Demographic and Regional Differences in Elasticity of Meat Consumption in the United States

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Abstract

In light of growing environmental concerns related to meat production, reducing meat consumption in the United States, a country with high consumption, is crucial for sustainability. For effective policy design aimed at reducing meat consumption in the United States, it is important to understand how prices affect consumer demand, known as the price elasticity of meat demand. Modern elasticity estimates of meat demand, updated from previous studies, as well as the factors that drive them, are key for policy that will be effective, considering current consumer behavior. This paper uses BLS household-level Consumer Expenditure (CEX) data to estimate own-price, cross-price, and income elasticities of meat consumption, as well as demographic effects on own-price elasticities. I use regional and time variation in beef, pork, and poultry prices from 1990-2024, while controlling for regional differences and time trends, to study own-price, cross-price, and income elasticities, as well as demographic effects on own-price elasticity. I find that beef and poultry are inelastic - a change in price leads to a lesser change in demand. Pork is elastic - a change in price leads to a greater change in demand. Beef and pork may act as substitutes for poultry when poultry prices are high, but meat types are otherwise viewed more as complements. Furthermore, elasticity has remained relatively constant over the period studied but is more inelastic at higher income brackets and for households with higher protein diets. This illustrates the importance of demographics in consumer response to prices; thus, I argue that price policies may be more effective when combined with efforts to change prior beliefs about meat consumption.

1 Introduction

Meat production is one of the biggest contributors to environmental degradation worldwide and is estimated to become unsustainable by 2050. Agriculture is cited as "one of the primary drivers of climate change," with total food production estimated to be responsible for 26% of global greenhouse gas emissions, and livestock production responsible for about half of agriculture's total emissions (Ritchie, 2019; Joshi et al., 2015). Emissions are produced both from livestock themselves and from the agricultural processes required to produce feed, a process that is highly inefficient. When considering both direct and indirect emissions from livestock, the carbon footprint of meat production is cited as “comparable to or exceeding the emissions impact of the global transportation sector” (Joshi et al., 2015) A 2014 study in the UK found that the total carbon footprint of meat eaters is nearly twice that of vegans (Scarborough et al., 2014)

Scarborough et al. (2014) calls for a reduction in meat consumption in order to reduce global greenhouse gas emissions and their effect on climate change, which will require the greatest reduction in areas with the most consumption. According to the 2010 study by Daniel et al., meat consumption is significantly higher in developed countries than in developing countries, and it continues to be on the rise. Moreover, the same countries have significant subsidies on their meat industries, which remain many times higher than subsidies on fruits and vegetables. The United States has the highest total meat consumption globally and some of the highest subsidies in the industry, amounting to $38 billion annually (Daniel et al. (2010), (Joshi et al., 2015). In 2015, the price of a big mac was about $5 under US subsidies, but an estimated $13 if subsidies were removed. In 2015, the price of a pound of beef was estimated to be $30 in the US in the absence of subsidies (Joshi et al., 2015). Furthermore, these estimates do not include the true cost of meat when factoring in externalities. Thus, prices remain artificially low, resulting in inefficiently large meat consumption in the United States.

Joshi et al. assert that raising the price of meat through removal of subsidies in the United States would significantly decrease consumption, leading to a more optimal and sustainable outcome. In order to test this hypothesis, or understand the effect of higher prices on meat consumption, it is important to measure the price elasticity of meat demand. I will estimate own-price, cross-price, and income elasticities of three types of meat across four US regions to better understand the effectiveness of price policies on the goal of reducing meat consumption, globally and in the United States.

Several previous studies have also examined elasticity of demand for beef, pork, and poultry, including Schulz, Schroeder & Xia (2012) and Okrent & Alston (2012). However, these studies have focused solely on nationwide elasticity estimates. I extend this literature base by also looking at elasticity differences across different regions of the United States and different demographic groups. Furthermore, since my data extends to 2024, my estimates are more modern and more policy-relevant than previous estimates. Demand may have changed following previous elasticity estimates, highlighting the importance of updated understanding. Finally, I offer a novel contribution to the literature by interpreting my findings in the context of policy solutions, based on true cost of meat estimates.

To answer this question, I combine detailed data on demographics, regional prices, and household consumption of beef, pork, and poultry, over the last 35 years. I estimate price elasticities using a probit regression model on binary purchase, followed by a standard OLS regression of quantity consumed, given positive reported purchase, both on prices for each type of meat, household income, and controls. Finally, I use several interaction OLS models to study demographic effects on elasticity. I find that beef and poultry are price inelastic, while pork is price elastic. Meat types act as complements in most cases, but beef and pork may be substituted for poultry when poultry prices are high. All three types of meat are very income inelastic, but own-price elasticity is significantly affected by income. Meat demand is less elastic as income increases and for households with higher protein diets.

2 Review of the Literature

2.1 Literature

There is a large literature studying global elasticity of demand for meat products. A meta-analysis of global studies by Gallet (2010) looks at 393 studies worldwide with a total of 3,357 elasticity estimates from many countries, including the United States. Analyzing all estimates from all types of meat worldwide and over time, the study finds an average elasticity of meat demand of 0.90. The paper also reports that beef and fish are more elastic, while pork, lamb, and poultry are inelastic.

Fewer studies exist on the United States alone. However, studies of meat demand typically use one of three types of data: scanner-based data, survey-based data, and discrete choice experiments. Schulz, Schroeder & Xia (2012) use a scanner-based approach, offering precise quantity and price information, as well as store variation. However, scanner-based approaches often lead to higher elasticity estimates and cannot capture income elasticities, or other demographic effects (Younghyeon et al., 2024). Lusk & Tonsor (2016) use a discrete-choice experiment to estimate own-price, cross-price, and income elasticities for various types of beef, pork, and poultry in the United States, and for various demographic groups. The paper also studies nonlinearity, finding its estimates to be significantly more inelastic at higher prices and in higher income groups. The discrete-choice experiment captures rich heterogeneity but represents stated preferences and only a brief period of time.

The price elasticity of beef demand is the most commonly studied meat elasticity in the US, with varying estimates. For example, using a standard OLS regression model similar to my framework, Nicholls & Kuehn (1978) estimate the elasticity of demand for fresh-choice beef from 1950-1978 at approximately -0.62. Moreover, using a translog model, Menkhaus, St. Clair, & Hallingbye (1985) obtain a much higher estimate for overall beef consumption, elastic on both own price and income. Many newer studies focus on ground beef, whose share of beef consumption is increasing, obtaining generally elastic demands. Schulz, Schroeder, & Xia (2012) cite previous estimates as closer to -1.1, providing their own non-linear estimates as between -.044 and -1.29, varying by leanness. These more elastic estimates are consistent with higher elasticity estimates obtained from scanner data (Younghyeon et al., 2024). The authors suggest that increases in income lead to increases in leanness of beef demanded, suggesting substitution within types of beef. Its discussion of income elasticity with respect to different leanness in ground beef makes this study unique.

Much less literature appears to exist on other types of meat; however, Lusk & Tonsor (2021) estimate the elasticities of pork demand in 51 different US markets, incorporating regional heterogeneity. They find that pork demand tends to be relatively elastic and more so when broken down into more specific pork categories.

Menkhaus, St. Clair, & Hallingbye (1985) study consumer behavior in markets for beef, pork, and poultry, estimating inelastic pork and poultry demand and elastic beef demand. Negative cross-price estimates suggest dominance of the income effect over the substitution effect, and the authors suggest that a decrease in income most significantly decreases beef consumption, only slightly decreases pork consumption, and may slightly increase chicken consumption. The higher income elasticity for beef is consistent with Nicholls & Kuehn (1978). However, the negative cross-price elasticities are inconsistent with Chalfant et al. (1991), who find high substitutability between beef and pork and beef and poultry in Canada.

Further recent estimates of own-price elasticities for broad meat categories include Hahn (1994), Okrent & Alsten (2012), and Huang (1993). Okrent & Alston estimate broad US elasticities of -0.70, -1.26, and -0.81 for beef, pork, and poultry, respectively, compared to -0.62, -0.73, and -0.45 for Huang (1993) (Okrent & Alston, 2012). Hahn (1994) suggests that consumer tastes play a key role in reliability of elasticity estimates, leading to fluctuations in demand.

To my knowledge, there exists little analysis of potential policy effects in meat markets. Okrent & Alston analyze policy implications by focusing on many different food products and their consumption during recessions. Anderson & Wilkinson (1985) focus on meat markets, analyzing welfare impacts of government agricultural policy. Their main findings are that changes to grain markets have the greatest impact on consumer welfare in meat markets, as policy affecting the market for a certain type of meat can be offset by substitution behavior. This suggests that policy aimed at reducing meat consumption may have a greater effect when aimed at grain markets. More research is needed into potential policy ideas to reduce meat consumption. While several studies have analyzed true costs of meat, including Joshi et al. (2015) and Impact Institute (2024), to my knowledge, studies have yet to factor both estimates for factors influencing meat consumption and true cost of meat estimates into a greater policy discussion.

2.2 Contribution

My study uses survey data, in order to capture elasticities on a broad, long-term scale and include demographic variation, unlike Lusk & Tonsor (2016) - discrete-choice experiment - or scanner-based studies. Several previous studies also use a survey-based approach, or time-series data, including Hahn (1994) and Okrent & Alston (2012), and other earlier studies. However, like Lusk & Tonsor (2016), I go beyond the typical time-series approach and also capture regional and demographic variation. Elasticity estimates for pork obtained by Lusk & Tonsor (2021) vary significantly between regional markets, suggesting a basis for studying regional variation. I expand on this study by capturing regional variation in three different meat markets. Furthermore, interacting demographic variables with price offers a novel contribution to the literature, which has historically only focused on singular elasticity estimates. Studying demographic variation allows for a better understanding of consumer tastes and more optimal policy design.

Furthermore, results for income and cross-price elasticities are inconsistent and incomplete in the literature, highlighting the niche for modern and US-based estimates my research fills. Finally, I offer a novel contribution to the literature by interpreting my results in the context of true cost of meat estimates and potential policy solutions.

3 Methodology

3.1 Data

I collect detailed data on household expenditures and demographics from the BLS Consumer Expenditure Survey (CEX). This survey includes a randomly selected representative sample of US households starting in January 1990. Households are asked to report quarterly data on many categories of household expenditures, including three categories of meat products: "beef and veal," "pork," and "poultry". It also includes household demographics, including yearly income, family size, and education level. Households are identified by a unique household ID and grouped by four US regions: west, midwest, south, and northeast. From this dataset I extract household ID, demographics, region, and expenditure on each of the three types of meat. Since a small percentage of households do not have region listed, I remove these observations from my dataset.

In order to estimate price levels, I combine these data with BLS CPI data, which provides price indices for many goods in a typical basket. It contains monthly indices, for each of the four regions in the CEX dataset, as well as national indices. From this dataset I extract regional price indices and the national price index for the "food at home" category for each month, the broadest category that includes the three meat categories and contains complete data. I extract data beginning in January 1990 to match the CEX dataset.

Finally, I combine these data with USDA ERS national price averages, beginning in 1970. It contains monthly country-wise estimates for retail meat prices, with the three categories "beef retail prices", "pork retail prices", and "broiler (chicken) retail prices". From this dataset, I extract monthly price estimates for each of the three types of meat, also beginning in January 1990. Since prices in this dataset are nominal, I first deflate them using national CPI series for "beef and veal", "pork", and "poultry", and setting 1990 as my base year. I also retain the nominal prices for later use in quantity proxy construction.

Using these data, I calculate price estimates for each type of meat, in each region, and in each year. Since the CPI data provides regional variation but only indices, and the USDA data provides only country-wide data but actual price values, I merge these two datasets together in order to obtain monthly regional price estimates for each type of meat. This price proxy captures national shocks to each type of meat and regional shocks to food as a whole. Many regional shocks affect food as a whole, through transportation costs, differences in cost of living, or agricultural policy. Likewise, shocks to each type of meat, such as changes in grain markets or to imports, are likely to affect the whole country relatively equally. Thus, the price proxy will capture large-scale shocks to both region and type of meat.

To merge the two price datasets and obtain monthly regional price estimates, I first divide each region's index by the national index to determine each region's price level in relation to the national price level. Then, I multiply this proportion by both the national nominal and national real price averages to estimate the regional monthly price, both in nominal and real dollars.

$$\hat{P}_{m,r,t} = P_m^{\text{nat}} \cdot \frac{CPI_{r,t}}{CPI_{nat,t}}$$

After merging these datasets, I have price estimates for each of the four regions, for each of the three types of meat, and for each month from 1990-2024, represented by $\hat{P}_{m,r,t}$. My price dataset is at the monthly level, where each row contains the price proxies for each type of meat, given one month in one year. In order to obtain the other variables in my regression, I merge in the CEX dataset. Since the frequency of the CEX data is quarterly, I first average my real and nominal price proxies to obtain quarterly estimates in my price dataset. Then, I merge my price dataset with my cleaned CEX dataset on region and quarter. This will match each household's information to the correct price estimates for the applicable region and year. Since I only have data on household expenditures, I obtain quantity consumed by dividing expenditure by price. Since expenditures are in nominal dollars, I construct a quantity consumed proxy for each type of meat by dividing expenditure by my retained nominal price estimate for given region and given quarter.

$$Q_{m,r,t,i} = \frac{\mathrm{Exp}_{m,r,t,i}}{\hat{P}_{m,r,t}}$$

Finally, I remove observations with zero or negative income, as these observations most likely represent lack of response, rather than true zero income. I deflate income, as it is also in nominal dollars. I use the regional CPI series for "all items" and 1990 as my base year, deflating income to 1990 dollars, by region.

My final dataset has approximately 270,000 observations. One unit of observation in my final dataset is a single household, contained in a single region and a single quarter. Each row has quantity proxies for each type of meat, as well as price estimates for each type of meat, which are common across all households in the same region and quarter. It also has household demographics, including age of reference person, sex of reference person, number of earners, persons under 18 or over 65, education level, and race, which are common across one household. Since I do not have observations for the same households over time, my dataset is a repeated cross-section. I construct control variables in order to compare households of similar demographics across years.

3.2 Descriptive Figures

3.2.1 Real Prices Over Time

After deflating prices, prices show variation across both region and time, as well as persistent differences between regions and trends over time. Real beef and poultry prices are generally decreasing, while real pork prices are generally increasing. In my empirical model, regional fixed effects necessarily control for persistent differences between regions, and consistent time trends are also controlled. After regional fixed effects and time trends, prices retain variation within each region over time, allowing identification.

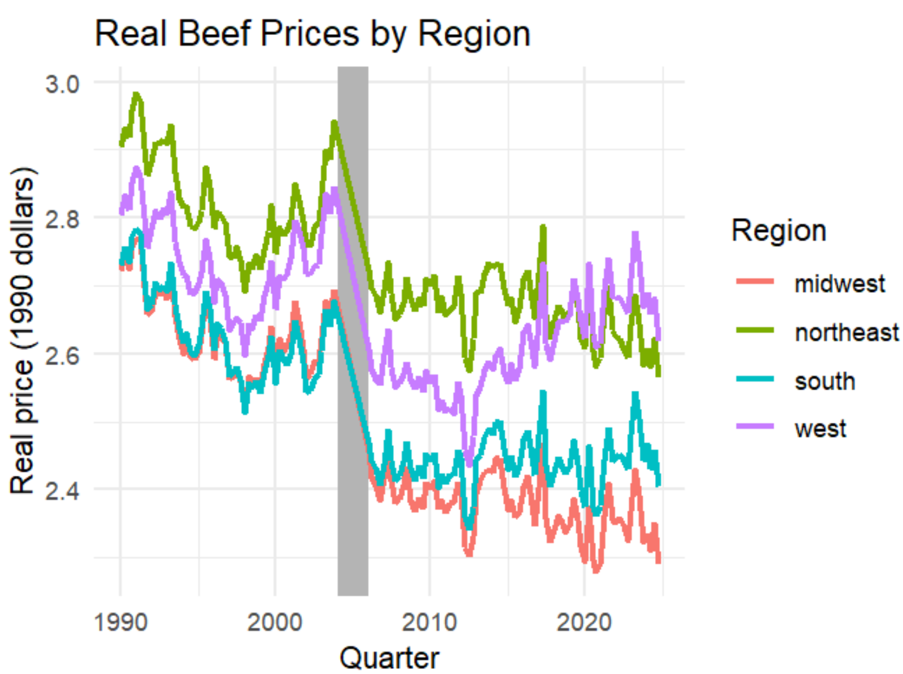

Figure 1: Regional Real Beef Price Trends Over Time

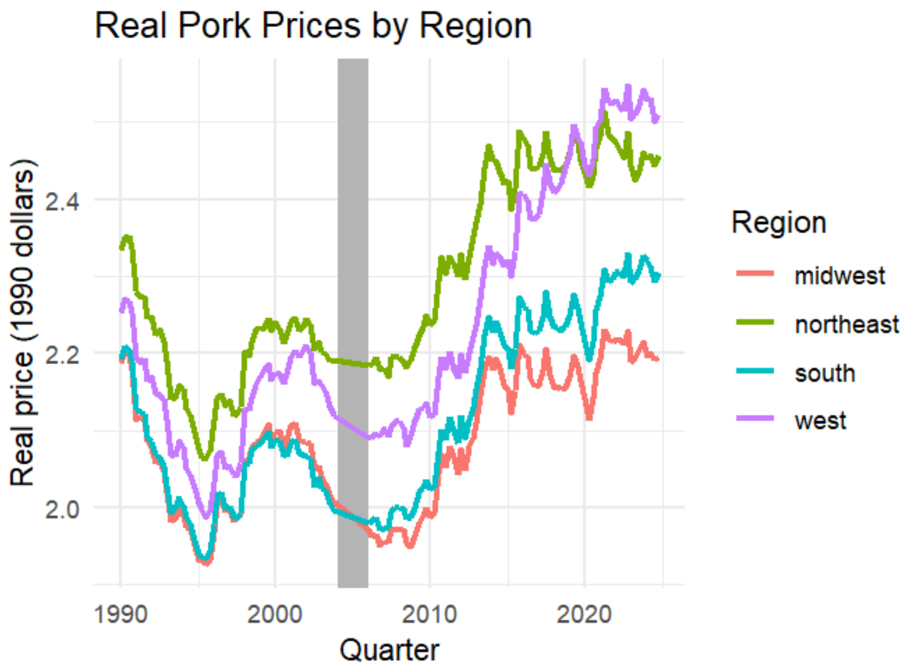

Figure 2: Regional Real Pork Price Trends Over Time

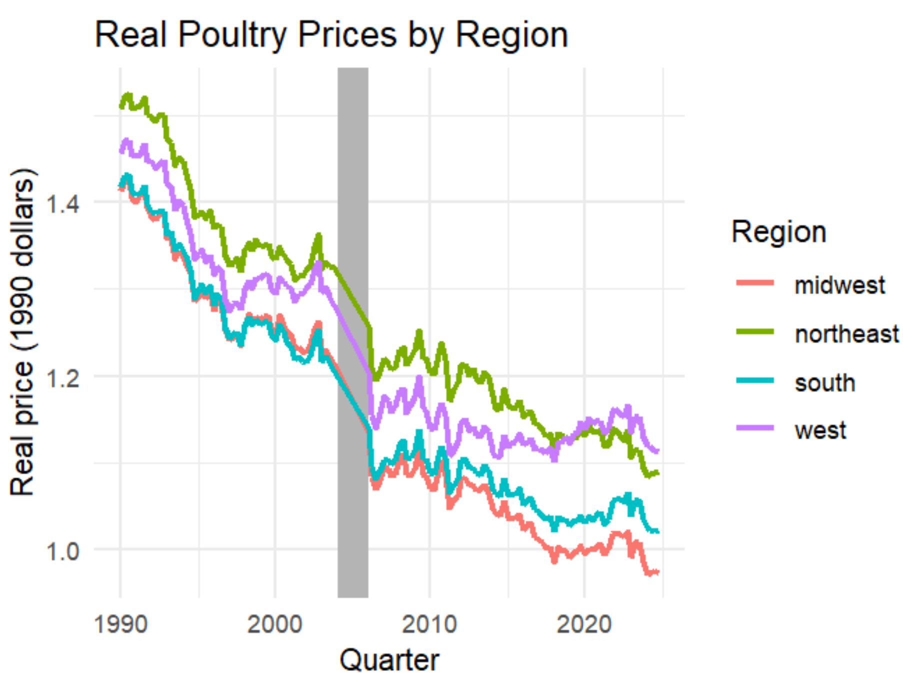

Figure 3: Regional Real Poultry Price Trends Over Time

3.2.2 Quantity Consumed on Price

Graphing average quantity consumed and price in a given region over time shows a general decrease in quantity consumed of beef and pork and increase in poultry. Both beef prices and quantity demanded are trending downward, suggesting a positive correlation over time. However, looking at variation over time, meat quantity demanded generally decreases when prices increase and vice versa, suggesting an overall negative correlation consistent with previous price elasticity of meat demand estimates. I hypothesize that my regression results will show a negative price elasticity of demand for each type of meat. See the appendix for all twelve graphs.

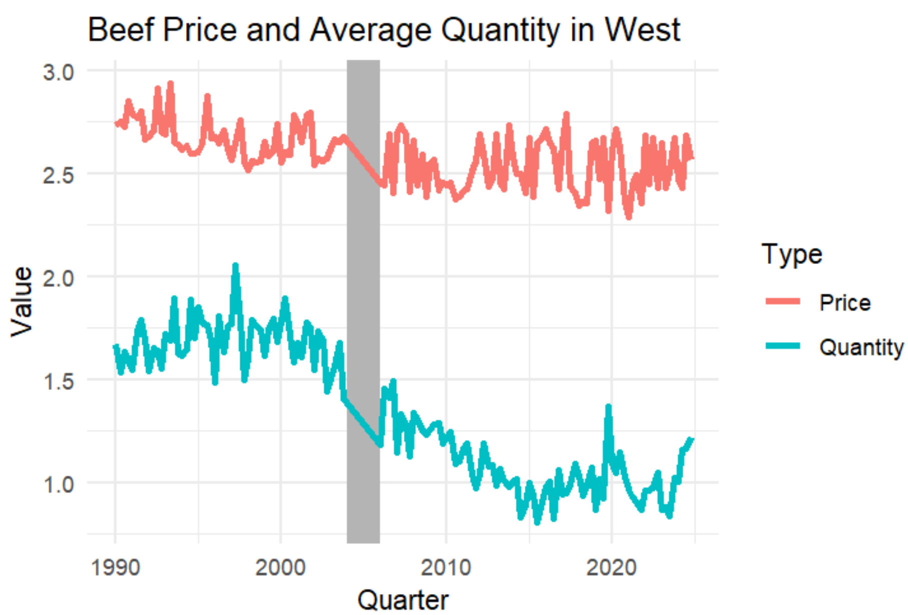

Figure 4: Average Beef Quantity and Price Over Time in the West

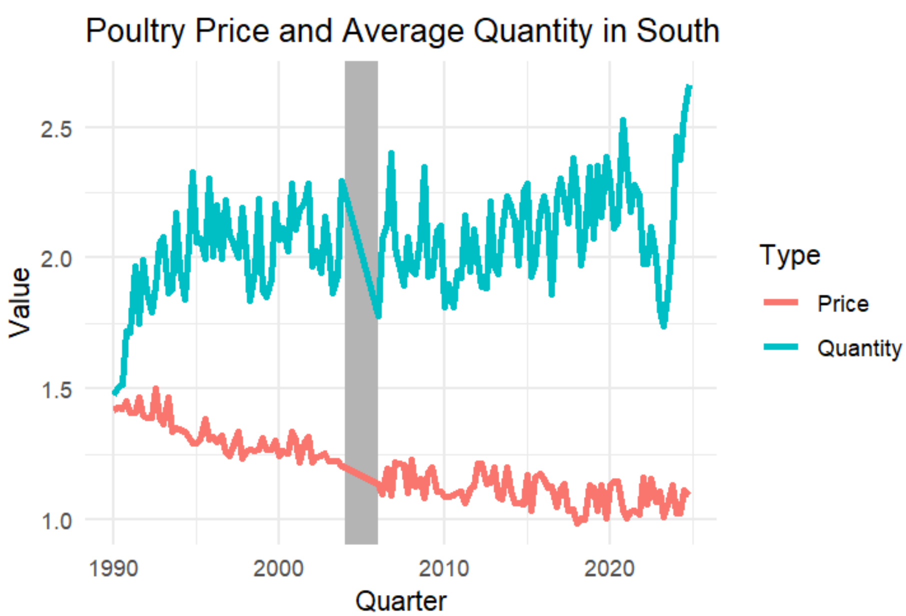

Figure 5: Average Poultry Quantity and Price Over Time in the South

To visualize whether there appears to be a negative relationship between change in price and change in quantity demanded, I calculate thirty-six observations of change in quantity on change in price, using three meat types, four regions, and three time periods (1990-2003, 2006-2010, and 2010-2024). I then put these observations on a scatterplot.

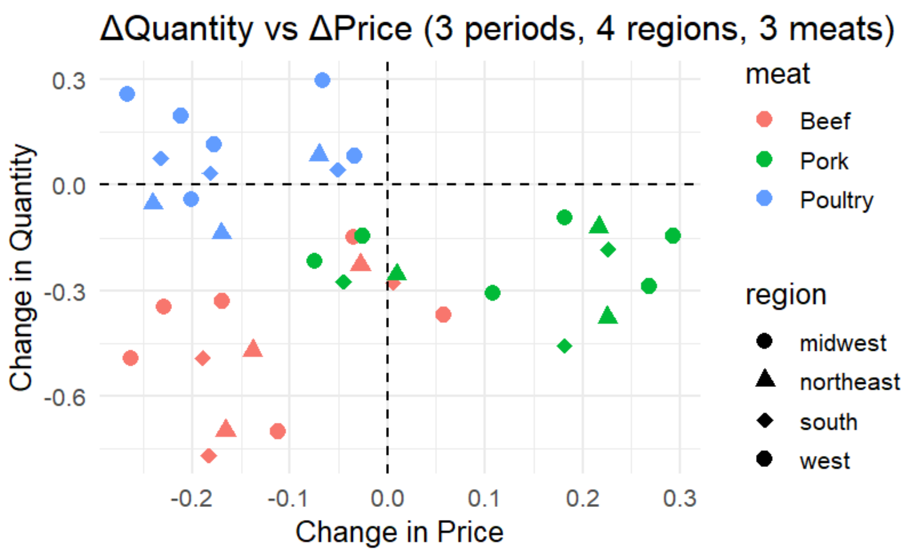

Figure 6: Scatterplot of Change in Quantity on Change in Price

The relationship shown by the scatterplot is different for each type of meat. Pork shows mostly positive change in price and negative change in quantity, and poultry shows mostly negative change in price and positive change in quantity, both consistent with a general negative trend, or the law of demand. However, beef shows almost exclusively negative quantity changes, consistent with the graph above. This suggests that beef demand is falling independent of price. I hypothesize that beef demand is more inelastic than pork and poultry demand, and other factors may be contributing more to generally falling beef demand.

3.2.3 Income Trends

Real income shows variation across time and region. Income is generally trending upward, with the exception of the 2008 recession, when there is a clear downward trend for several years. See appendix for graph.

3.2.4 Demographic Summary Table

This table shows the percentages of observations that belong to each category, or the mean for continuous variables, given weighted data. Variables for sex, education (college degree is greater than value of 13), and age represent the reference person for the household.

Variable	**Summary**
Total Observations (unweighted)	301586
Male	49.8%
College Degree	36.5%
Age	50.07
Earners	1.34
HH_Size	2.56
Over65	37%
Under18	66%

Table 1: Summary Table of Sample Characteristics

3.3 Empirical Model

I use a weighted OLS regression as a log-log model for elasticity estimation, clustering my standard errors at the regional by quarter level. The log-log model relies on having values greater than 0, creating an issue with the CEX data, where many households report zero consumption in all meat categories. I first attempt to filter out true non-consumption values from households that did not complete the detailed expenditure section of the survey by deleting rows that show zeros for all food-related expenditure categories, including the total food at home expenditure category. If every column in this list contains a 0 for a given row, it suggests that the household simply did not complete this section, and that the zeros are not necessarily true zero consumption values. If any of these categories is positive, the row remains in my final dataset. After this cleaning step, 34% of the households still report zero expenditures in all three meat categories. Since only 2% of the population does not consume meat, this suggests that these households did not purchase meat for that particular quarter, that they only ate meat away from home, or that they reported their meat expenditures in a different category, such as oth_meat.

Deleting 34% of the rows in my dataset would significantly reduce my data and introduce selection bias into the model, since the model would calculate elasticity based on only households that reported a purchase that quarter. Thus, the outcome of quantity consumed would be related to the sample on which it is regressed, as many of the same variables may affect whether or not the household purchases at all. To solve this problem, I consider a Heckman (1979) 2-Stage Selection Model, which allows for biased conditional participation through a 2-stage regression. However, the Heckman Model requires a valid exclusion restriction, or variable that explains the decision of whether to purchase but is uncorrelated with the decision of how much to purchase. Since all the variables in my dataset are likely correlated with both decisions, I do not have a valid exclusion restriction. Thus, I run a simple two-regression model, which, like Heckman (1970), uses a probit on purchase in the first regression and an OLS on quantity purchased in the second regression.

This model separately predicts the effects of my variables on probability of purchase and then on quantity of purchase, given positive reported purchase. Its limitation from Heckman (1979) is that it cannot measure or control for selection bias. However, the total elasticity can still be estimated using intensive and extensive margin elasticities.

The first regression is a probit model that predicts the likelihood of a given household reporting a meat purchase that quarter. It tests for significance of each of the independent variables on whether or not purchase is positive.

$$D^*_{irtm} = \alpha + \beta_1 \ln P_{rtm} + \sum_{m' \neq m} \beta_{2m'} \ln P_{rtm'} + \beta_3 \ln Y_{irt} + \gamma' X_{irt} + \delta_r + \tau_1 t + \tau_2 t^2 + u_{irtm} \quad (1)$$

$$D_{irtm} = \begin{cases} 1 & \text{if } D^*_{irtm} > 0 \\ 0 & \text{otherwise} \end{cases} \qquad u_{irtm} \sim N(0,1) \quad (2)$$

Here, D_{irtm} is a binary variable of whether or not the household reported a purchase, which varies by household, region, quarter, and meat type. P_{rtm} is the price for each of the three meat types, varying by region and quarter. Y_{irt} is household income, unique to each household and, thus, varying also by region and quarter. X_{irt} is a vector of demographic variables: family size, number of earners, number of children, number of people over 65, number of earners, age of the reference person, sex of the reference person, and education level of the reference person. δ_r is regional fixed effects, t and t^2 are linear and quadratic time trends, and u_{irtm} is the error term for the selection model. Since my data varies across time and region, I include regional fixed effects to control for persistent, time-invariant differences between regions, as well as linear and quadratic time trends, to control for persistent, region-invariant time trends. I choose to include time trends since most of my variation in price occurs over time, and this variation would be absorbed in time fixed effects. While time trends do not allow for short-term shocks, they allow me to retain my price variation and to test for trends in consumption over time. Regional fixed effects control for, and illustrate, differences in baseline consumption between regions.

The second regression is the standard log model, used to determine elasticities from only the households that reported a positive purchase in that meat category and during that quarter. Since there is no bias correction term like in Heckman (1970), the second regression is entirely separate from the first and based on the biased sample. However, while I cannot measure the bias in the model this way, I can still estimate total elasticities from both models, using both models. The first regression calculates the extensive margin elasticity, or responsiveness in participation, while the second model calculates the intensive margin elasticity, or responsiveness of those participating in the market. Together, they can be used to calculate the total elasticity. I run three separate OLS regressions, given participation, to obtain estimates, for each of the three types of meat:

$$\ln Q_{irtm} = \alpha + \beta_1 \ln P_{rtm} + \sum_{m' \neq m} \beta_{2m'} \ln P_{rtm'} + \beta_3 \ln Y_{it} + \gamma' X_{it} + \delta_r + \tau_1 t + \tau_2 t^2 + \varepsilon_{irtm} \quad (3)$$

Here, quantity demanded, varying by meat type, household, region, and quarter, is regressed on the same variables as the first regression. The coefficients on own-price, cross-price, and income, Y_{ti}, represent their respective elasticity estimates.

In both stages, I cluster standard errors at the region_quarter level. Since all households in a given region and quarter face the same price, I assume correlation in the standard errors, which may lead to artificially small standard errors in an unclustered OLS model. Clustering by region_quarter treats each set of households in the same region and quarter as one group, thus using only 528 observations to calculate standard errors and more accurately reflecting the precision of the model. However, clustering at this level assumes lack of correlation between households in the same region but different quarters and households in the same quarter but in different regions, both of which are unlikely to be truly independent. Thus, while clustering significantly improves accuracy of model precision, it may still overstate statistical significance of my results.

I first run three separate models of increasing complexity in order to capture how estimates change as variables are added into the equation. The first includes only prices, income, and time trends. The second adds regional fixed effects. The third adds the above vector of demographic control variables. Both stages of my model include CEX household weights to obtain estimates that are demographically representative of the United States population.

Finally, I run a series of OLS models (second stage only) using interaction terms to capture differences in elasticity between different demographic groups, regions, and time periods. I first create several new variables. I create income and time quartile categorical variables to study how elasticity has changed over time or as income increases. These are created by dividing the the total sample into four equally-sized increasing buckets, such that time quartiles represent four equal time periods from 1990-2024, and income quartiles four equal income brackets from lowest to highest reported income. I create binary variables college_degree, kids, male, and retired that take a value of 1 if the reference person has a college degree, if the household has kids, if the reference person is male, and if the household has adults over 65, respectively, and 0 otherwise. Finally, I retain the region and age variables. This leads to a total of eight separate interaction term regressions for each meat type.

While I run each regression separately for interpretability, in reality, my interaction models are likely highly correlated, specifically with income. For example, having a college degree, having kids, and living in wealthier regions of the US - such as the northeast - are correlated with having higher income. Thus, rather than interpreting the findings from my models separately, I will combine all general findings for an overall demographic picture.

4 Results

4.1 Beef

4.1.1 Model 1: Probit

Table 2: Beef Purchase Decision (Probit)

	(1) Baseline	(2) + Region FE	(3) + Demographics
Log Price Beef	0.235***	0.352***	0.379**
	(0.188)	(0.183)	(0.180)
Log Price Pork	-0.950***	-0.884***	-0.958***
	(0.137)	(0.138)	(0.138)
Log Price Poultry	0.665***	0.761***	0.587***
	(0.191)	(0.189)	(0.191)
Log Income	0.062***	0.064***	0.033***
	(0.003)	(0.003)	(0.003)
Region Fixed Effects	No	Yes	Yes
Time Trend (t, t^2)	Yes	Yes	Yes
Demographic Controls	No	No	Yes
Observations	301,586	301,586	301,586

Probit model on probability household reports a positive purchase of beef. Model 1 tests income and price effects on probability of purchase using time trends as controls. Model 2 adds regional fixed effects, and model 3 adds demographic controls.
Clustered standard errors (region $\times$ quarter) in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

4.1.2 Model 2: OLS

Table 3: Beef Quantity Conditional on Purchase (OLS)

	(1) Baseline	(2) + Region FE	(3) + Demographics
Log Price Beef	-0.619***	-0.698***	-0.593***
	(0.197)	(0.187)	(0.172)
Log Price Pork	-0.902***	-0.948***	-1.020***
	(0.124)	(0.121)	(0.117)
Log Price Poultry	1.097***	1.053***	0.808***
	(0.197)	(0.186)	(0.171)
Log Income	0.073***	0.073***	0.041***
	(0.002)	(0.002)	(0.002)
Region Fixed Effects	No	Yes	Yes
Time Trend (t, t^2)	Yes	Yes	Yes
Demographic Controls	No	No	Yes
Observations	125,447	125,447	125,447

OLS model on Log Quantity Beef. Model 1 tests own-price, cross-price, and income elasticities using time trends as controls. Model 2 adds regional fixed effects, and model 3 adds demographic controls.
Clustered standard errors (region × quarter) in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

4.1.3 Demographic Interactions

Table 4: Beef Elasticity – Income Interaction

Own Price Elasticity	-0.6145**
	(0.1882)
Price × Income Q2	0.0468***
	(0.0090)
Price × Income Q3	0.0873***
	(0.0111)
Price × Income Q4	0.1654***
	(0.0136)
Time Trend	y
Region FE	y
Demographics	y

OLS model of log price beef, (log price beef × income), and demographics on log quantity beef.
Clustered standard errors (region × quarter) in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5: Beef Elasticity – College Interaction

Own Price Elasticity	-0.7500***
	(0.1916)
Price × College	0.3506***
	(0.1055)
Time Trend	y
Region FE	y
Demographics	y

OLS model of log price beef, (log price beef × college), and demographics on log quantity beef.
Clustered standard errors (region × quarter) in parentheses.

Table 6: Beef Elasticity – Male Interaction

Own Price Elasticity	-0.5557**
	(0.1902)
Price × Male	0.0402
	(0.0827)
Time Trend	y
Region FE	y
Demographics	y

OLS model of log price beef, (log price beef × male), and demographics on log quantity beef.
Clustered standard errors (region × quarter) in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Beef Elasticity – Kids Interaction

Own Price Elasticity	-0.7146***
	(0.1871)
Price × Kids	0.4531***
	(0.0788)
Time Trend	y
Region FE	y
Demographics	y

OLS model of log price beef, (log price beef × kids), and demographics on log quantity beef.
Clustered standard errors (region × quarter) in parentheses.

Table 8: Beef Elasticity – Retired Interaction

Own Price Elasticity	-0.4444*
	(0.1891)
Price × Retired	-0.3425***
	(0.0873)
Time Trend	y
Region FE	y
Demographics	y

OLS model of log price beef, (log price beef × retired), and demographics on log quantity beef.
Clustered standard errors (region × quarter) in parentheses.

Table 9: Beef Elasticity – Age Interaction

Own Price Elasticity	-0.0583
	(0.2241)
Price × Age	-0.00945***
	(0.00232)
Time Trend	y
Region FE	y
Demographics	y

OLS model of log price beef, (log price beef × age), and demographics on log quantity beef.
Clustered standard errors (region × quarter) in parentheses.

Table 10: Beef Elasticity – Region Interaction

Own Price Elasticity	-0.6832***
	(0.1988)
Price × Northeast	0.4133*
	(0.2140)
Price × South	0.4394**
	(0.1652)
Price × West	-0.1682
	(0.2512)
Time Trend	y
Region FE	y
Demographics	y

OLS model of log price beef, interactions with region, and demographics on log quantity beef.
Clustered standard errors (region × quarter) in parentheses.

Table 11: Beef Elasticity – Time Interaction

Own Price Elasticity	-1.0897***
	(0.1673)
Price × Time Q2	0.0209
	(0.0158)
Price × Time Q3	-0.0893***
	(0.0241)
Price × Time Q4	0.0098
	(0.0347)
Time Trend	y
Region FE	y
Demographics	y

OLS model of log price beef, interactions with time quartile, and demographics on log quantity beef. Clustered standard errors (region × quarter) in parentheses.

4.1.4 Interpretation

The probit model for beef purchase shows a positive correlation between beef price and probability of reported purchase. Since beef is unlikely to be a Giffen good, these results are unreliable and may be caused by time trends in buying habits correlated with price trends that are not fully absorbed by time controls in the model. The positive coefficient may also suggest that price is not a strong factor in choosing whether to buy and may play a stronger role in the decision of how much to buy. The coefficients on pork and poultry prices suggest differences in substitutability between beef and pork and beef and poultry. Probability of beef purchase increases as a result of an increase in poultry price but a decrease in pork price. Low, positive coefficients on income suggest that probability of beef purchase may increase with an increase in income, but only slightly.

Elasticity estimates can be obtained directly from the coefficients in the log-log OLS model. Own-price elasticity is negative and significant at the 0.01 level, suggesting that price is considered when choosing how much beef to purchase, and the relationship between beef price and quantity is negative. The beef own-price elasticity estimate of about -0.6 signifies that a 1% increase in beef price is associated with a 0.6% decrease in quantity of beef consumed, or an inelastic beef demand. A 1% increase in pork price is associated with a 0.9% decrease in beef quantity consumed, while a 1% increase in poultry price is associated with a 1.1% increase in beef quantity consumed, both significant at the 0.01 level. Consistent with purchase probit results, consumers show substitution between poultry and beef but treat pork and beef as complements. Furthermore, consumers show greater elasticity in beef demand from changes in pork and poultry prices than from changes in beef price. Income elasticity is positive and significant at the 0.01 level, suggesting that increases in income correlate with increases in quantity of beef demanded. However, consistent with the purchase probit results, income effects are small.

My interaction models suggest that demographics play a strong role in elasticity. Beef becomes more inelastic by a magnitude of 0.05 in income Q2 compared to Q1, 0.09 in Q3 compared to Q1, and 0.17 in Q4 compared to Q1. Beef is more inelastic by a magnitude of 0.35 when the reference person has a college degree, which is likely also a proxy for higher income. Beef becomes more inelastic by a magnitude of 0.45 when the household has kids and more elastic by 0.34 percentage points when the household has retired adults. Beef becomes more elastic by a magnitude of 0.009 for a 1-year increase in age of the reference person. Regional variation is limited by the fact that price in each region varies only by time. However, compared to the midwest, beef shows a statistically significant increase in elasticity in the northeast and south and decrease in the west. Beef is statistically significantly more elastic in time Q3, as compared to Q1, however, only by a slight amount. Overall, beef shows little variation over my time period studied.

4.2 Pork

4.2.1 Model 1: Probit

Table 12: Pork Purchase Decision (Probit)

	(1) Baseline	(2) + Region FE	(3) + Demographics
Log Price Pork	-0.867***	-0.622***	-0.684***
	(0.160)	(0.138)	(0.138)
Log Price Beef	-0.245	0.197	0.216
	(0.229)	(0.180)	(0.180)
Log Price Poultry	0.759***	1.121***	1.000***
	(0.203)	(0.191)	(0.192)
Log Income	0.047***	0.049***	0.031***
	(0.003)	(0.003)	(0.003)
Region Fixed Effects	No	Yes	Yes
Time Trend (t, t^2)	Yes	Yes	Yes
Demographic Controls	No	No	Yes
Observations	301,586	301,586	301,586

Probit model on probability household reports a positive purchase of pork. Model 1 tests income and price effects on probability of purchase using time trends as controls. Model 2 adds regional fixed effects, and model 3 adds demographic controls.
Clustered standard errors (region $\times$ quarter) in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

4.2.2 Model 2: OLS

Table 13: Pork Quantity Conditional on Purchase (OLS)

	(1) Baseline	(2) + Region FE	(3) + Demographics
Log Price Pork	-1.509***	-1.474***	-1.392***
	(0.139)	(0.138)	(0.131)
Log Price Beef	-0.122	-0.059	-0.041
	(0.190)	(0.199)	(0.188)
Log Price Poultry	0.913***	0.966***	0.821***
	(0.167)	(0.168)	(0.159)
Log Income	0.043***	0.044***	0.029***
	(0.002)	(0.002)	(0.002)
Region Fixed Effects	No	Yes	Yes
Time Trend (t, t^2)	Yes	Yes	Yes
Demographic Controls	No	No	Yes
Observations	118,561	118,561	118,561

OLS model on Log Quantity Pork. Model 1 tests own-price, cross-price, and income elasticities using time trends as controls. Model 2 adds regional fixed effects, and model 3 adds demographic controls.
Clustered standard errors (region × quarter) in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

4.2.3 Demographic Interactions

Table 14: Pork Elasticity – Income Interaction

Own Price Elasticity	-1.5363***
	(0.1236)
Income Q2 Interaction	0.0150
	(0.0117)
Income Q3 Interaction	0.0525***
	(0.0143)
Income Q4 Interaction	0.1362***
	(0.0172)
Time Trend	y
Region FE	y
Demographics	y

OLS model of log price pork, (log price pork × income), and demographics on log quantity pork.
Clustered standard errors (region × quarter) in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 15: Pork Elasticity – College Interaction

Own Price Elasticity	-1.576***
	(0.1242)
Price × College	0.3538***
	(0.0755)
Time Trend	y
Region FE	y
Demographics	y

OLS model of log price pork, (log price pork × college_degree), and demographics on log quantity pork.
Clustered standard errors (region × quarter) in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 16: Pork Elasticity – Male Interaction

Own Price Elasticity	-1.577***
	(0.1290)
Price × Male	0.1606*
	(0.0660)
Time Trend	y
Region FE	y
Demographics	y

OLS model of log price pork, (log price pork × male), and demographics on log quantity pork.
Clustered standard errors (region × quarter) in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 17: Pork Elasticity – Kids Interaction

Own Price Elasticity	-1.4410***
	(0.1270)
Price × Kids	-0.1115
	(0.0755)
Time Trend	y
Region FE	y
Demographics	y

OLS model of log price pork, (log price pork × kids), and demographics on log quantity pork.
Clustered standard errors (region × quarter) in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 18: Pork Elasticity – Retired Interaction

Own Price Elasticity	-1.5164***
	(0.1245)
Price × Retired	0.1121
	(0.0809)
Time Trend	y
Region FE	y
Demographics	y

OLS model of log price pork, (log price pork × retired), and demographics on log quantity pork.
Clustered standard errors (region × quarter) in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 19: Pork Elasticity – Age Interaction

Own Price Elasticity	-1.4905***
	(0.1578)
Price × Age	0.00002
	(0.0021)
Time Trend	y
Region FE	y
Demographics	y

OLS model of log price pork, (log price pork × age), and demographics on log quantity pork.
Clustered standard errors (region × quarter) in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 20: Pork Elasticity – Region Interaction

Own Price Elasticity	-1.3378***
	(0.1829)
Price × Northeast	-0.4874*
	(0.2001)
Price × South	-0.2626
	(0.1878)
Price × West	0.0933
	(0.1822)
Time Trend	y
Region FE	y
Demographics	y

OLS model of log price pork, (log price pork × region), and demographics on log quantity pork.
Clustered standard errors (region × quarter) in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 21: Pork Elasticity – Time Interaction

Own Price Elasticity	-1.3994***
	(0.1334)
Price × Q2	0.0302
	(0.0229)
Price × Q3	-0.0010
	(0.0330)
Price × Q4	0.0899*
	(0.0429)
Time Trend	y
Region FE	y
Demographics	y

OLS model of log price pork, (log price pork × time), and demographics on log quantity pork.
Clustered standard errors (region × quarter) in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

4.2.4 Interpretation

The probit model for pork purchase shows a strong negative correlation between pork price and probability of reported purchase, suggesting that a 1% increase in pork price is associated with a decrease of 0.867 percentage points in likelihood of reported purchase. While this is consistent with the Law of Demand for normal goods, these results, similar to those for beef and poultry, may be more influenced by unabsorbed time trends, rather than actual consumer behavior. The negative coefficient on beef price suggests that consumers may substitute pork when beef prices are high, but this is not significant and contradictory to the complementary behavior observed in the beef probit. The positive and statistically significant coefficient on poultry price suggests that consumers may treat pork as a complement to poultry. Low, positive coefficients on income suggest that probability of poultry purchase may increase with an increase in income, but, once again, only slightly.

Own-price elasticity is negative and significant at the 0.01 level, suggesting that price is considered when choosing how much pork to purchase, and the relationship between pork price and quantity is negative. The pork own-price elasticity estimate of about -1.4 signifies a 1.4% decrease in quantity of pork consumed associated with a 1% increase in pork price, suggesting that modern pork demand is highly elastic. A 1% increase in beef price is associated with a 0.04% decrease in pork quantity consumed, but this result is not statistically significant, suggesting that price of beef does not significantly affect quantity of pork purchased. A 1% increase in poultry price is associated with a statistically significant 0.9% increase in pork quantity consumed, suggesting consumer tendency to substitute pork when poultry prices are high. However, consumers show greater own-price elasticity of pork demand than cross-price elasticities. Income elasticity is positive and significant at the 0.01 level, suggesting that increases in income correlate with increases in quantity of beef demanded. However, consistent with previously discussed models, income effects are small.

Pork shows statistically significant difference in elasticities at the third and fourth income quartiles, compared to the fourth, with demand more inelastic by a magnitude of 0.05 in Q3 and 0.14 in Q4, compared to Q1. Pork is more inelastic by a magnitude of 0.35 when the reference person has a college degree. Pork is more inelastic by 0.16 percentage points when the reference person is male. While regional interactions are limited by the fact that price only varies by time in each region, pork is statistically signficantly more elastic by a magnitude of 0.49 in the northeast, as compared to the midwest. The time interaction suggests that pork became slightly more inelastic in Q4 compared to Q1, but pork elasticity generally shows little time variation.

4.3 Poultry

4.3.1 Model 1: Probit

Table 22: Poultry Purchase Decision (Probit)

	(1) Baseline	(2) + Region FE	(3) + Demographics
Log Price Poultry	0.689**	0.427***	
	(0.249)	(0.081)	
Log Price Pork	-0.052	-0.228*	
	(0.163)	(0.095)	
Log Price Beef	0.369	0.044	
	(0.235)	(0.234)	
Log Income	0.066***	0.067***	
	(0.003)	(0.003)	
Region Fixed Effects	No	Yes	
Time Trend (t, t^2)	Yes	Yes	
Demographic Controls	No	No	
Observations	301,586	301,586	

Probit model on probability household reports a positive purchase of poultry. Model 1 tests income and price effects using time trends as controls. Model 2 adds regional fixed effects. The demographic specification did not converge and is therefore omitted.

Clustered standard errors (region $\times$ quarter) in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

4.3.2 Model 2: OLS

Table 23: Poultry Quantity Conditional on Purchase (OLS)

	(1) Baseline	(2) + Region FE	(3) + Demographics
Log Price Poultry	-0.593***	-0.819***	-0.862***
	(0.150)	(0.148)	(0.177)
Log Price Pork	-0.319**	-0.466**	-0.466***
	(0.115)	(0.146)	(0.131)
Log Price Beef	0.730***	0.443**	0.452*
	(0.148)	(0.141)	(0.197)
Log Income	0.063***	0.063***	0.029***
	(0.002)	(0.002)	(0.002)
Region Fixed Effects	No	Yes	Yes
Time Trend (t, t^2)	Yes	Yes	Yes
Demographic Controls	No	No	Yes
Observations	112,688	112,688	112,688

OLS model on log poultry quantity conditional on purchase. Model 1 estimates baseline price and income elasticities, model 2 adds regional fixed effects, and model 3 adds demographic controls.
Clustered standard errors (region $\times$ quarter) in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

4.3.3 Demographic Interactions

Table 24: Poultry Elasticity – Income Interaction

Own Price Elasticity	-0.9759***
	(0.1627)
Income Q2 Interaction	-0.0188
	(0.0316)
Income Q3 Interaction	0.1874***
	(0.0360)
Income Q4 Interaction	0.5296***
	(0.0436)
Time Trend	y
Region FE	y
Demographics	y

OLS model of log price poultry, (log price poultry $\times$ income), and demographics on log quantity poultry.
Clustered standard errors (region $\times$ quarter) in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 25: Poultry Elasticity – College Interaction

Own Price Elasticity	-0.7313***
	(0.1623)
Price × College	-.0728
	(0.0544)
Time Trend	y
Region FE	y
Demographics	y

OLS model of log price poultry, (log price poultry $\times$ college), and demographics on log quantity poultry.
Clustered standard errors (region $\times$ quarter) in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 26: Poultry Elasticity – Male Interaction

Own Price Elasticity	-0.8096***
	(0.1626)
Price × Male	0.0879**
	(0.0420)
Time Trend	y
Region FE	y
Demographics	y

OLS model of log price poultry, (log price poultry × male), and demographics on log quantity poultry.
Clustered standard errors (region × quarter) in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 27: Poultry Elasticity – Kids Interaction

Own Price Elasticity	-0.8096***
	(0.1625)
Price × Kids	0.0868*
	(0.0443)
Time Trend	y
Region FE	y
Demographics	y

OLS model of log price poultry, (log price poultry × kids), and demographics on log quantity poultry.
Clustered standard errors (region × quarter) in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 28: Poultry Elasticity – Retired Interaction

Own Price Elasticity	-0.7565***
	(0.1609)
Price × Retired	-0.0682
	(0.0440)
Time Trend	y
Region FE	y
Demographics	y

OLS model of log price poultry, (log price poultry × retired), and demographics on log quantity poultry.
Clustered standard errors (region × quarter) in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 29: Poultry Elasticity – Age Interaction

Own Price Elasticity	-0.8060***
	(0.1669)
Price × Age	0.0007
	(0.0011)
Time Trend	y
Region FE	y
Demographics	y

OLS model of log price poultry, (log price poultry × age), and demographics on log quantity poultry. Clustered standard errors (region × quarter) in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 30: Poultry Elasticity – Region Interaction

Own Price Elasticity	-0.7643***
	(0.1624)
Price × Northeast	0.3169***
	(0.0868)
Price × South	-0.1066
	(0.0816)
Price × West	-0.0464
	(0.0947)
Time Trend	y
Region FE	y
Demographics	y

OLS model of log price poultry, (log price poultry × region), and demographics on log quantity poultry. Clustered standard errors (region × quarter) in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 31: Poultry Elasticity – Time Interaction

Own Price Elasticity	-0.7108***
	(0.1813)
Price × Q2	0.0400
	(0.0607)
Price × Q3	-0.4112***
	(0.1063)
Price × Q4	-0.3045*
	(0.1574)
Time Trend	y
Region FE	y
Demographics	y

OLS model of log price poultry, (log price poultry × time), and demographics on log quantity poultry.
Clustered standard errors (region × quarter) in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

4.3.4 Interpretation

The third probit model does not converge with clustered standard errors, suggesting that there is not a great enough proportion of reported poultry purchasers to obtain accurate results. An increase in poultry price is correlated with a strong increase in likelihood of poultry purchase, suggesting that poultry purchase may once again be more affected by time trends that are not fully controlled for in the model and that these results are unreliable. Beef price does not show a statistically significant affect on likelihood of poultry purchase, but there is a mildly significant decrease in likelihood of poultry purchase equal to 0.052 percentage points associated with a 1% increase in pork price. Income coefficients are positive and statistically significant but small, suggesting that income increases increase likelihood of poultry purchase but only slightly.

Own-price elasticity is negative and significant at the 0.01 level, suggesting that price is considered when choosing how much poultry to purchase, and the relationship between poultry price and quantity is negative. The pork own-price elasticity estimate of about -0.8 signifies a 0.8% decrease in quantity of poultry consumed associated with a 1% increase in poultry price, suggesting that modern poultry demand is relatively inelastic. A 1% increase in beef price is associated with a 0.45% decrease in poultry quantity consumed, and a 1% increase in pork price is associated with a 0.47% decrease in poultry quantity consumed, suggesting substitution of poultry for pork but beef and poultry as complements. However, consumers show greater own-price elasticity of poultry demand than cross-price elasticities. Income elasticity is positive and significant at the 0.01 level, suggesting that increases in income correlate with increases in quantity of poultry demanded. However, consistent with previously discussed models, income effects are small. Furthermore, income effects become much smaller once demographic controls are added, suggesting that income may be proxying the effects of other demographics in the first two models.

Poultry is more inelastic by a magnitude of 0.19 in the third income quartile and 0.53 in the fourth income quartile, as compared to the first income quartile. Poultry is more inelastic by a magnitude of 0.9 both when the reference person is male and when the household has kids. While regional variation is limited by only time series price variation, the northeast has a statistically significant more inelastic demand for poultry by a magnitude of 0.32, as compared to the midwest. The time interaction model suggests the poultry became more elastic in time Q3 and then slightly more inelastic again in Q4.

4.4 Results Summary

In the probit models, beef and poultry have positive own-price coefficients on the likelihood of purchase, while pork's coefficient is negative. These are consistent with the general trends in average consumption highlighted by the descriptive figures in section 3.2, suggesting that time trends in consumption may be rendering the probit models' results unreliable. Income shows a very small influence on both likelihood of purchase and quantity of purchase for all three types of meat, suggesting that the income variable may be unreliable or overshadowed by other variables. Since the probit results are unreliable, I do not calculate elasticities using the intensive and extensive margins. Instead, I focus on the OLS estimates, using only households that reported positive purchases in a given meat category. This remains applicable to policy, as efforts to decrease meat consumption should be aimed at households who regularly purchase meat.

Beef and poultry are inelastic with estimates of -0.6 and -0.8, respectively. Pork is highly elastic, with an estimate of -1.5. Cross-price elasticities are higher than own-price elasticity for beef, but lower for pork and poultry. Consumers show unidirectional substitutions of beef and pork for poultry. However, consumer behavior models complementary goods in all other models.

As previously mentioned, my interaction models are highly correlated with one another, so I interpret them together in order to obtain a more accurate understanding of overall demographic effects on meat consumption. There are three strong overall takeaways from my interaction models -

elasticities have remained relatively constant over the period studied, income plays a large role in elasticity magnitudes, and the goal of a higher protein or calorie diet may also play a role in elasticity magnitudes.

Interacting beef, pork, and poultry price with income quartiles shows statistically significant increases (more inelastic) in elasticity as income increases, particularly in the third and fourth quartiles. This suggests that consumer demand is less responsive to price at higher income levels and is consistent with expected consumer behavior. This is also evidenced by my other variables that are likely proxies for income - college degree, kids, and region. Beef and pork become significantly more inelastic when the reference person has a college degree and when the household has kids, both indicative of higher income. Beef and poultry appear to be significantly more inelastic in the northeast compared to the midwest. The more inelastic estimates for beef and poultry in the northeast are consistent with my income findings, since the northeast tends to have higher income than the midwest. Interestingly, pork being more elastic in the northeast is inconsistent with other general income trends, perhaps highlighting a difference in taste, more than channeling income. Beef and pork elasticities appear to have remained relatively constant during my studied time period.

Having kids makes beef and poultry more inelastic, which, while potentially a proxy for higher income, also may suggest that households consider meat to be more of an essential part of a diet when kids are present. Contrarily, beef becomes significantly more elastic when there are retired adults in the household, suggesting that beef is viewed as less essential as a household ages. This is consistent with the fact that beef also becomes more elastic as the reference person ages. This hints at a trend of meat being viewed as more important at younger ages, when diets need more protein and calories, suggesting that meat continues to be viewed as an important part of these diets. This is corroborated by the fact that pork and poultry also become slightly more inelastic when the reference person is male. According to Lombardo (2025), men require more protein than women and are more likely to turn to meat for their daily requirements. This is consistent with my theory that meat is viewed as an important part of a higher protein diet.

5 Discussion

5.1 Literature Context

My estimates for beef, pork, and poultry are about -0.6, -1.5, and -0.8, respectively. The most recent own-price estimates for beef, pork, and poultry using survey data in the literature are Okrent & Alsten (2012), who estimated -0.70, -1.26, and -0.81. My results are fairly consistent, suggesting that beef and poultry remain relatively inelastic in modern years, while pork has followed its upward trend seen in the literature, becoming even more elastic than previous studies. Beef shows a trend of becoming more elastic in the literature, but my estimate is lower than more recent estimates, perhaps showing a reverse of this trend. My poultry estimate is extremely consistent with the Okrent & Alsten (2012) estimate, suggesting that poultry elasticity has steadied following its upward trend in older literature.

My cross-price estimates suggest that consumers are likely to substitute beef and pork when poultry prices are high, but otherwise treat different meat types as complements, consistent with Menkhaus, St. Clair, & Hallingbye (1985). This may indicate a consumer tendency to treat meat as category more than substituting between meat types.

Income shows small effects on both probability of purchase and quantity of purchase for meat. Low income elasticities are inconsistent with previous studies, including Menkhaus, St. Clair, & Hallingbye (1985) and Nicholls & Kuehn (1978), who found high income elasticities for beef. Since income is reported, it could be inconsistent and lead to my income variable not having strong explanatory power on meat purchase. However, previous studies that found high income elasticity are also antiquated. This means that it is possible that, as incomes have increased in the United States in more recent years since these previous studies, meat purchase has become significantly less dependent on income, and my models are capturing this trend. If this were the case, it would suggest that households are already rich enough to purchase meat, and changes in income do not much affect this. However, I do find that own-price elasticity is significantly more inelastic for higher income brackets, suggesting that income effects on own-price elasticity are much more significant than income elasticities. This is consistent with the theory that households have reached a level where changes in income do not much affect meat demand, but households that have higher income to begin with are less likely to respond to changes in meat prices.

5.2 Policy Implications

5.2.1 Price Policies

Beef, pork, and poultry all show highly significant downward sloping demand curves, suggesting that price policies, specifically removing subsidies and instead taxing meat, are likely to be an effective tool for reducing consumption. This is especially true for pork, whose demand is very elastic. Beef and poultry have relatively inelastic demands, suggesting that, while price policies would have an effect on reducing consumption, combining them with other efforts would be more effective, as other factors beyond price are playing a significant role in demand. Furthermore, my time interaction models suggest that elasticity has remained relatively constant over time, demonstrating that price policies are not likely to change in effectiveness in the future.

The own-price elasticity represents the percent change in quantity resulting from a one percent change in price. Assuming the own-price elasticity remains constant for all values of price and quantity, I can use my estimates to also estimate the demand curve, which is smooth and concave for a constant-elasticity. Price policies cause movement along this demand curve, through supply shifts due to subsidy removal or taxation, which directly raises the price for both producers and consumers. Thus, I can use my estimates to calculate the expected reduction in meat quantity, based on the demand curve, given a change in price from a price policy.

This approach does have several limitations. Since my probit models are unreliable, I must use the elasticity estimates obtained only from the subset of the population that regularly purchases meat. However, price policy is also most relevant to this subset of the population, since targeting households that regularly purchase meat will have the biggest impact of consumption. In addition, in reality, the demand elasticity is likely not constant for all price levels. Furthermore, other demand or supply shifters may occur at the same time as price policies that would cause the actual reduction in consumption to deviate from my estimates. For example, if subsidies on soybeans and corn are removed, not only would the cost of meat increase, but the cost of alternatives, such as tofu, would increase, as well. In this case, reductions in meat consumption might be lesser than estimated due to the lack of affordable substitutes. Removing subsidies on grains used for livestock production, while retaining subsidies when grains are used directly for human consumption, might help alleviate this.

While my policy analysis is limited by assuming linear demand and no other shifts to supply or demand, it is useful to estimate the overall likelihood of effectiveness of price policies. For example, Joshi et al. (2015), argues that the cost of a Big Mac would increase from \$5 to \$13 if subsidies were removed, or a 160% increase.

The definition of demand elasticity implies that the percent change in quantity can be calculated by multiplying the elasticity and the percent change in price. However, this linear approach only works for small scale price changes, shown in this case, since a 160% increase in price implies an unrealistic 96% decrease in beef quantity consumed. In reality, a constant-elasticity demand curve is inwardly-bowed, so a more generalized approach is necessary for large-scale price policy analysis. Thus, I use the constant-elasticity form obtained from the log-log regression model where:

$$\ln Q = \beta \ln P \tag{4}$$

implies that

$$\frac{Q_2}{Q_1} = \left(\frac{P_2}{P_1}\right)^{\beta} \tag{5}$$

holding other regression variables constant.

Using this formula, I estimate the quantity reduction

$$\frac{Q_2}{Q_1} = \left(\frac{13}{5}\right)^{-0.6} \tag{6}$$

$$\frac{Q_2}{Q_1} = 2.6^{-0.6} \approx 0.56 \tag{7}$$

This estimates that removal of subsisides would lead to a 44% decrease in consumption of beef in the United States (since beef consumption would fall to 56% its original value), showing that subsidy removal would significantly decrease consumption, holding all else constant.

This same analysis can be applied using true cost of meat estimates from a UK Impact Institute (2024) report. External costs of meat are calculated using environmental costs, such as carbon emissions and water pollution, and social costs, such as labor welfare. Although the exact price values are calculated in pounds, they remain good proxies for meat costs in the US, since most of the external costs of meat production are global, and thus equal between countries. While initial prices are different between the US and the UK, I use the estimated market prices and external costs to calculate the price ratio from incorporating true costs into prices in the UK. Assuming a similar percent increase in the US and my US elasticities, I can estimate reductions in consumption for each type of meat in the US.

Incorporating the true cost of beef into the price of beef leads to an estimated price ratio of 3.84. My estimated elasticity for beef is -0.6. Thus:

$$\frac{Q_2}{Q_1} = 3.84^{-0.6} \approx 0.44 \tag{8}$$

Beef consumption in the US would decrease to about 44% of its current value (a decrease of 56%) resulting from the market price being equal to the true cost of beef.

Incorporating the true cost of pork into the price of pork leads to an estimated cost ratio of 5.56. My estimated elasticity for pork is -1.5. Thus:

$$\frac{Q_2}{Q_1} = 5.56^{-1.5} \approx 0.076 \tag{9}$$

Pork consumption in the US would decrease to about 7.6% of its original value (a 92.4% decrease) resulting from the market price being equal to the true cost of pork.

Incorporating the true cost of poultry into the price of poultry leads to an estimated cost ratio of 10.6. My estimated elasticity for poultry is -0.8. Thus:

$$\frac{Q_2}{Q_1} = 10.6^{-0.8} \approx 0.15 \tag{10}$$

Poultry consumption in the US would decrease to about 15% of its original value (an 85% decrease) resulting from the market price being equal to the true cost of poultry.

My basic policy analysis demonstrates that incorporating the true cost of meat into market prices through taxation and subsidy removal has the potential to significantly reduce consumption. While in reality, other factors do not remain constant, likely overstating my calculations, this illustrates that price policies could be quite effective at reducing meat consumption. Furthermore, while true cost of meat pricing is also unrealistic, my analysis shows that increased prices of meat could go a long way towards a healthier and more sustainable level of production.

5.2.2 Demographics

However, my analysis also shows that prices are not the only factor influencing meat consumption, particularly for beef and poultry, which have inelastic estimates. Moreover, my demographic interactions suggest that elasticities vary widely between demographic groups, showing that price policies would have very different results for different groups. Thus, combining price policies with campaigns targeted by demographic group is likely to have a greater effect on meat consumption overall.

While income elasticities for all three types of meat are low, own-price elasticities are significantly more inelastic at higher income brackets. Demand for all three types of meat is also more inelastic when the reference person has a college degree and when the household has kids, likely both proxies for income. Finally, my regional interaction model is also likely a proxy for income, as the northeast has a much more inelastic demand for beef and poultry compared to the midwest, consistent with income trends. These interaction models suggest that households with higher income are much less affected by changes in price, consistent with the Engel Curve. This illustrates that meat is treated more as a necessity when households have higher income, showing that meat remains highly coupled with income, and consuming less meat is seen as only necessary when incomes are lower.

This suggests that price policies would have a much bigger effect on lower income households than on higher income households. Therefore, while price policies would achieve a reduction in meat consumption, they could also lead to greater inequality between income groups, as lower income households would need to change their consumption behavior much more than higher income households. Furthermore, price policies would do little to change the view of meat as a necessary good. Higher income households are likely to continue consuming significant amounts of meat even in the presence of higher prices and external consequences. Higher prices resulting from policy could reinforce the view of meat as a luxury and widen the consumption gap between low and high income households. Thus, combining price policies with campaigns aimed at decoupling meat consumption from income may be more effective than price policies alone because they would target the highly inelastic high income households. Policies to decouple consumption from income would be based on making meat seem like a less luxurious and desirable good. This could include educational campaigns that make other protein choices, such as tofu or eggs, appear higher-end or more desirable. Furthermore, since higher income households have more resources to devote towards health, public campaigns on the health consequences of eating meat or health warnings on meat products would likely be effective at shifting consumer behavior away from meat as a necessity, especially at higher income brackets.

Furthermore, my demographic interactions suggest that meat may still be viewed as an important source of protein and calories. Male-headed households have a more inelastic demand for meat, and males generally need to consume more calories and protein. Having kids in the household also makes meat demand significantly more inelastic, consistent with the theory that meat is seen as important for protein and calories as kids are growing. While having kids may be a proxy for income, I posit the large elasticity effect may not be only due to income effects and may also be influenced by consumption differences. Finally, age seems to show a slightly positive relationship with elasticity - older households (measured both by age of reference person and the variable retired) have a more elastic demand for meat. These three findings corroborate my theory that meat remains highly coupled with higher protein or calorie diets. Policies aimed at making the health risks of meat more apparent are, thus, also likely to be effective for this behavior. Furthermore, policies that promote the high protein content of healthie and more sustainable alternatives may help reduce dependency on meat as a part of a high protein and calorie diet.

5.3 Limitations

5.3.1 Model Endogeneity and Omitted Variables

Finally, the least squares regression model assumes a lack of correlation between independent variables and the error term. However, since both quantity and price are determined simultaneously from the same factors in a supply and demand model, factors causing changes in price may cause changes in quantity demanded, independent of price. For example, an outward demand shock might increase both price and quantity, but the effect on quantity demanded is absorbed in the error term, causing a correlation between the price and the error term. This violates the lack of endogeneity assumption of the model.

Instrumental variables is a common approach to controlling for model endogeneity. The independent variable is regressed on a set of instrumental variables, which have strong explanatory power on the independent variable but are exogenous to the error term. The dependent variable is then regressed on the prediction of the first model. An instrumental variable in my model would, thus, need to be a variable that affects the supply curve but is exogenous to the demand curve. I consider the prices of corn, soybeans, and oil as explanatory variables for the price of meat. Since these variables are key inputs into meat production, I hypothesize that combining them may have a statistically significant effect on price. However, these inputs are likely still correlated with demand and, thus, the error term. Increased demand for meat may increase the supply of agricultural feed or the share of transportation going to meat production, which would in turn decrease the input prices. This illustrates the biggest challenge with instrumental variables; meeting one assumption is likely to, as least somewhat, violate the other.

Since I do not have data for an effective instrument, I cannot adequately control for model endogeneity. Thus, demand shocks are a source of omitted variable bias in my model. If an outward demand shift occurs simultaneously with an inward supply shift, the estimated demand curve is more inelastic than the real curve (positive bias). If an outward demand shift occurs simultaneously with an outward supply shock, the estimated demand curve is more elastic than the real curve (negative bias). If an inward demand shift occurs simultaneously with an inward supply shock, the estimated demand curve is more inelastic than the real curve (positive bias). If an inward demand shift occurs simultaneously with an outward supply shock, the estimated demand curve is more elastic than the real curve (negative bias). Since many different supply and demand shocks occur simultaneously in my model, my results may be positively or negatively biased by omitted demand shocks.

5.3.2 Selection Linearity

A Heckman (1979) model both controls for and measures selection bias in a log-log regression, by running a two-stage model similar to mine. The first stage calculates the Inverse-Mills Ratio, which is a measurement of the selection bias in the first stage. This is used as a regressor to control for selection bias in the second stage. The second stage also calculates the correlation between the two error terms, generating a measurement of the degree of selection bias present between the two stages. This is a measurement of whether or not the Heckman model was necessary for accurate estimates in the second stage. An effective Heckman model, however, requires an exclusion restriction, a variable that affects only the decision to purchase and not how much to purchase.

Heckman (1979) is most relevant in the case of labor economics, where the decision of whether or not to work is likely explained by different variables than those that explain the decision of how much to work, given one has a job. In the case of my model, though, it is challenging to find a variable that only affects the decision to purchase meat because any variable that affects how much meat a household purchases is likely to also affect whether it purchases in the first place. Thus, I do not have a valid exclusion restriction to use a Heckman model and use a basic two-stage model in its place. I cannot control for nor measure the selection bias in my model, meaning that my results for the second-stage model are based on a non-representative sample - only the population that reported a positive meat purchase that quarter. This is likely similar to the population that regularly purchases meat, meaning my estimates in stage two are based only on those households who regularly purchase meat, rather than the population as a whole. This is likely to miss the households who infrequently purchase meat and may choose not to purchase at all when prices become too high; thus, I hypothesize that the selection bias in my model biases my results towards more inelastic.

While my sample for stage two is a non-representative sample of the United States, it is also the most important population to target when making policy decisions. Households that regularly purchase meat contribute most to the problem of over-consumption of meat in the United States. Thus, designing policies based on their decisions will be the most effective.

6 Conclusion

Meat consumption in the United States is one of the primary drivers of environmental degradation globally, caused by the impact of livestock production. In order to reduce meat consumption in the US, effective policy that relies on an understanding of consumer response to meat prices is crucial. Using a model with two regression equations, a probit on participation followed by an OLS on quantity consumed, given participation, I aim to estimate the own-price, cross-price, and income elasticities of beef, pork, and poultry, as well as the effects of demographics on own-price elasticities. I find that the probit models are unreliable, but the OLS models give statistically significant elasticity estimates consistent with previous literature and expected consumer behavior. The estimates from the second model are relevant for policy, since households that regularly purchase meat, despite changing economic conditions, are most important in studying effective reduction of meat consumption.

I obtain own-price elasticity estimates of -0.6, -1.5, and -0.8 for beef, pork, and poultry, respectively. My beef and poultry estimates are quite consistent with previous literature, while my model suggests pork has become more elastic following earlier literature. My cross-price elasticity estimates suggest that consumers may substitute beef or pork when poultry prices are high, but otherwise consumers are more likely to treat meat types as complements.

Income elasticity estimates are very small, inconsistent with previous literature, suggesting either that consumer meat demand is not very responsive to changes in income, or that my income variable does not capture income changes well. However, interacting income brackets with meat prices shows that meat demand becomes significantly more inelastic as income levels increase. Thus, while consumers do not respond to changes in income, their responsiveness to the price of meat depends heavily on their base income level. This income effect is also highlighted by the significantly more inelastic demands in households with college educations, households with kids, and households in the northeast (for beef and poultry), all potential proxies for higher income. This demonstrates that US consumers continue to view meat as a desirable part of a diet, treating it as more and more of a necessity with increasing income.

My interaction models suggest that elasticity has remained relatively constant over the period studied. Furthermore, meat demand is more inelastic at higher income brackets, evidenced both by my income model itself, as well as the models for college degree, kids, and region, which are likely proxying the effects of income. My results also suggest that consumers viewing meat as a necessary source of protein or calories may play a role in demographic elasticity differences. This is seen by more elastic demand in older households, more inelastic demand in households with kids, and more inelastic demand in male-headed households.

While price policies, such as taxation or subsidy removal, would decrease meat consumption in the United States, my elasticity difference by demographic group suggests that combining public campaigns with price policies may have a greater effectiveness. In the absence of policy, rising incomes are likely to lead to increased dependence on meat in diets. Policies that decouple income from meat consumption by changing consumer views on meat as a diet necessity are likely to be more effective at reducing meat consumption than price policies alone, and would reduce the unequal effects of price policies on lower, versus higher, income households. These policies, such as health warnings or educational campaigns on the health and environmental consequences of meat consumption, could be aimed at making meat less desirable. Public campaigns could also include the promotion of alternatives as more desirable, such as highlighting the health benefits of plant-based protein sources, or promoting alternatives as upscale options. Furthermore, campaigns that promote alternative protein sources as just as healthy or healthier than meat options, or that highlight the potential health consequences of meat, may also be effective at targeting the protein-reliant subset of the population.

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ChatGPT5: Used in the collection and initial cleaning of data, as well as initial analysis and preparation of figures. As the author, I have verified and take responsibility for all thesis empirical content.

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7 Appendix

7.0.1 More Price and Quantity Graphs

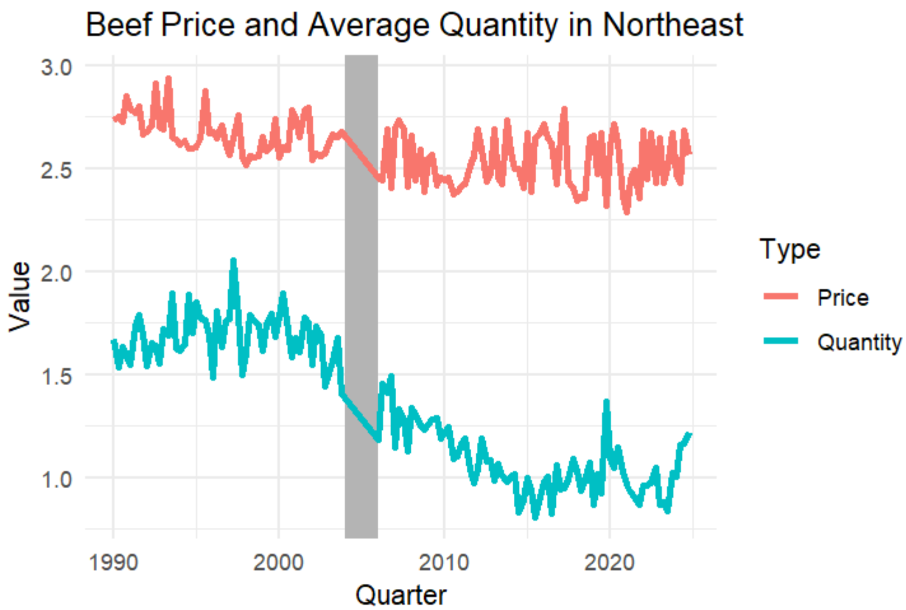

Figure 7: Average Beef Quantity and Price Over Time in the Northeast

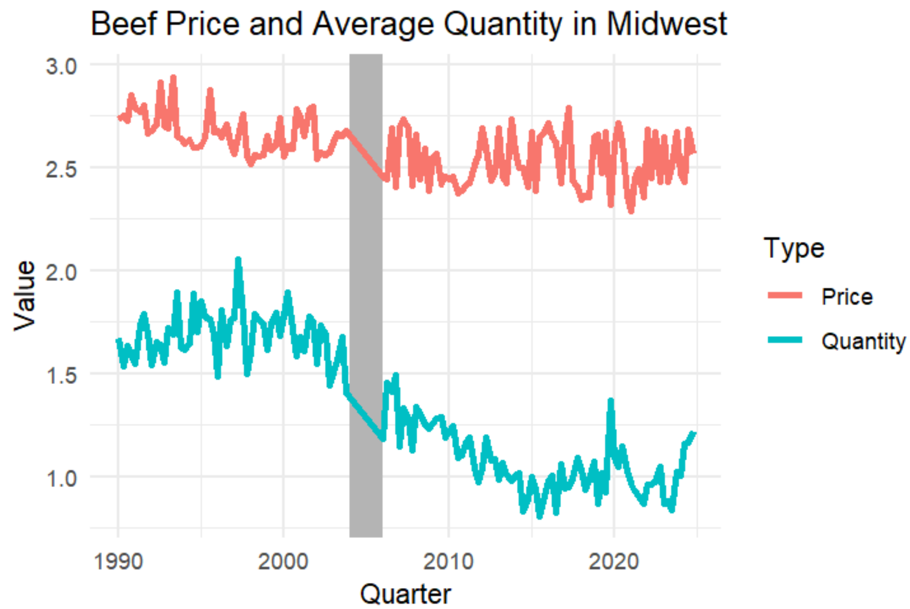

Figure 8: Average Beef Quantity and Price Over Time in the Midwest

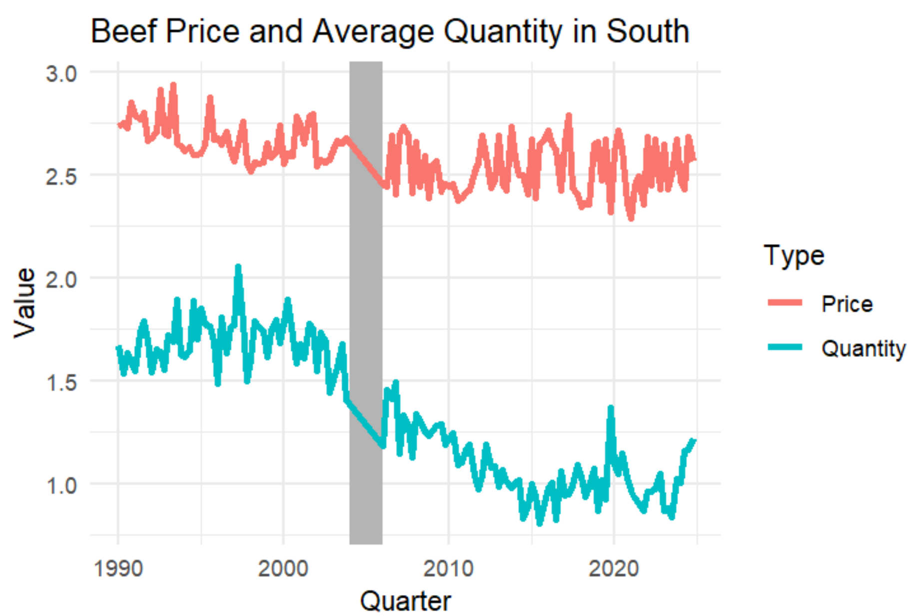

Figure 9: Average Pork Quantity and Price Over Time in the South

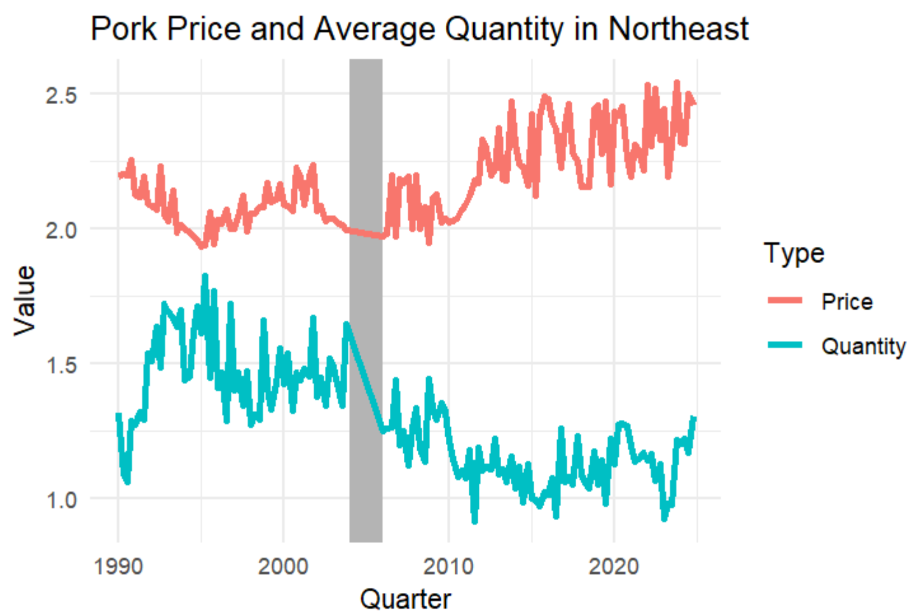

Figure 10: Average Pork Quantity and Price Over Time in the Northeast

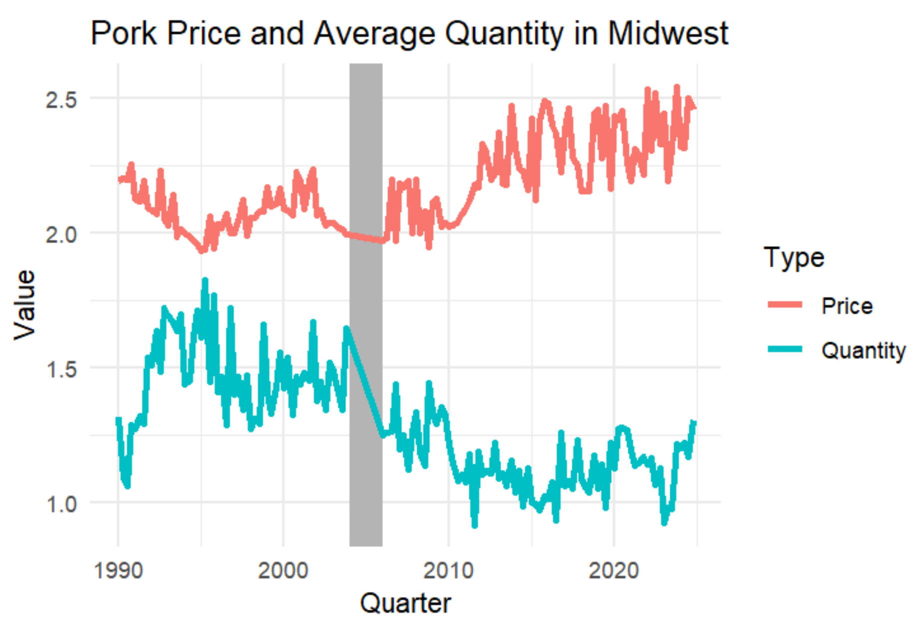

Figure 11: Average Pork Quantity and Price Over Time in the Midwest

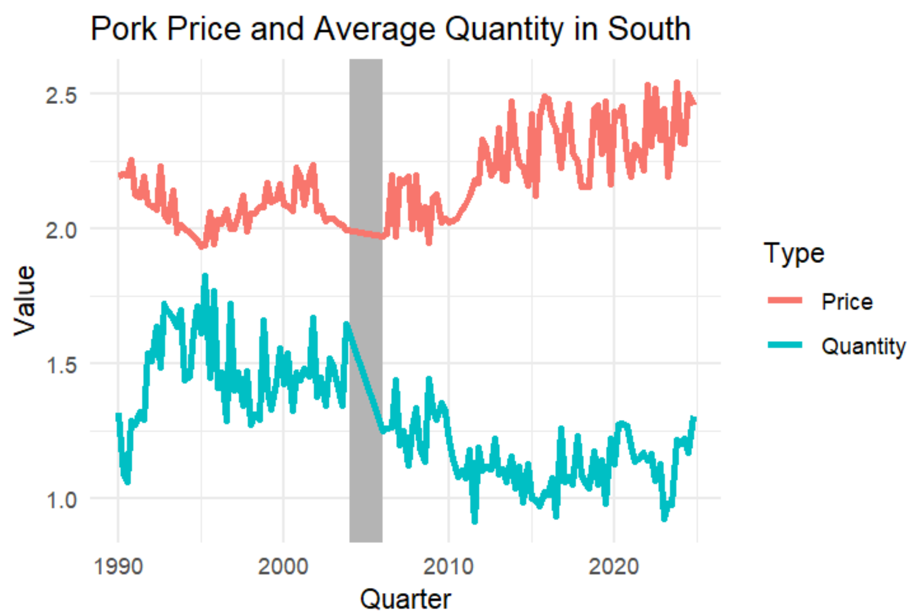

Figure 12: Average Pork Quantity and Price Over Time in the South

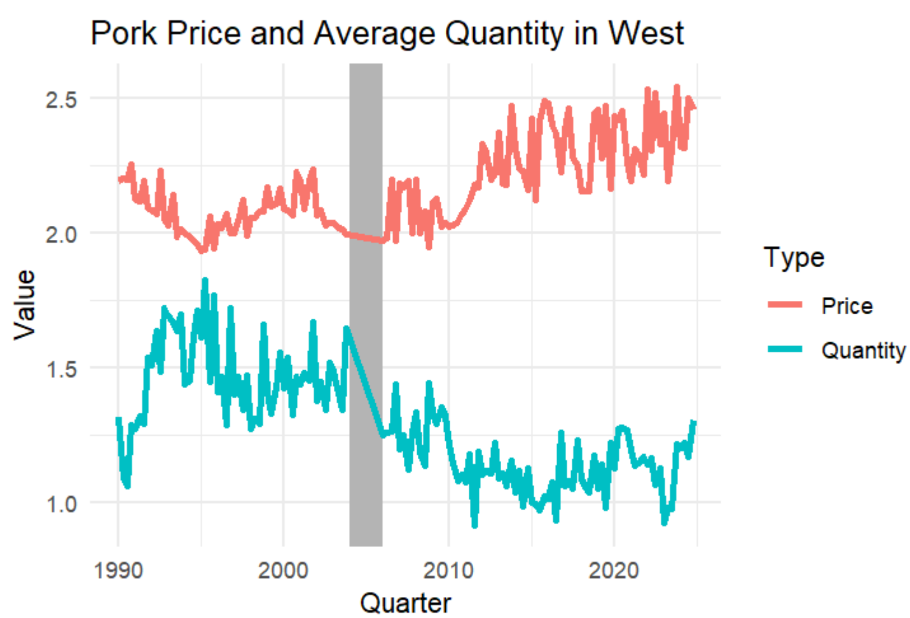

Figure 13: Average Pork Quantity and Price Over Time in the West

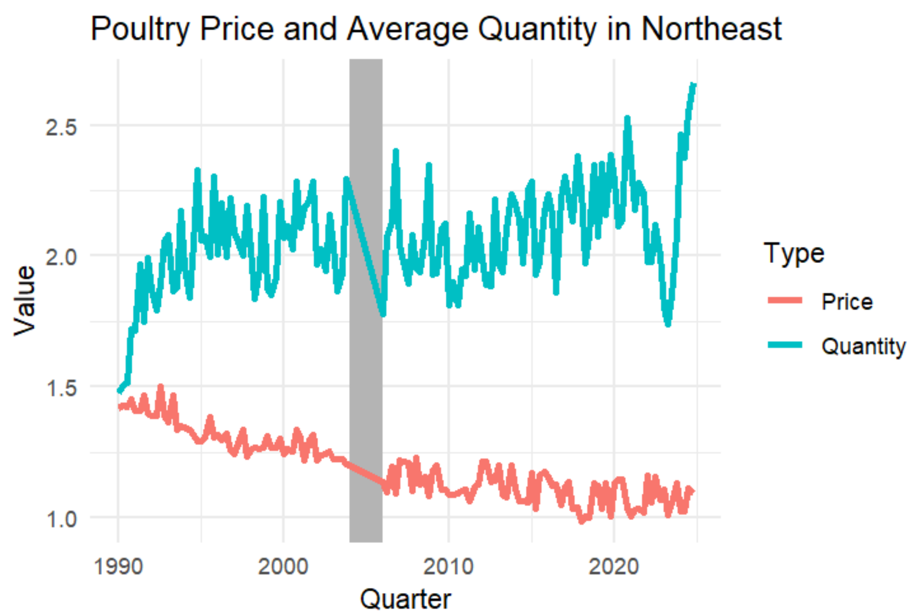

Figure 14: Average Poultry Quantity and Price Over Time in the Northeast

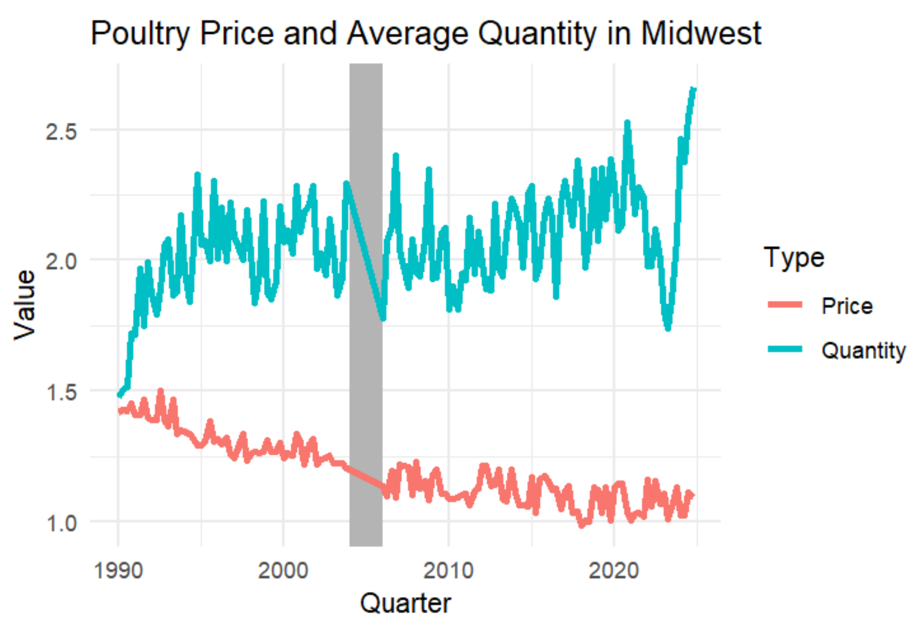

Figure 15: Average Poultry Quantity and Price Over Time in the Midwest

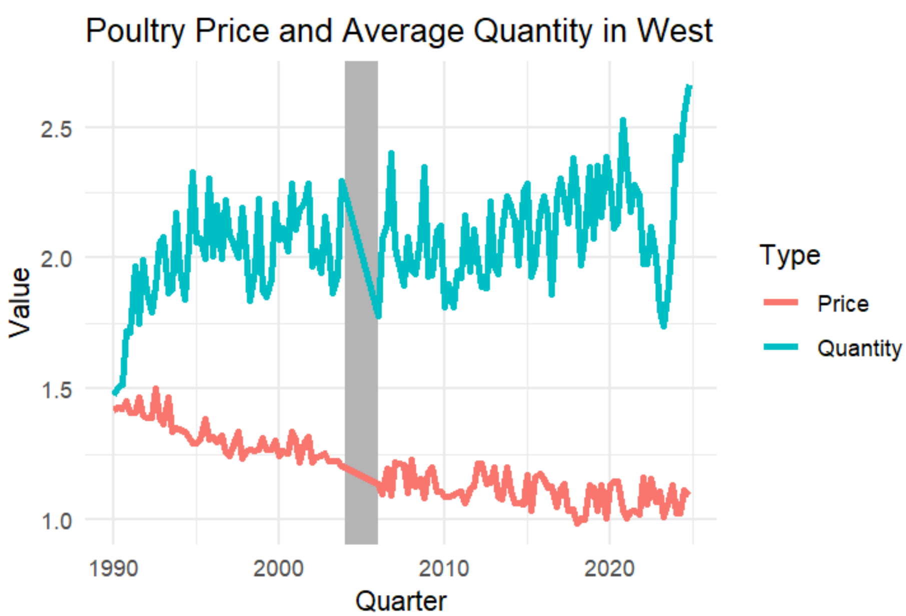

Figure 16: Average Poultry Quantity and Price Over Time in the West

7.0.2 Income Trends

When I scatterplot income on quantity consumed, in log-log form and conditional on buying, there is a positive, but weak, correlation, suggesting that beef, pork, and poultry are normal goods, but that variation in quantity consumed is much more explained by other factors, such as price and demographics. Poultry appears to have the weakest correlation, and higher quantities of poultry are consumed at all income levels. Based on these graphs, I hypothesize that my regression results will show positive, but very small, income elasticities. The below graph shows real income over time by region:

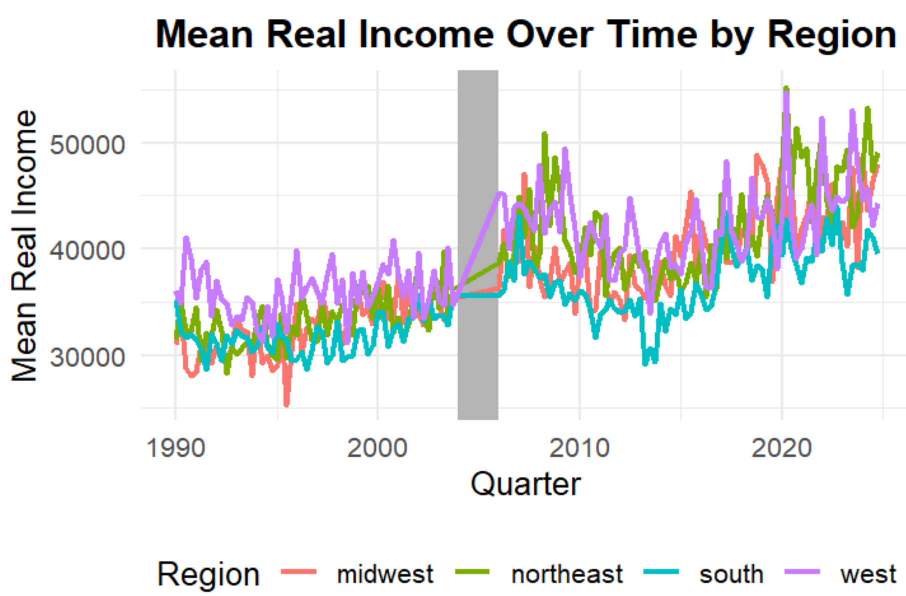

Figure 17: Regional Real Income Mean Trends Over Time