60]. As seen in Figure 3.1, the United

States is one of the largest consumers of beef per capita, following only Argentina [44], but its level of consumption will not be sustainable for long. The beef market can be a textbook example of an industry with market failures. The market for beef is rife with externalities that are not considered during the production or consumption decisions. In fact, climate change effects, natural resource degradation, chronic diseases, and animal cruelties are all intensified by the beef industry in the United States. Rather than helping both sides of the market internalize the externalities presented by the beef industry, the federal government indirectly incentivizes further beef production through crop subsidies.

Figure 3.1: Beef and Veal Kilograms/capita

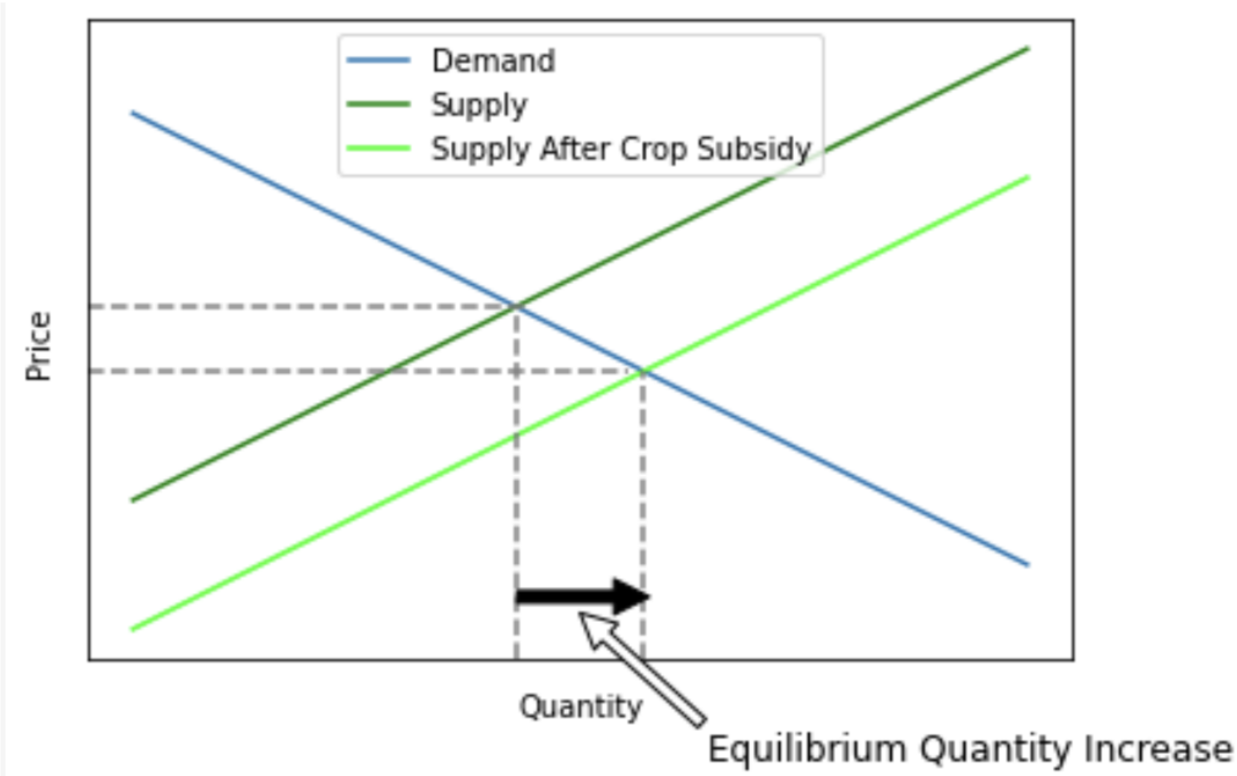


Obtaining beef as a final product in grocery stores is an extremely complex process. Chamanara et al., (2021) describes the different nodes of the production process, from cow-calf production to retail, in order to estimate the effect of the meat supply chain of the wholesale retail company, Costco. Harris Ranch, the country's seventh largest beef producer, is the meat packer that supplies Costco's huge inventory of beef [6]. The most crucial step in the production process is the feedlots stage, which can also be referred to as concentrated animal feedlot operations (CAFOs), or, more colloquially, factory farms. They are generally considered the most environmentally harmful part of the beef production process, as well as the cruelest. At this point of production, cattle are usually fed grains to speed up their muscle mass growth, rather than allowing them to naturally graze on grass [19]. Among other factors, beef is kept relatively inexpensive by the commodity crop subsidies that are specifically geared to livestock production, rather than that of other fruits and vegetables [52].

This study uses a random coefficient logit model to estimate the effect of federal feed crop subsidies on the marginal cost of producing beef. Using marginal cost estimates, this study discusses how lowering the marginal cost of producing beef could make it easier for farmers to raise cattle, effectively leading to an increase in the environmental and health externalities of eating beef. The theoretical effect of lowering the cost of an input good is that the marginal cost of making the good should also decrease. This study tests whether there is empirical evidence to suggest that federal crop subsidies truly have that effect. As seen in Figure 3.2 below, we would expect to see that the Price Loss Coverage Program (PLC) and the Agricultural Risk Coverage (ARC) Program subsidies artificially shift the supply curve of beef-producing firms out, which results in more beef being produced than we would otherwise see in equilibrium. Along with the excess quantity of beef produced, due to the crop subsidy, there will be additional carbon equivalent emissions, water use and pollution, land use, antibiotic resistance, healthcare costs, and animal suffering. Since these externalities are tied to the quantity of beef produced, we can expect their negative outcomes to increase with production.

While there were multicollinearity issues in estimating this model, I find that there is a small and insignificant negative effect of feed crop subsidies on the marginal cost of producing beef. Part of the purpose of this study is to examine the environmental toll beef production has to demonstrate that government intervention in the marginal cost of beef may have a negative impact on society. There are a variety of vegetables available to subsidize that are meant for

Figure 3.2: Theoretical Effect of a Crop Subsidy



human consumption. Investing in them could have environmental benefits because feed crop subsidies are currently lowering the marginal cost of beef and therefore encouraging greater production. I also find that consumers have a preference for smaller packages of meat. They would also have a higher willingness to pay for the product if it were not plant-based and not ground beef. While there may be a marginal benefit to people enjoying the taste of beef, investing in the research and development of plant-based meats could help fill the need for taste preferences.

To my knowledge, this is the only study attempting to estimate the demand and supply side of the aggregate beef market. While Smith, (2019) begins the conversation by questioning the merit of feed crop subsidies by outlining their history and explaining how they incentivize cattle production, this is the first paper to use a random coefficient logit model to quantify the effects. Using federal feed crop subsidies is very interesting because we can see how policy initiatives can have an impact on consumer food choices. As seen in the literature review below, many studies have identified the environmental consequences of cattle raising and beef consumption. However, this study frames these issues as the externalities associated with beef production since it assists in the analysis of whether crop subsidies are a positive use of government funds. As previously mentioned, there are many externalities associated with the production of beef. Since beef suppliers are not required to factor those impacts into their marginal cost, there are already market failures present. Federal feed crop subsidies are not working toward alleviating any of the externalities associated with beef production based on the negative sign on the marginal cost estimate of this model. That being said, the results should be studied further, because the negative marginal cost estimate was small and insignificant. These results may be due to multicollinearity issues, so future papers should run a similar model if more micro-level data on crop subsidies, or more varied product characteristics, can be found.

The rest of this chapter also follows a similar format to the first two, Section 3.2 describes the relevant feed crop subsidies and the environmental externalities associated with animal-based beef consumption. Section 3.3 highlights the data used to conduct the analysis. Section 3.4 outlines the empirical model for the random coefficient logit, which is also based on the foundational demand estimation models in the Industrial Organization field. Section 3.5 reports the random coefficient logit results on the effect of federal feed crop subsidies on marginal cost and the effect of other product characteristics on an agent's willingness to pay. Section 3.6 concludes the study and highlights opportunities for future research.

3.2 Literature Review

3.2.1 Feed Crop Subsidies

While crop subsidies are meant to protect farmers, their societal benefit is questionable. Two significant subsidies still available today are the Price Loss Coverage Program (PLC) and the Agricultural Risk Coverage (ARC) Program. Both subsidy programs were authorized by the 2014 and 2018 Farm Bills and were meant to protect farmers from crop price drops or other revenue losses [64]. Previously, there was a direct payments program that subsidized regardless of whether sales were doing well or poorly. Due to the negative connotations around such a program, commonly referred to as "welfare for farmers", it was not renewed after 2014 and most payments ended in 2018. To capture the effect of the most significant federal subsidy programs for farmers, payments for all three programs were summed by year at the state level.

Other subsidies that livestock farmers benefit from include the Livestock Forage Disaster Program, which works as a form of insurance for farms that lose cattle through drought-related deaths. Farmers are eligible for these subsidies when their county is affected by a D2 level drought, indicating a severe drought or higher [63]. These subsidies were not included in the analysis, because the adverse effects of the drought on the costs of production would outweigh the insurance benefit provided by this specific type of subsidy program. Testing the effect of crop subsidies on the marginal cost of beef production works well because they lower the price of one of the beef industry's most essential inputs. In fact, out of all the factors that contribute to the cost of beef production, feed crop costs are the highest, accounting for up to 70% of the cost of raising the livestock [33]. With the federal government's help through subsidies, the marginal cost of beef production decreases due to the lower overall cost of feed grains like corn.

Crop subsidies for the beef industry would make sense if the economic benefit of the marginal beef produced outweighed the negative environmental impacts. To evaluate whether or not that possibility holds, Navarrete-Molina et al., (2019) estimate the economic environmental impact of the beef cattle industry in an arid region of Northern Mexico. Without considering the cost of externalities like water scarcity or a large carbon footprint, the beef cattle industry in Comarca Lagunera, Mexico is economically beneficial [42]. Under similar assumptions, crop subsidies in the United States are given without internalizing any of the social costs associated with beef production. However, Navarrete-Moline et al, (2019) finds that there are significant carbon equivalent emissions and Blue Water Footprint (BWF) costs that ultimately make the marginal cost of beef production in the arid region of Mexico higher than the economic benefits. The BWF is a measure of the water taken from surface or groundwater bodies and then used in the production of a good [68]. The same issues with beef production are present in the US beef industry, which should make the federal government consider whether crop subsidies that lower the marginal cost of beef will have positive marginal social benefits.

3.2.2 Externalities

The negative environmental effects of beef are multi-dimensional and each section below highlights the relevant externalities. The social costs incurred due to cattle raising and beef consumption are not internalized by the meat industry. As a result, it is important to identify the main costs borne by society to examine whether a feed crop subsidy is socially optimal.

Carbon-Equivalent Emissions

Anthropogenic climate change refers to the effect that humans have on the environment through activities that release greenhouse gasses (GHGs). Agriculture is one of the biggest economic sectors contributing to climate change, and within this sector, beef production is the highest emitter [15]. Even between different meat types, beef production results in five times more carbon-equivalent emissions than the average of other animal-based food categories [15]. The magnitude of beef's effect on the environment through carbon-equivalent emissions demonstrates that there may be huge inefficiencies if consumers do not face the true costs of the beef on their plate. While cattle are raised, they release methane through enteric fermentation [31], which is a greenhouse gas with 28 times the warming potential of carbon dioxide on a 100-year timescale [17]. Beef production is also associated with carbon dioxide and nitrous oxide emissions as well [25]. Climate change has the potential to cause economic disasters ranging from lower crop yields to higher sea levels destroying ocean-front areas, resulting in slower economic growth rates [61]. The global implications of such climate effects are part of the social costs that the model above attempts to minimize.

Excess water use and water pollution

While water is a renewable resource, there is an ever-increasing demand for it. As David Zetland explains in <u>The End of Abundance</u>, when there is enough water to cover basic uses such as drinking, bathing, and irrigation, societies find other uses for water, including swimming pools and yard irrigation. In agriculture, growing populations and tastes for water-intensive foods, such as meat, have increased the threat of water scarcity [14]. Of all animals used for animal products, beef cattle have the highest water footprint at the end of their lifetime [38]. One might think that the final price of beef products found in grocery stores will reflect a rise in water prices that is meant to help mitigate the effects of water scarcity, but water markets are not well defined and water is often not priced. Instead, water rights are simply given to farmers, who have little ability to trade [71]. With water markets functioning imperfectly, consumers do not face the actual cost of the large quantities of water used in beef production.

Beef production is also likely to cause water pollution because minerals and nutrients present in fertilizer or waste run off into large bodies of water [46]. Such runoff causes uncontrolled growth of algae, leading to eutrophication. With eutrophication, a body of water may become anoxic and could potentially kill any wildlife present. There is a social cost associated with eutrophication-based water pollution. If large bodies of water undergo eutrophication, there is lost value in recreational uses, lower real estate prices in an area, smaller reserves of drinking-quality water, and the need to repopulate the area with endangered species [12]. It may seem odd to connect a hamburger to water pollution, but there are undeniable externalities associated with beef production that must be faced to avoid unnecessary natural resource destruction.

Land Use

An externality associated with using land for animal-oriented production is the increase in GHG emissions when land is shifted from carbon-absorbing forest use to cropland and pastureland [32]. Once land used for animal feed is included, meat and other animal by-products account for 65 percent of all land use change from a natural environment to crop or pasture lands [3], so the cost of shifting land use for beef, over any source of plant-based proteins, is relatively greater per gram of protein. Livestock production requires the largest use of land globally [15]. For feed crops, 139 million hectares (Mha) of land is used globally, which is almost as large as the 140 Mha area used to produce all the vegetables that humans consume [3]. This large difference in the externality cost of land use is added to the GHG creation that arises directly from animal-oriented production.

Antibiotic Resistance

Since demand for beef is high in industrialized countries and growing greatly in developing economies, there has been a huge shift toward CAFOs. To maintain animal health in such concentrated facilities, the use of antibiotics is required. Antibiotics control disease when healthy animals are put in conditions where illness is likely to spread, and they can promote growth so animals more quickly reach an appropriate weight for slaughter [53]. The antibiotics given to animals through their feed can affect human health because they promote resistant bacteria that can infect humans through the consumption of animal flesh or other animal products such as milk and eggs [37]. This antibiotic resistance externality makes human healthcare more expensive because new and more powerful antibiotics will have to be developed. Slowing beef production may have increasing marginal benefits regarding antibiotics because fewer cattle concentrated in the same place will decrease the likelihood of disease developing in the first place.

Healthcare costs

There is significant evidence from the medical community that animal-based foods are associated with higher rates of heart disease and mortality from all causes, while consumption of plant-based proteins is correlated with lower mortality rates [54]. Heart disease is the leading cause of death in the United States [41], so lowering beef consumption per capita could have major health benefits. While consumers should take the health impacts of beef into consideration when making a decision on how much to eat, diet seems to be more closely related to the culture of where one lives. For example, Northern Europeans consume extremely high amounts of dairy, which is highly correlated with coronary heart disease (CHD), while countries that consume more fish and plant protein, like Japan, have significantly smaller death rates from CHD [39]. In the beef market specifically, there are higher levels of particulate matter ($PM_{2.5}$) pollution in areas around cattle feedlots. These feedlots account for one-third of the anthropogenic $PM_{2.5}$ pollution in the San Joaquin Valley of California [6]. The health effects of particulate matter ingestion are not accounted for in the price of beef products. People who live less than one kilometer away from feedlots in California are more likely to suffer from asthma and cardiovascular disease and have children with low weight at birth [6]. If the equilibrium quantity of beef produced were lower, we would likely see healthcare costs from treating these chronic diseases drop.

Animal Cruelty Concerns

While animal rights may not be at the forefront of everyone's mind and raising animals for meat could be considered natural or simply an unfortunate part of a complete diet, they are an important externality to mention. Apart from the base need to kill an animal for its meat, production has been greatly industrialized with the advent of CAFOs, to the detriment of the animal's day-to-day conditions while alive. It is very difficult for the public to learn about the realities of the beef that they are eating because meatpacking companies do not want people to witness their operations. In fact, the meat and dairy industry in the United States promotes legislative measures to make documenting the operations of CAFOs through undercover investigation illegal [19]. Vegan diets are becoming more popular around the world. At least six percent of Americans now identify as vegans [11]. People can adopt a vegetarian diet for a myriad of reasons, including religious, health, environmental, and animal welfare concerns [58]. Raising fewer animals in a CAFO setting will decrease the animal suffering externalities associated with beef production.

3.3 Data

Once again the Consumer Panel, from the Nielsen database, was used as the basis of this study.[1] As previously mentioned, Nielsen does not clearly categorize products by whether their source is animal- or plant-based. Therefore, the same list of plant-based meat alternatives, as described in Chapter 1, is employed. The plant-based characteristic was more relevant to the previous chapter of this study because it was used in a nested logit model to estimate its effect on various meat products. Here, it is not included in the random coefficient estimation, because there were too few purchases in the sample, and when included the model becomes collinear. As a result, the plant-based beef purchases were left in the sample, with the assumption that they do not benefit from crop subsidies, but the difference in the probability between choosing products from the animal-based or plant-based beef nests was not estimated. The Nielsen database does not clearly categorize meat type by UPC either. To identify beef products, a combination of product descriptions, product group descriptions, and department descriptions was employed.

Subsidy data is obtained from the Environmental Working Group, which compiled payments the USDA made to farmers. With the compilation provided by the Environmental Working Group, crop subsidies from the Price Loss Coverage Program (PLC), the Agricultural Risk Coverage (ARC) Program, and the direct payments program are used as cost shifters. These data comprise of yearly payments made by the federal government to these programs, broken down by state. Since this model estimates the demand and supply side of the beef market from 2016-2019, there is variation over time and across states.

There were many multicollinearity issues that needed to be accounted for in this study.

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

The underlying issue behind the multicollinear nature of the data was a lack of variation between the product characteristics and subsidies. Running into this type of issue makes sense, because nutrient content product characteristics, which would not change very much in a sample of only beef products, were originally included as linear regressors in the demand side estimation. Instead of using nutritional characteristics, I have identified other product characteristics, including whether the product is plant-based or ground beef, through the UPC product descriptions. Then, I made boolean variables for those product characteristics and included them in the model. Finally, to limit the multicollinearity between the products, they were aggregated by groups into similar products by each firm. Therefore, the UPC descriptions were used to identify whether products from the same brand should be aggregated into a larger product type. The final product groups were ground beef, burger, steak, veal, roast, sausage, and canned. The same was done to group the plant-based beef, but only by ground beef and burger, because the other product types are not similar enough to compare. Products that could not be identified were left with the UPC as their product ID. All numerical data was scaled using the robust scaling function from the sklearn Python package.

3.4 Empirical Methods

The ultimate goal of this model is to identify how federal subsidies for feed crops act as cost shifters that influence equilibrium quantity demanded. For that identification, agent utility, which depends on both individual characteristics, like income, as well as the product's characteristics, must be maximized. This model also identifies the supply side by deriving marginal costs through profit maximization. Here, product characteristics are price, the size of the package in ounces, and plant-based and ground beef booleans. Other product characteristics, including animal treatment, taste, and cultural importance may be difficult to quantify or could be completely unobservable to the researcher. As a result, an agent's utility function can be characterized by (1), which is based off the models from Berry et al., (1995) and Nevo (200), because it can capture the observable and unobservable product characteristics and agent preferences that would factor into their utility.

$$U(\alpha_i, y_i, p_{jt}, x_{jt}, \xi_{jt}; \theta) = x_{jt}\beta_i + \alpha_i log(y_i - p_{jt}) + \xi_{jt} + \epsilon_{ijt} \tag{3.1}$$

Following the BLP and Nevo model, p_{jt} is the price of each good j in market t, while x_{jt} and ξ_{jt} are vectors of the observable and unobservable characteristics of product j in market t, respectively. Although the utility specification includes the term $log(y_i - p_j)$, it is much more simple to solve the model with the approximation p_j/y_i [10]. As presented in Pinter (2021), the distribution of the unobserved product characteristics is assumed. While the original BLP model had a vector, ζ_i, that represented all individual characteristics of interest for agent i, this model does not specify the vector for agent heterogeneity. Instead, a Monte Carlo integration is used to represent a homogenous sample of individuals. The error term ϵ_{ijt} is assumed to be i.i.d. and follows the type I extreme value distribution. Lastly, θ is a vector of the parameters that need to be estimated.

An agent's utility function is maximized when they choose the good j that gives them more utility than any other good. As depicted in Berry et al. (1995), the set of goods that meets that criteria can be represented by (2).

$$A_j = \{\zeta : U(\zeta, p_j, x_j, \xi_j : \theta) \geq U(\zeta, p_r, x_r, \xi_r; \theta) \; for \; r = 0, 1, ..., J\} \tag{3.2}$$

To determine the market share of each product in the model, this study will measure it directly at the beef brand and plant-based meat company level. Their observed market shares are calculated by taking the total number of goods sold divided by the total number of households in the market. Each market is defined by DMA code and quarters from 2016 to 2019. Therefore, the purchases data are aggregated up to that level. When household preferences and characteristics are allowed to be heterogeneous, market shares will depend on the distribution of the different parameters, which in this model are the α_i, β_i, and y_i. Below in (3), the general form for market shares is represented as seen in Berry et al., (1995), where ζ is a vector of consumer characteristics that contains α_i, β_i, y_i, and the error term (ϵ_{ij}).

$$s_{jt}(p, x, \zeta; \theta) = \int_{\zeta \in A_j} P_0(d\zeta) \tag{3.3}$$

Differences in product characteristic preferences are fixed at zero, meaning that agents are homogeneous in product characteristic preferences to shorten computation time. For the final form of market shares as shown in (4), a specification similar to Conlon and Gortmaker, (2020) is used. Here individual demands, and their resulting market shares, are integrated over all consumer preferences with this multinomial logit kernel, where $f(\alpha_i, \beta_i|\theta)$ represents the mixing distribution of the various agent preferences [43].

$$s_{jt}(p, x, \alpha, \beta, \xi, \theta) = \int \frac{e^{x_{jt}\beta_i - \alpha_i p_{jt} + \xi jt}}{1 + \sum\limits_k e^{(x_{kt}\beta_i - \alpha_i p_{jt} + \xi_{kt})}} f(\alpha_i, \beta_i|\theta) \tag{3.4}$$

This version of the model cannot be linearized until it is re-parametrized by incorporating mean utility [10]. With the re-parametrization, all of the aspects of utility that consumers agree on can be separated out of the function [10]. The mean, defined below in (5), depends on characteristics that do not vary by individual.

$$\delta_{jt}(\theta) = x_{jt}\overline{\beta} - \alpha p_{jt} + \xi_{jt} \tag{3.5}$$

After the re-parametrization, the market share formula can be simplified to:

$$s_{jt}(\delta_{jt}, \theta) = \int \frac{e^{(\delta_{jt}+\mu_{jt})}}{1 + \sum\limits_{k} e^{(\delta_{kt}+\mu_{ikt})}} f(\mu_{it}|\theta) \tag{3.6}$$

Once market shares are defined, each firm's profit maximization problem can be calculated. The profits of a firm depend on the number of products it produces, the quantity sold, and its market power. Once the entire market, of size M, is taken into consideration, the number of products sold can be captured through market shares and demand. Then, market power can be seen through their ability to mark up prices beyond marginal cost (mc). Berry et al., (1995) identify profits through (7), which is the specification that will be used in this model.

$$\pi_f = \sum_{j \in F_f} (p - mc_j) * M s_j(p, x, \alpha, \beta, \xi; \theta) \tag{3.7}$$

Marginal cost has its own functional form, seen in (8), that depends on the observable cost characteristics (w_j), the unobservable cost characteristics (ω_j), and the vector of parameters to be estimated (γ). For this model, crop subsidies are used as the cost characteristic that affects marginal costs.

$$ln(mc_j) = w_j\gamma + \omega_j \tag{3.8}$$

To maximize profits, all products that the firms produce must satisfy their first-order conditions, as shown in (9):

$$s_j(p, x, \alpha, \beta, \xi, \theta) + \sum_{r \in F_f} (p_r - mc_r) \frac{\partial s_r(p, x, \alpha, \beta, \xi, \theta)}{\partial p_j} = 0 \tag{3.9}$$

Since the firms must maximize their profits across all products, there will be J first-order conditions. These first-order conditions will form a JxJ matrix, where each element is the Δ_{jr} seen in (10) [4].

$$\Delta_{jr} = \begin{cases} -\frac{\partial s_r}{\partial p_r} & \text{if r and j produced by the same firm} \\ 0 & \text{otherwise} \end{cases} \tag{3.10}$$

The first-order conditions can also be written in vector form as in (11) [4].

$$s(p, x, \alpha, \beta, \xi, \theta) - \Delta(p, x, \alpha, \beta, \xi, \theta)[p - mc] = 0 \tag{3.11}$$

Once all of the first-order conditions are found, price can be solved for as a function of market shares, by inverting the JxJ matrix, shown below at (12).

$$p = mc + \Delta(p, x, \alpha, \beta, \xi, \theta)^{-1} s(p, x, \alpha, \beta, \xi, \theta) \tag{3.12}$$

Prices are additively separable in marginal costs, which means that the final vector of J market power, represented as $b(p, x, \alpha, \beta, \xi, \theta)$ in (13), can be estimated [4].

$$b(p, x, \alpha, \beta, \xi, \theta) \equiv \Delta(p, x, \alpha, \beta, \xi, \theta)^{-1} s(p, x, \alpha, \beta, \xi, \theta) \tag{3.13}$$

With the market power vector, marginal costs for each product can be derived as seen in (14). The γ estimates will represent the effect that crop subsidies have on the marginal cost of beef.

$$ln(p - b(p, x, \alpha, \beta, \xi, \theta)) = w\gamma + \omega \tag{3.14}$$

To estimate the final results, this model is run with a one-step generalized method of moments (GMM) estimator. Here, PyBLP optimizes the objective function in (15), as seen in Conlon and Gortmaker, (2020), to minimize θ. The weighting matrix is denoted as W.

$$\min_{\theta} q(\theta) = \overline{g}(\theta)' W \overline{g}(\theta) \tag{3.15}$$

3.4.1 Demand and Supply Instruments

Since price is endogenous to our demand estimation from (11), demand instruments must be used to obtain final estimates for demand. In this paper, a variety of nutrient and environmental characteristics are used as regressors, because they will directly affect the agent's purchasing choice. In Berry et al., (1995), the demand instruments were the characteristics themselves, the sum of characteristics of other goods within the same brand, and the sum of characteristics of goods from other brands, as demonstrated in (16).

$$z_{jk}, \sum_{r \neq j, r \in F_f} z_{rk}, \sum_{r \neq j, r \notin F_f} z_{rk} \tag{3.16}$$

Demand instruments are necessary because the unobserved demand-side characteristics (ξ_j) are expected to be correlated with price, which would cause an endogeneity issue [48]. However, in this model, these demand instruments do not work, because the number of products available is so large that they become too weak. This can happen when there is a weak correlation between the residual function and instruments that are away from the true parameter value [23]. Consequently, the local difference instruments, developed in Gandhi and Houde, (2019), are used, as seen in (17).

$$A_j(x_t) = \{x_{jt}, \sum_{j'} 1(|d^1_{jtj'} < sd_1), ..., \sum_{j'} 1(|d^1_{jtj'} < sd_K)\} \tag{3.17}$$

Similarly the supply side requires instrumenting as well, because the quantity of subsidies given in each traditional beef market may be endogenous to price. Subsidies would be endogenous if the market power of the brand influences both the amount they are awarded in subsidies and their price. To ensure that there is no endogeneity issue, the national average price of feed grains every quarter, taken from the USDA, is used as an instrument for the amount of subsidies awarded by the USDA's Price Loss Coverage Program (PLC) and Agricultural Risk Coverage (ARC) Program.

3.4.2 PyBLP Formulations

To estimate the demand and supply side in the beef market with a random coefficient model, the PyBLP package, developed by Conlon and Gortmaker, (2020) was used. To employ this model prices, market IDs, product IDs, shares, nutritional characteristics, subsidies, and household characteristics had to be included. To properly estimate the model and to avoid making the problem unsolvable through collinearity, feed crop prices were used as a supply instrument, and the local demand instruments, from the Conlon and Gortmaker, (2020) package, were employed as well. Demand and marginal cost estimates are found from 2016 to 2019. While 2020 is available in the Nielsen dataset, it was avoided because the COVID-19 pandemic disrupted many supply chains and led to the temporary shutdown of some meat-packing plants [34]. Additionally, plant-based products became more popular during quarantine in 2020 [40]. Since both factors could potentially skew the marginal cost estimates, the relevant dataset was limited to 2019.

The final formulation for the demand model that is used while running PyBLP has three components. The first part of the formulation includes all of the linear factors affecting demand, the second specifies the random coefficients that need to be estimated, while the last captures the supply side with the product characteristics that will affect marginal cost. A constant was not included in the first two parts of the formulation because it would cause the problem to be collinear. A constant is usually meant to capture the correlation between goods within each brand [10], but it was not possible to use in this model due to the naturally high correlation among the sample.

$$product\ formulations = \begin{cases} X_1 : (Pyblp.Formulation(1 + size1Amount + plantBased + ground), \\ X_2 : (Pyblp.Formulation(1 + size1Amount + plantBased + ground), \\ X_3 : (Pyblp.Formulation(0 + subsidy) \end{cases} \tag{3.18}$$

3.5 Results and Interpretation

As discussed in the empirical model, γ represents the effect of crop subsidies on the marginal cost of beef. Based on the results from the random coefficient supply estimation, seen in Table 3.1, we can see that crop subsidies do not have a significant effect on marginal costs. The magnitude of the effect is also quite small, which may be due to the fact that the subsidies were listed at the dollar level before scaling, so the change in one dollar of subsidies per state in a quarter is likely not to have a large effect on the marginal cost. While these results do not conclusively show that crop subsidies provided by the federal government increase the equilibrium quantity of beef available in the market, it is reasonable to question whether they are the best use of subsidy funds and if they are generally beneficial to society. Greater beef production and consumption is fraught with environmental, health, and animal cruelty externalities. Rather than incentivizing farmers to produce feed crops that are generally used to feed cattle, the agricultural industry can pivot to producing more vegetables that are meant to go toward direct human consumption.

Table 3.1: Marginal Cost Estimates for 2016-2019

Variables	Gamma	Robust SE	t-statistic
crop subsidies	-3.9e-8	2.5e-7	-0.156

Based on the beta coefficients, seen in Table 3.2, for each variable and their robust SE, it is evident that all estimates are statistically significant because their t-statistics are greater than 1.96. The magnitude of all of the estimates is small, but they suggest that people prefer small packages of beef. They also prefer that it be animal-based and not ground. The sign of these estimates indicates that as the size of the package increases, the likelihood of a producer choosing the product and their willingness to pay for said product goes down. Then for the boolean regressors, it similarly means that if the products are plant-based, or ground beef, their probability of getting chosen is smaller. These results are sensible because beef can go past its prime quickly, people have not yet accepted plant-based meats as a perfect substitute, and ground beef is generally of lower quality. Extensions of a project in this field should try to identify product characteristics with greater variation because this study is limited by multicollinearity issues which may be biasing the results.

Sigma is the Cholesky root of the covariance matrix for the unobserved factors that affect demand [10]. Since the covariance between the linear regressors was fixed at zero, only the initial value chosen for the square root of the variance, effectively the standard deviations, is presented in Table 3.3. Future iterations of the paper should allow for the covariance between the variables to be non-zero to get a better sense of the observed taste heterogeneity. When

Table 3.2: Demand Estimates for 2016-2019

Variables	Beta	Robust SE	t-statistic
constant	-0.014	0.00036	-38.9*
size1 amount	-0.38	0.0077	-49.4*
plant based	-0.0015	0.000081	-18.5*
ground	-0.006	0.0001	-60*

covariances are estimated, there should be a nonzero sigma restriction, because it does not make sense to have negative standard deviations [10].

Table 3.3: Sigma Estimates for 2016-2019

Variables	Standard Deviations	Robust SE	t-statistic
constant	0.12	0.000046	2608*
prices	0.24	0.00078	307.7*
size1 amount	-0.88	0.017	-51.8*
plant based	0.34	0.000027	12592*
ground	0.44	0.00002	22000*

3.5.1 Mitigating Protein Externalities

There are many ways to mitigate the effect of diet on the environment. As previously discussed, relying on beef as a major source of nutritional protein has major environmental and health costs. While beef can be raised on land that is not suitable to produce many vegetables, there are about 32 million hectares of high-quality land in the US, currently used to produce crops for feed, that can be rededicated to other protein-rich foods [16]. Beef provides the lowest food energy and protein delivery per hectare that could result from using that land to grow other crops or even dedicating the land to other animal-based meat types. Using plant-based protein alternatives, like legumes, can help reduce many of the externalities associated with beef. It can also provide anywhere from 2 to 20 times more calories than beef can, given the same resources [16].

Another option that could suitably lower the externalities involved in protein production and consumption would be the adoption of plant-based meat alternatives. To see a substantial change in the negative environmental externalities from the animal-based beef industry, consumers need to not only adopt plant-based meats but also use them in place of traditional beef. Currently, it appears that the adoption of plant-based meats is not lowering the quantity of animal-based meats produced yet [36]. Plant-based beef can be used as an alternative to traditional beef. Technological advances, like the products made by Beyond Meat and Impossible Foods, have made the appearance and taste of plant-based beef much more similar to its traditional counterpart. For all of the externalities discussed in this study, producing plant-based meats would have a much smaller impact. While the share of plant-based meats in grocery stores is still relatively small, the growing number of people concerned with the environmental and health consequences of beef may make the plant-based industry grow.

3.6 Conclusions and Future Research

The role of government subsidies is usually to help alleviate market failures by making the private marginal cost of a product closer to societal marginal costs. Federal subsidies for feed crops may have the opposite effect because they are shown to lower the marginal cost of beef production at an insignificant level. It is still important to question the role of these subsidies because lowering marginal cost could increase the equilibrium quantity for firms in the beef industry. When cattle production rises, the negative environmental, health, and social externalities associated with beef consumption grow. The problems associated with beef production have been studied from a public health and environmental lens [22] [60]. This study analyzes how these externalities already fail to be captured in a firm's production decision for beef, and how the federal government effectively promotes greater beef production through crop subsidies that lower marginal cost. While there may be a marginal benefit to people enjoying the taste of beef, there are many environmental externalities that should be taken into consideration in the production decision. This study dives into the market effects of subsidies that benefit the livestock industry and discusses the benefits of limiting beef consumption.

When plant-based beef captures a larger share of the market and gets to the point where it is replacing animal-based beef consumption, more work can be done on estimating which cost shifters are most likely to have a significant effect on plant-based meats, rather than animal-based meats. If the government decides to encourage the production of plant-based alternatives, due to their vast environmental and health advantages, knowing which factors have the biggest impact on cost will help focus subsidy efforts. Since producing beef is so resource-intensive, it is likely that the marginal costs of water and land use will be much smaller for any plant-based protein production. On the other hand, plant-based meat alternatives will most likely have much higher sunk costs in research and development. Sunk costs should not be included in a model like this, because they would not affect the production decisions of the firm. However, understanding the biggest obstacles that plant-based meats must face before reaching price parity with animal-based alternatives will be essential for a transition away from animal-based beef. If animal-based beef is not subsidized, and therefore closer in price to alternatives like plant-based beef, consumers may be more inclined to try the new technology. Such a shift in consumption patterns would have significant positive effects on the environment.

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Appendix A

Plant-based Meat UPCs

Product ID	Product Name	Product Type
86000153362	Meatless Ground Beef	beef
816697021002	Impossible Ground Beef	beef
816697021019	Impossible Patty	beef
852629004583	Beyond Burger	beef
850004207093	Beyond Ground Beef	beef
852629004774	Beyond Sausage Brat Original	pork
852629004767	Beyond Sausage Sweet Italian	pork
852629004750	Beyond Sausage Hot Italian	pork
850004207789	Beyond Meatballs	beef
852629004897	Beyond Breakfast Sausage Classic Patties	pork
850004207314	Beyond Breakfast Sausage Spicy Patties	pork
850004207475	Beyond Breakfast Sausage Classic Links	pork
850004207888	Beyond Burger Classic Cookout	beef
852629004170	Beyond Beef Crumbles Beefy	beef
852629004132	Beyond Beef Crumbles Feisty	beef

852629004163	Beyond Chicken Tenders	poultry
852629004033	Beyond Chicken Strips Grilled	poultry
759283002231	Boca Extra Large All American Veggie Burgers	beef
759283600079	Original Chik'n Veggie Patties	poultry
759283600086	Spicy Chik'n Veggie Patties	poultry
759283334455	Boca Original Vegan Veggie Burgers	beef
759283600161	Boca Non-GMO Soy All American Veggie Burgers	beef
759283600116	Non-GMO Original Chik'n Veggie Patties	poultry
759283600147	Non-GMO Spicy Chik'n Veggie Patties	poultry
759283600154	Boca Non-GMO Original Vegan Veggie Burgers	beef
759283601069	Boca Original Veggie Crumbles	beef
759283601113	Boca Original Chik'n Veggie Nuggets	poultry
759283601120	Boca Non-GMO Original Chik'n Veggie Nuggets	poultry
80868029061	Perfect Chik'n Spinach Pesto Burger	beef
80868029016	Perfect Burger	beef
80868029023	Perfect Turk'y Burger	poultry
80868029054	Perfect Plant Based Ground	beef
80868260006	Classic Chik'n Tenders	poultry
80868003115	Sunday Funday Veggies Sausages	pork
80868000336	All American Veggie Burgers	beef
80868260112	Grandpa Mel's BBQ Chick'n Tenders	poultry
80868260105	Gametime Buffalo Chik'n Tenders	poultry
638031612178	Smoked Apple & Sage Plant-Based Sausages	pork

638031612154	Italian Garlic & Fennel Plant-Based Sausages	pork
638031612161	Spicy Mexican Chipotle Plant-Based Sausages	pork
638031612192	Caramelized Onions & Beer Plant-Based Bratwursts	pork
638031684160	Classic Recipe Plant-Based Breakfast Sausage Patties	pork
638031612185	Apple & Maple Plant-Based Breakfast Sausages	pork
638031606504	Chef's Signature Plant-Based Burgers	beef
638031684151	Classic Nugget Plant-Based Nuggets	poultry
638031612383	Miniature Corn Dogs Plant-Based Corn Dogs	pork
638031613236	Buffalo Wings Plant-Based Wings	poultry
638031002511	Signature Stadium Dog Plant-Based Hot Dogs	pork
638031612284	Classic Smoked Plant-Based Frankfurters	pork
638031605026	Mushroom & Balsamic Plant-Based Deli Slices	pork
638031605019	Lentil & Sage Plant-Based Deli Slices	pork
638031605033	Smoked Tomato Plant-Based Deli Slices	pork
638031612208	Classic Pizzeria Plant-Based Pepperoni	pork
638031601042	Celebration Roast Plant-based Roast	pork
638031601158	Hazelnut & Cranberry Plant-Based Roast	pork
842234002341	Ultimate Plant-Based Chick'n Tenders	poultry
842234002321	Ultimate Plant-Based Chick'n Filets	poultry
842234002331	Ultimate Plant-Based Chick'n Nuggets	poultry
842234403529	Chipotle Georgia Style Chick'n Wings	poultry
842234403505	Nashville Hot Chick'n Tenders	poultry
842234403499	Crispy Golden Chick'n Nuggets	poultry
842234001626	Chick'n Strips	poultry

842234000995	Teriyaki Chick'n Strips	poultry
842234001008	Crispy Chick'n Patty	poultry
842234000803	Chipotle Lime Fingers	poultry
842234000797	Barbecue Chick'n Wings	poultry
842234403512	Spicy Gochujang Style Chick'n Wings	poultry
842234000520	Seven Grain Crispy Tenders	poultry
842234000742	Mandarin Crispy Chick'n	poultry
842234000964	Turk'y Cutlet	poultry
842234007151	Plant-Based Turk'y Roast	poultry
842234000926	Plant-Based Savory Stuffed Turk'y	poultry
842234000483	Chick'n Scallopini	poultry
842234007123	Ultimate Plant-Based Burger	beef
842234000827	Ultimate Beefless Burger	beef
842234000513	Beefless Tips	beef
842234401020	Sliced Italian Saus'age	pork
842234002128	Sweet and Sour Porkless Bites	pork
842234001381	Szechuan Beefless Strips	beef
842234003316	Original Breakfast Saus'age Patties	pork
842234003323	Spicy Breakfast Saus'age Patties	pork
842234000971	Meatless Meatballs	beef
842234000988	Beefless Ground	beef
842234002111	Mini Crabless Cakes	fish
842234001664	Golden Fishless Filet	fish
43454001001	Plant-Based Burgers	beef
43454100803	Smart Dogs	pork
43454100124	Smart Dogs Jumbo	pork
43454001018	Plant-Based Ground	beef

43454100155	Smart Ground Original	beef
43454100186	Smart Ground Mexican	beef
43454000042	Smart Menu Plant-Based Meatballs	beef
43454002169	Plant-Based Breakfast Patties	pork
43454002176	Plant-Based Breakfast Links	pork
43454400101	Gimme Lean Sausage	pork
43454101046	Smart Bacon	pork
43454001162	Plant-Based Bratwurst Sausages	pork
43454100629	Smart Sausage Italian	pork
43454100650	Smart Sausage Chorizo	pork
43454100308	Smart Deli Bologna	pork
43454100701	Smart Deli Ham	pork
43454100209	Smart Deli Turkey	pork
43454305109	Smart Tenders Plant-Based Chicken	poultry
43454478452	Plant-Based Chicken Fillets	poultry
43454478469	Plant-Based Chicken Tenders	poultry
28989103161	Incogmeato Sweet BBQ Plant-based Chik'n Tenders	poultry
28989103789	Incogmeato Plant-based Chik'n Tenders	poultry
28989103239	Incogmeato Mickey Mouse Shaped Plant-Based Chik'n Nuggets	poultry
28989103338	Incogmeato Plant-based Ground Patties	beef
28989103468	Incogmeato Plant-Based Ground	beef
28989103567	Incogmeato Italian Plant-Based Sausage	pork
28989103482	Incogmeato Plant-Based Original Bratwurst	pork
28989103901	Incogmeato Plant-Based Maple Breakfast Sausage Links	pork

28989103956	Incogmeato Plant-Based Breakfast Sausage Links	pork
28989103921	Incogmeato Plant-Based Ground Breakfast Sausage	pork
28989055347	MorningStar Farms Veggie Grillers Prime Burgers	beef
28989569103	MorningStar Farms Veggie Grillers Original Burgers	beef
28989102218	MorningStar Farms Vegan Meat Lovers Burger	beef
28989971951	MorningStar Farms Veggie Bacon Strips	pork
28989569127	MorningStar Farms Veggie Original Sausage Patties	pork
28989971104	Morningstar Farms Veggie Breakfast Sausage Links	pork
28989100948	MorningStar Farms Veggie Hot & Spicy Sausage Patties	pork
28989437808	MorningStar Farms Veggie Maple Flavored Sausage Patties	pork
28989102393	MorningStar Farms Veggie BBQ Chik'n Nuggets	poultry
28989101082	MorningStar Farms Veggie Chik'n Nuggets	poultry
28989786012	MorningStar Farms Veggie Buffalo Chik Patties	poultry
28989101020	MorningStar Farms Veggie Original Chik Patties	poultry

28989103802	MorningStar Farms Veggie Zesty Ranch Chik'n Nuggets	poultry
28989103888	MorningStar Farms Veggie Sweet Mustard Chik'n Nuggets	poultry
28989975003	MorningStar Farms Veggie Corn Dogs	pork
28989577993	MorningStar Farms Veggie Dogs	pork
28989979483	MorningStar Farms Veggie Grillers Crumbles	beef
28989101297	MorningStar Farms Veggie Chik'n Strips	poultry
28989102874	MorningStar Farms Veggie Italian Sausage Crumbles	pork
28989102539	MorningStar Farms Veggie Chorizo Crumbles	pork
28989103208	MorningStar Farms Veggie Meatballs	beef
28989101105	MorningStar Farms Veggie Buffalo Wings	poultry
28989101129	MorningStar Farms Veggie Parmesan Garlic Wings	poultry
28989102850	MorningStar Farms Veggie Spicy Popcorn Chik'n	poultry
837735002588	Quorn Vegan Meatless Chipotle Cutlets	poultry
833735001701	Quorn Vegan Meatless Spicy Patties	beef
833735002601	Quorn Vegan Meatless Buffalo Dippers	poultry
833735002431	Quorn Vegan Fishless Sticks	fish
833735000201	Quorn Meatless Fillets	poultry
833735000140	Quorn Meatless Meatballs	beef
833735000089	Quorn Meatless Patties	beef
833735001376	Quorn Meatless Gourmet Burgers	beef
833735000126	Quorn Meatless Pieces	poultry
833735003181	Quorn Meatless Kickin' ChiQin Cutlets	poultry

833735000065	Quorn Meatless Nuggets	poultry
833735000164	Quorn Meatless Vegetarian Turkey Roast	poultry
833735001371	Quorn Meatless Gourmet Burgers	beef
833735002891	Quorn Meatless Cheesy Nuggets	poultry
833735002731	Quorn Meatless Strips	poultry
833735000409	Quorn Meatless Sharp Cheese Cutlets	poultry
833735002151	Quorn Meatless Turkey-Style Deli Slices	pork
16741431119	Benevolent Bacon - Frozen	pork
16741411111	Benevolent Bacon - Refrigerated	pork
16741000940	Sweet Earth Awesome Grounds	beef
16741740174	Sweet Earth Awesome Burger	beef
16741851542	Sweet Earth Awesome Bacon Burger	beef
16741311770	Sweet Earth Chipotle Style Seitan Strips	poultry
16741311551	Sweet Earth Traditional Seitan Strips	poultry
16741311336	Sweet Earth Traditional Seitan Slices	pork
16741173125	Sweet Earth Chipotle Chik'n Marinated Plant-Based Shreds	poultry
16741340558	Sweet Earth Korean BBQ Style Chik'n Marinaded Plant-Based Shreds	poultry
16741000780	Sweet Earth Mindful Chik'n? Strips	poultry
16741941021	Sweet Earth Seasoned Chik'n Marinated Plant-Based Shreds	poultry
16741242241	Sweet Earth Applewood Smoked Flavor Ham Deli Slices	pork
16741000414	Sweet Earth Harmless Ham Deli Slices	pork
16741481671	Sweet Earth Italian-Style Pepperoni Deli Slices	pork

16741597907	Sweet Earth Oven Roasted Turkey Deli Slices	pork
16741279186	Sweet Earth Chik'n Apple Sausage	pork
16741140912	Sweet Earth Chorizo-Style Sausage	pork
16741623460	Sweet Earth Ginger Scallion Sausage	pork
16741910089	Sweet Earth Green Chile Chedd'r Sausage	pork
16741253070	Sweet Earth Jumbo Vegan Hot Dogs	pork
25583005204	Lightly Seasoned Plant-Based Chick'n	poultry
25583005259	Thai Basil Plant-Based Chick'n	poultry
25583005235	Sesame Garlic Plant-Based Chick'n	poultry
25583005211	Barbecue Plant-Based Chick'n	poultry
25583007222	Smoked Ham Plant-Based Deli Slices	pork
25583668737	Oven Roasted Plant-Based Deli Slices	pork
25583004221	Peppered Plant-Based Deli Slices	pork
25583668744	Hickory Smoked Plant-Based Deli Slices	pork
25583004276	Bologna Plant-Based Deli Slices	pork
25583004337	Italian Plant-Based Deli Slices	pork
25583004252	Roast Beef Plant-Based Deli Slices	pork
25583006058	Spinach and Pesto Plant-Based Artisan Sausage	pork
25583006041	Andouille Plant-Based Artisan Sausage	pork
25583006027	Italian Plant-Based Original Sausage	pork
25583006034	Kielbasa Plant-Based Original Sausage	pork
25583006010	Beer Brats Plant-Based Original Sausage	pork
25583006584	Jumbo Hot Dogs	pork
855099007566	Alpha Chik'n Nuggets	poultry
855099007559	Alpha Chik'n Burger	poultry
855099007603	Alpha plant-based original beefy crumble	beef

855099007610	Alpha plant-based meatless sausage crumble	pork
855099007597	Alpha Chik'n Strips	poultry
855099007344	ALPHA PATTY	beef
855099007504	Alpha BBQ Chik'n Pizza	beef