THE MEXICAN MEAT MARKET:

AN ECONOMETRIC ANALYSIS OF DEMAND PROPERTIES AND TRADE

BY

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ABSTRACT

The world meat market is experiencing increasing trends in consumption, production, and trade. The Mexican market is becoming very important for U.S. and Canadian meat exporters not only because its large size, rapid expansion, and meat offal preference, but also because Mexican per capita meat consumption still remains low compared to equivalent of the United States and Canada. This study provides an in-depth analysis of the Mexican meat market demand while using a theoretically and methodologically sound research approach that updates Mexican meat demand elasticities. The study considers table cuts of meats (i.e., beefsteak; ground beef; pork steak; ground pork; chicken legs, thighs and breast; fish, etc.), estimates elasticities at the table cut level (which are currently not available for Mexico), identifies likely trends in Mexican consumption and trade, and captures regional and urbanization differences among consumption of table cuts of meats. The study is theoretically and methodologically sound because it uses the entire target population, incorporates scales to compute the number of adult equivalents, applies a price imputation approach to account for censored prices, employs a consistent censored demand system estimated in two steps to account for censored quantities, and includes estimation techniques used in stratified sampling theory.

Mexican meat demand parameters are estimated employing a consistent censored demand system computed in two steps. In the first step, maximum-likelihood probit estimates are obtained; while in the second step, a system of equations is calculated by seemingly unrelated regressions. Since the sample is stratified, techniques used in stratified sampling theory are incorporated into the estimation procedure. Standard errors of parameters are approximated applying a nonparametric bootstrap procedure. In general, the bootstrap is a resampling technique that can be used to estimate standard errors of parameter estimates when other techniques are inappropriate or not feasible. It is a simple way to obtain standard errors when asymptotic theory leads to complex estimators. In addition, Marshallian and Hicksian price elasticities as well

as expenditure and income elasticities are reported with their corresponding level of statistical significance. Expenditure and income elasticity levles suggest that as the Mexican economy grows, consumption on all meat cuts will increase. Moreover, they imply that all meat cuts are necessary commodities. However, pork cut expenditure elasticities are the most inelastic compared to the equivalent of beef and chicken cuts (but excluding processed meat cuts). Marshallian and Hicksian price elasticities are used to identify substitute and complement meat products.

Elasticities are also estimated by region. As expected, regional differences are found in Mexican consumption of table cuts of meats. Elasticities are also employed in a simulation analysis of Mexican meat consumption and imports. Consumption and import projections for the period 2009-2018 are presented at the table cut level of disaggregation. The results not only indicate that Mexican meat consumption and imports may grow at different rates across table cuts of meats, but also that there might be differences in meat consumption across regions. Moreover, it was found that Mexico seems to be following the U.S. preferences for beef cuts, but not following the U.S. preferences for chicken cuts.

The study may be useful to U.S. and Canadian meat exporters in forecasting future trade with Mexico, conducting long-term investment decisions in the meat industry, or identifying regional trends in Mexican consumption of specific table cuts of meats. It may provide insight into positioning U.S. meat products in Mexican markets. That is, it may reveal where in Mexico a particular meat cut will sell better. The study also contains information that may be relevant and useful, for meat producers and Mexican policy makers, in quantifying how changes in prices, income, regional location, or urbanization level affect the consumption of a particular meat cut. Elasticities by region may not only facilitate positioning meat products in the appropriate Mexican markets but also managing prices more effectively.

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CHAPTER I
PROBLEM STATEMENT AND OBJECTIVES

1.1 Introduction

As world meat consumption and trade liberalization increase, it becomes very important for meat exporters to appropriately understand the most relevant foreign markets. The Mexican meat market is critical for meat exporters not only because its large size, rapid expansion, and meat offal preference, but also because Mexican per capita meat consumption still remains low compared to the equivalent in the United States and Canada. Better understanding of Mexican meat consumption will benefit U.S. meat exporters, policy makers, and researchers to appropriately comprehend Mexicans' response to price and income changes, current and future trends in specific meat cuts, and the nature of Mexican meat preferences for meat cuts.

The Mexican meat market is large and rapidly expanding. Mexico accounts for 8% of the 1997-2006 total world meat import average of 13,195,000 MT (United States Department of Agriculture, 2009). This places Mexico among the largest meat importers of the world. Additionally, Mexican meat imports more than doubled (increased by 147%) from 1997 to 2006. They went from 568,000 MT in 1997 to 1,405,000 MT in 2006 and experienced the fastest growth among the leading meat importing countries.

However, in today's world meat market most trade is in the form of table cuts (Dyck and Nelson, 2003). In fact, differences among the volumes at which the table cuts of meats are traded in Mexico suggest that consumer preferences and tastes may vary across meat cuts. For example, from 2003 to 2007 exports of Mexican bovine meat (except for bovine meat carcasses and half-carcasses) have increased drastically while Mexican imports of bovine meat have remained stable (Figure 1.6). In the case of Mexican swine meat, only exports of boneless swine seem to be demanded by the international market, while Mexican demand for foreign swine hams, boneless swine meat and swine remains have slightly increased (Figure 1.8). In the case of

Mexican chicken meat, exports have remained volatile but imports have experienced a drastic increase in boneless chicken, chicken legs and thighs, and whole chicken from 2003 to 2007 (Figure 1.10). More importantly, Mexicans seem to have a high preference for animal remains because it imports more than other cuts of meats. For example, imports of bovine animal remains are larger than imports of bovine meat carcasses and half-carcasses and other cuts of bovine meat with bone in (Figure 1.6). Similarly, imports of swine remains are larger than imports of boneless swine meat and swine meat carcasses and half-carcasses (Figure 1.8). Likewise, in the case of chicken, imports of other chicken cuts and offal are larger than imports of whole chicken (Figure 1.10).

Furthermore, Mexico is not only important because of the quantity it imports and its relatively high preference for animal remains, but also because its per capita meat consumption still remains low compared to the equivalent of the United States and Canada. For instance, from 1997 to 2006, Mexico averaged a per capita meat consumption of 60.78 kg per year, while the United States and Canada averaged 121.61 and 98.38 kg per year respectively (United States Department of Agriculture, 2009). This suggests that Mexican per capita meat consumption could continue growing, and consequently, Mexico will remain an important market for years to come.

1.2 Researchable Topic and Objectives

Given that Mexico is a very important market for large meat exporters, the general objective of this study is to provide an in-depth analysis of Mexican meat consumption while using a theoretically sound research approach that updates Mexican meat demand elasticities. Unlike previous studies, the analysis presented in this research considers table cuts of meats (i.e., beefsteak, ground beef, pork steak, ground pork, chicken legs, thighs and breast, fish, etc.) rather than meat aggregates (i.e., beef, pork, and chicken). For example, previous Mexican meat studies such as Erdil (2006), Malaga, Pan, and Duch (2006), Dong, Gould, and Kaiser (2004), Golan, Perloff, and

Shen (2001), Dong and Gould (2000), García Vega and García (2000), and Heien, Jarvis, and Perali (1989) have all aggregated Mexican meat into broad categories or analyzed meat as one product within a more general demand system (i.e., including cereals, meat, dairy, fats, fruit, vegetables, etc.). In the United States, meat demand studies at the disaggregated level have provided additional insights about the nature of the demand for meat (see Taylor, Phaneuf, and Piggott, 2008, Yen and Huang, 2002, and Medina, 2000). Therefore, this study explores whether consumer tastes and preferences vary across meat cuts. In particular, by estimating meat demand elasticities at the disaggregated level, this study identifies further cases of (gross and net) substitutability and complementarity within and among cuts of beef, pork, and chicken. Estimates of expenditure, Marshallian and Hicksian price elasticities at the disaggregated level are currently not available for Mexico. Consequently, the study not only provides elasticity estimates that have never been reported before, but will also update the literature with recent findings. Finally, if consumer tastes and preferences vary across meat cuts, the elasticity estimates provided by previous studies, which have used meat aggregates, are not appropriate for analyzing Mexican meat consumption.

Furthermore, this study uses a theoretically and methodologically sound research approach. For example, the model is specifically designed to address a very common problem of consumer survey data, which is the existence of censored observations. Not all previous studies on Mexican meat demand have used a model that accounts for censored observations. Moreover, previous studies on Mexican meat demand (Malaga, Pan, and Duch, 2007; 2006; Dong, Gould, and Kaiser, 2004; Gould and Villarreal, 2002; Gould et al., 2002; Golan, Perloff, and Shen, 2001; Sabates, Gould, and Villarreal, 2001; Dong and Gould, 2000; García Vega and García, 2000; Heien, Jarvis, and Perali, 1989), which have used the same data source *(Encuesta Nacional de Ingresos y Gastos de los Hogares (ENIGH), 2006)*, have neither taken into account the fact that the sample is stratified nor provided an explanation for excluding stratification variables. Ignoring stratification variables (e.g., weight and strata) results in parameter estimates that may not be representative of the population or that may not capture potential differences among the subpopulations (Lohr, 1999, pp. 221–254). In addition, using a stratified sample has implications in the way descriptive statistics and standard errors of parameter estimates are calculated. Therefore, this study incorporates stratification variables into the analysis and estimates standard errors of parameter estimates by using the bootstrap procedure. In general, the bootstrap is a resampling technique that can be used to estimate standard errors of parameter estimates when other estimation techniques are inappropriate or not feasible. "[B]ootstrap methods for statistical inference... have the attraction of providing a simple way to obtain standard errors when the formulae from asymptotic theory are complex" (Cameron and Trivedi, 2005, p. 355). In addition, incorporating stratification variables is very important not only because ENIGH is a stratified sample but also because there is statistical evidence, according to DuMouchel and Duncan's (1983) test, suggesting that the inclusion of weights is necessary when using ENIGH. Finally, this study found evidence of different consumption patterns among table cuts of meats across Mexican regions.

To accomplish the general objective, this study estimates Mexican meat demand parameters using a two-step censored regression model that not only incorporates stratification variables into the estimation procedure but also captures regional and urbanization differences in the consumption of table cuts of meats. In the first step, maximum-likelihood probit estimates are obtained; while in the second step, a system of equations is estimated by using seemingly unrelated regressions. Parameter estimates are reported and their standard errors are approximated using a nonparametric bootstrap procedure. In addition, a simulation analysis of Mexican meat consumption at the table cut level is presented. Price elasticities allow exploring the impacts of different scenarios of exchange rate and prices on Mexican exports and imports as well as on consumption of meat cuts. Finally, expenditure elasticities allow exploring the effects of changes in per capita income on Mexican exports and imports and consumption of meat cuts.

The specific objectives of this study are:

- Determine the factors affecting the Mexican meat demand;
- Estimate Mexican demand parameters of the different table cuts of meats;
- Calculate Marshallian and Hicksian price and expenditure elasticities at the table cut level of disaggregation;
- Compare and contrast the estimated elasticities with previous findings;
- Capture regional preferences for meat consumption at the table cut level;
- Identify current and future trends and growth rates in the consumption and imports of specific table cuts of meats;
- Forecast Mexican consumption of table cuts of meats through changes in real per household income; and
- Simulate future Mexican imports of table cuts of meats under alternative changes in real per household income and real exchange rate.

In the following section, an analysis identifying trends in meat consumption, production, imports and exports is presented. Section 1.3 provides a description of the major players (i.e., countries) in the international meat market and explains the role Mexico plays. In particular, the most important meat cuts Mexico imports and exports, and the most important countries Mexico trades with are analyzed. In general, Section 1.3 familiarizes the reader with Mexican meat consumption and trade at the international level.

1.3 Mexico and the World Meat Market

In this section, an analysis identifying trends in Mexican and world meat consumption, production, imports and exports is presented. In particular, the ten most important countries are identified and their market shares and growth rates are analyzed. The section uses the Production, Supply, Distribution (PSD) online database provided by the Economic Research Service (ERS) of the United States Department of Agriculture (USDA).[1] Since the USDA-ERS-PSD online database reports quantities, all figures and tables were computed by the author. In addition, the world total amounts reported by the USDA-ERS-PSD database does not include all countries in the real world, but rather a list of countries which represents over 90% of real world total amounts. Furthermore, in order for the USDA-ERS-PSD list of countries to appropriately represent the major players, the list is updated periodically. The list of countries in the USDA-ERS-PSD database is an efficient forecasting basis for identifying world trends. In the USDA-ERS-PSD database, beef and pork quantities are reported in metric tons (MT) and in carcass weight equivalent (CWE). CWE is the weight of an animal after slaughter and removal of most internal organs, head, and skin. Poultry meat quantities are reported in metric tons (MT) and ready to cook equivalent. Finally, in this section, total meat is the sum of beef (beef and veal), pork (swine meat), and poultry meat (broiler and turkey).

Additionally, to facilitate the discussion in this section, a world region such as the European Union is referred to as a country. During the period under consideration (1997-2006), not all 25 European Union countries were part of the European Union (EU). For example, according to the Microsoft Encarta Online Encyclopedia (2008), from 1986 to 1994, the European Union (EU-12) consisted of France, Germany, Italy, Belgium, Netherlands, Luxembourg, United Kingdom, Denmark, Ireland, Greece, Spain, and Portugal. However, in 1995, Australia, Finland and Sweden joined the European Union bringing the total number of nations to 15. Therefore, in January 1996, the EU consisted of 15 nations. However, in May 2004, ten more countries were added (Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Slovakia, and Slovenia), bringing the total number of nations to 25. Then, in January 2007, two more countries were added (Romania and Bulgaria), bringing the total number of nation to 27. Because the period under consideration in this section is 1997-2006, it is assumed that the EU consisted of 25 countries since 1996. This

[1]From here on, it will be referred to as USDA-ERS-PSD.

implies that those countries that were added to the EU in 2004, if they appeared in the USDA-ERS-PSD database, were added to the EU-15 total to compute a new EU-25 total.

In the case of Mexican imports and exports, an analysis employing market shares and growth rates is presented, which identifies the most important cuts of bovine, swine, and chicken meats as well as the most relevant countries currently trading with Mexico. This analysis uses data from the Mexican Ministry of Economy, Sistema de Información Arancelaria Via Internet (SIAVI) online database, which provides information on imports and exports (kg and dollars) of meat commodities at the 8-digit level of disaggregation from chapter 2 (meat and edible meat offal) of the Harmonized System. However, only the most relevant meat commodities in chapter 2 of the Harmonized System were included in the analysis.[2] All figures and tables used in the analysis were computed by the author.

1.3.1 Production

World meat production increased 27% from 1997 to 2006 (see Appendix, Table A.1). Swine meat presents the largest annual world production volume for the whole period with an average share of 45%. It is followed by poultry meat with an average share of 29% and beef with 26%. Annual swine production is experiencing an increasing tendency (a growth rate of 34% from 1997 to 2006). Only in 1997 and 1998 beef production was larger than poultry meat production. Since the year 2000, annual poultry meat production has been larger than annual beef production. Nonetheless, production of both meats have an increasing tendency. Poultry meat production inreased 36% while beef grew 9% during the same period.

The world's largest meat producing countries, in descending order, are People's Republic of China, European Union, United States, Brazil, Mexico, Canada, Russian Federation, Argentina, India, and Australia (Figure 1.1). Together these ten coun-

[2] That is, the analysis excludes exotic meats such as ovine and caprine meats, horse, dunkey, mule, etc.

tries account for 89% of the total world meat production. Additionally, Figure 1.1 shows that European Union, United States, and Brazil produce considerably above all other countries. However, most countries have experienced a rapid growth rate. For example, from 1997 to 2006, India, Brazil, Peoples Republic of China, Mexico, Canada, Australia and United States grew 116%, 74%, 48%, 42%, 36%, 18%, 17% respectively (Appendix, Table A.2).

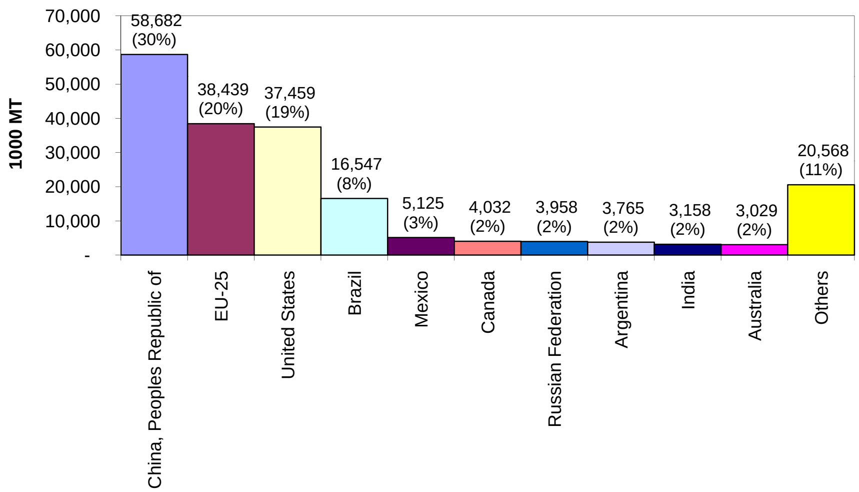

Figure 1.1: World's Largest Meat Producing Countries, Average 1997-2006.

Source: USDA-ERS-PSD Online Database, computed by author.

In Mexico, poultry meat has the largest annual production with an average share of 41% from 1997 to 2006 (see Appendix, Table A.7). It is closely followed by beef production with an average share of 38%, and then swine meat production with an average share of 21% for the same period. Poultry meat production shows the highest growth rate (a 74% increase) in the analized period . However, beef production is larger than poultry meat production from 1997 to 1999. Nonetheless, all three meats (beef, swine, and poultry) show an increasing tendency in production. From 1997 to 2006, beef production increased 21% while swine production grew by 28%.

1.3.2 Consumption

World meat consumption increased 26% from 1997 to 2006 (see Appendix, Table A.1). Similar to the world meat production case, swine shows the largest annual world consumption level with an average share of 45%. It is followed by poultry meat with an average share of 29% and beef with 26%. Annual swine and poultry meat consumption are experiencing a rapidly increasing tendency. They increased by 33% and 35% respectively. Beef consumption is also increasing (7% from 1997 to 2006).

The world's largest meat consuming countries, in descending order, are Peoples Republic of China, European Union, United States, Brazil, Russian Federation, Mexico, Japan, Argentina, Canada, and India (Figure 1.2). Together these ten countries account for 89% of the total world meat consumption. Additionally, Figure 1.2 shows that the European Union, United States, and Brazil consume considerably higher volumes than all other countries. However, most countries are experiencing a rapid meat consumption growth rate. For example, from 1997 to 2006, India, Mexico, Peoples Republic of China, Brazil, and the United States grew 100%, 53%, 48%, 41%, and 18% repectively (Appendix, Table A.3).

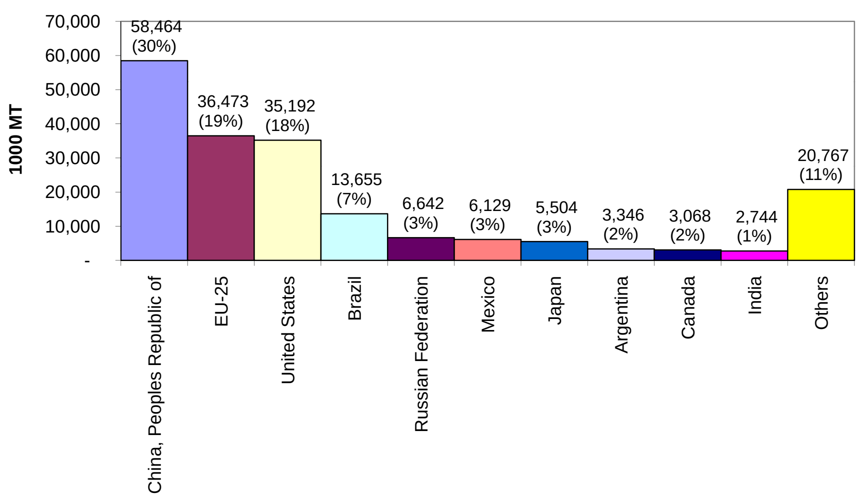

Figure 1.2: World's Largest Meat Consuming Countries, Average 1997-2006.

Source: USDA-ERS-PSD Online Database, computed by author.

However, if annual per capita meat consumption is considered, the order in which countries are ranked changes (Figure 1.3). For example, the United States has the largest annual per capita meat consumption (121.61 kg/person) followed by Canada (98.38 kg/person), Argentina (89.37 kg/person), EU-25 (80.14 kg/person), Brazil (76.73 kg/person), Mexico (60.78 kg/person), Peoples Republic of China (45.61 kg/person), Russian Federation (45.41 kg/person), Japan (43.25 kg/person), and India (2.56 kg/person). Note that Mexico annual per capita meat consumption is low compared to the equivalent in the United States and Canada. This suggests that Mexican per capita meat consumption could continue growing (from 1997 to 2006, the growth rate is 39%, Appendix, Table A.4). Additionally, given that Mexico is a neighbor country to the United States, Mexico represents a key market for U.S. exporters. For example, there are other countries with lower annual per-capita meat consumption than Mexico such as Peoples Republic of China, Russian Federation, Japan and India, but the United States does not enjoy the same competitive advantage in transportation costs with these countries as it does with Mexico.[3] Furthermore, from 1997 to 2006, the meat consumption growth rates for India, Mexico, Peoples Republic of China, Brazil, United States, Japan, and Russian Federation are 72%, 39%, 39%, 24%, 8%, 4%, and 1% respectively (see Appendix, Table A.4). That is, Mexico has the second highest growth rate among the largest meat consuming contries and it does not have a religious barrier with respect to the consumption of beef as opposed to India (e.g., some Hindus).

Different from world production and consumption, but similar to Mexican production, Mexican poultry meat consumption has the largest average share (41%, Appendix, Table A.7). It is closely followed by beef consumption with an average share of 38% and then swine meat consumption with an average share of 22% (see Appendix, Table A.7). Poultry meat consumption has the highest growth rate from 1997 to 2006. However, beef consumption was larger than poultry meat consumption

[3]For recent issues related to road transport and protectionist pressures refer to *The Economist (2009).*

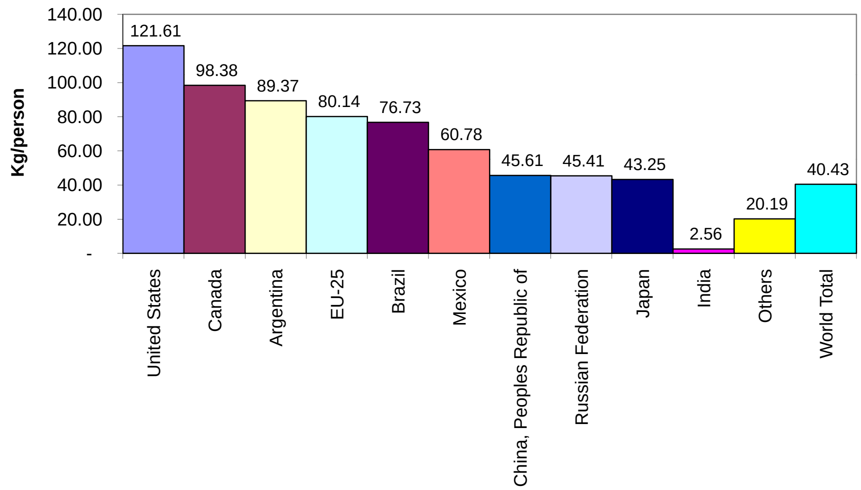

Figure 1.3: Per Capita Meat Consumption of Selected Countries, Average 1997-2006.

Source: Consumption from USDA-ERS-PSD Online Database, computed by author. Population from IMF-IFS Online Database.

from 1997 to 1999 and it was about the same in 2000. All three meats (beef, swine, and poultry) have an increasing tendency with growth rates of 80%, 26%, and 61% respectively from 1996 to 2007.

1.3.3 Imports and Exports

World meat imports increased 28% from 1997 to 2006 (Appendix, Table A.1). Beef has the largest annual world imports with an average share of 38%. It is followed by poultry meat with an average share of 35% and swine meat with 26%. However, annual beef imports are not increasing (0.2% decrease). Nonetheless, annual beef imports are larger than swine and poultry meat imports. On the other hand, swine meat imports and poultry meat imports are rapidly increasing (64% and 41% respectively).

The world's largest meat importing countries, in descending order, are Russian Federation, Japan, United States, Mexico, European Union, Hong Kong, Peoples Republic of China, Republic of Korea, Saudi Arabia, and Canada (Figure 1.4). Together these ten countries account for 88% of the total world meat imports. Additionally, Figure 1.4 shows that Russian Federation, Japan, United States, Mexico and the European Union import at least twice as much as all other countries. These five countries experienced average shares of 20%, 20%, 14%, 8%, and 7% respectively from 1997 to 2006. However, most countries are experiencing rapid growth rates during the same period: Mexico (147%), Hong Kong (61%), Republic of Korea (53%), European Union (43%) and the United States (42%) (see Appendix, Table A.5).

As the most rapidly growing meat importing country, Mexico is a very important market for the United States. From 1997 to 2006, Mexico meat imports went from 568,000 MT to 1,405,000 MT (see Appendix, Table A.5). The volume Mexico imports is rapidly getting closer to that of the United States (1,925,000 MT in 2006) and is already above the volume the European Union imports (1,272,000 MT in 2006).

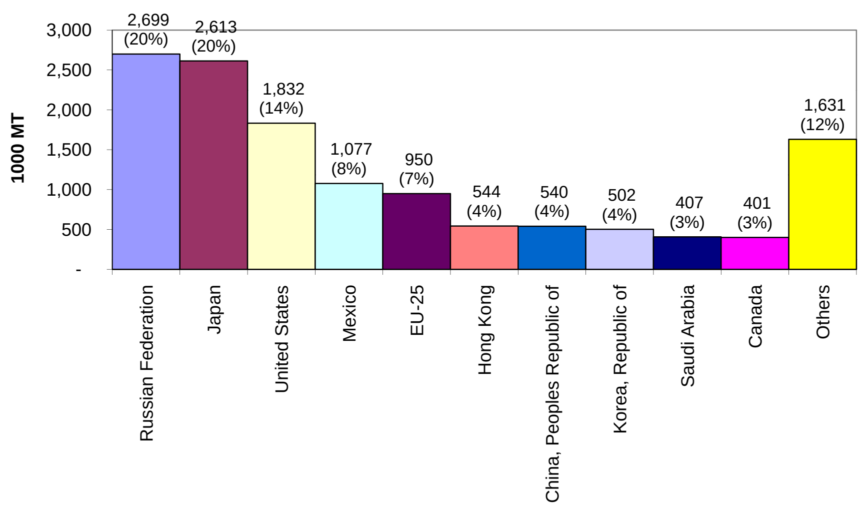

Figure 1.4: World's Largest Meat Importing Countries, Average 1997-2006.

Source: USDA-ERS-PSD Online Database, computed by author.

World meat exports increased 48% from 1997 to 2006 (Appendix, Table A.1). Similar to imports, beef is the most exported meat (average share of 42%), but it is closely followed by poultry meat (average share of 41%). On the other hand, the volume of swine meat exported (average share of 18%) is lower than the volume imported (average share of 26%). From 1997 to 2006, annual swine exports have the largest growth rate (135%) followed by poultry meat (53%) and beef (21%). However, swine exports are still low compared to the volume of beef and poultry meat exports.

The world's largest meat exporting countries, in descending order, are United States, Brazil, EU-25, Canada, Australia, Peoples Republic of China, New Zealand, Argentina, India, and Thailand (Figure 1.5). Together these ten countries account for 94% of the total world meat exports. Additionally, Figure 1.5 shows that United States, Brazil, Canada and Australia export considerably higher volumes than all other countries. In the case of the European Union, meat exports decreased by 56% from 1997 to 2006 (see Appendix, Table A.6). On the contrary, the most impressive increase in meat exports is observed in Brazil (a 437% increase). India follows Brazil with an increasing growth rate of 249%, but the volume India exports is about seven times lower than Brazil's volume. Moreover, Brazil is consistently increasing exports of beef, swine and poultry meat, while the increase in India meat exports is only due to beef exports. It is not surprising that India is only exporting beef. As mentioned earlier, a significant portion of the Indian population does not eat beef because of their religion (e.g., some Hindus). Therefore, Indian people consume more swine and poultry meat. Finally, the meat volume Brazil exports has been larger than the volume the United States exports since 2004. In general, however, most countries are experiencing rapid growth rates in meat exports from 1997 to 2006: Canada (96%), Peoples Republic of China (48%), Thailand (44%), Argentina (35%), and Australia (21%). Mexico is not among the largest meat exporting countries (Figure 1.5).

A comparison of Figure 1.4 with Figure 1.5 reveals the countries that are net importers and exporters. For example, from 1997 to 2006 all meat exporting countries in Figure 1.5 are net exporting countries while in Figure 1.4 Russian Federation (average net imports of 2,671,000 MT), Japan (2,610,000 MT), Mexico (1,003,000 MT), Hong Kong (540,000 MT), Republic of Korea (458,000 MT), and Saudi Arabia (391,000 MT) are net importing countries.

In Mexico, similar to Mexican production and consumption, poultry meat imports has the largest average share (39%), Appendix, Table A.7. It is followed by beef imports (average share of 33%) and then by swine meat imports (average share of 28%). However, from 1997 to 2006, Mexican swine meat imports had the highest

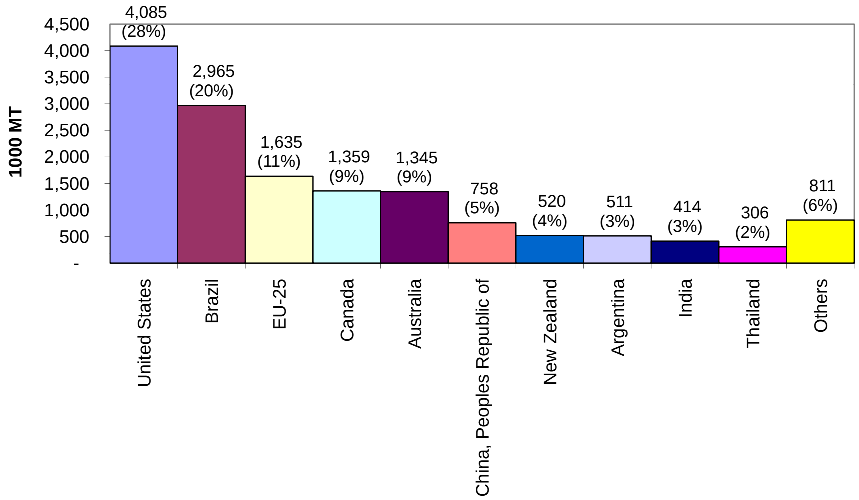

Figure 1.5: World's Largest Meat Exporting Countries, Average 1997-2006.

Source: USDA-ERS-PSD Online Database, computed by author.

growth rate (449%) while Mexican poultry meat imports more than doubled and beef imports experienced a high growth rate (80%).

On the other hand, the volume of total meat Mexico exported from 1997 to 2006 is on average about 15 times lower than what it imported (see Appendix, Table A.7). Swine meat has the highest volume of Mexican meat exported (average share of 74%). It is followed by beef (average share of 20%) and poultry meat exports (average share of 5%). Despite the low volumes of total Mexican meat exports, they more than doubled from 1997 to 2006.

More interestingly, an analysis of Mexican imports and exports by meat cuts reveals that the most imported bovine meat for the period 2002-2007 is boneless meat, which has an average share of 75% (Figure 1.6). It is followed by imports of bovine remains (average share of 22%). Imports of other bovine meat cuts with bone in and bovine meat carcasses and halfcarcasses have average shares of only 2% and 0.3% respectively. Mexican bovine imports of these four cuts averaged 1 billion dollars for the same period (Mexican Ministry of Economy, 2008). Figure 1.7 shows that Mexican bovine imports from the United States on average account for about 79% of the total Mexican bovine imports. Together the United States and Canada account for about 93% of the total Mexican bovine imports. Consequently, Mexico is an important market for U.S. beef exports.

On the other side, the most exported Mexican bovine meat for the period 2002-2007 is also boneless bovine meat, which has an average share of 57% (Figure 1.6). It is followed by other bovine meat cuts with bone in (29%), bovine remains (12%), and bovine meat carcasses and halfcarcasses (2%). From 2002 to 2007, Mexico on average exported about 88.3 million dollars per year (Mexican Ministry of Economy, 2008). Mexican exports and imports of bovine meat are shown in Figure 1.6. Then, Figure 1.7 shows that the United States is the main destination for Mexican bovine exports. However, Mexican imports (kg) from the United States are on average about 33 times bigger than Mexican exports (kg) to the United States (Figure 1.7), but on average only about 16 times bigger when considering nominal dollars (Mexican Ministry of Economy, 2008).

When analyzing swine meat, the most imported cut is swine hams, shoulders and cuts thereof with bone in, which has an average share of 46% (Figure 1.8). It is followed by swine remains (36%), boneless swine meat (18%) and swine meat carcasses and halfcarcasses (0.2%). Mexican swine imports of these four cuts averaged 563 million dollars from 2002 to 2007 (Mexican Ministry of Economy, 2008). Figure 1.9 shows that Mexican swine imports from the United States on average account for about 84% of the total Mexican swine imports.

On the other side, the most exported Mexican swine meat is boneless swine meat, which has an average share of 95% (Figure 1.8). Therefore, the other three swine cuts (carcasses and halfcarcasses; hams, shoulders and cuts thereof; and swine remains) have each an average share that is less than 3%. From 2002 to 2007, Mexico on average exported about 173 million dollars per year (Mexican Ministry of Economy, 2008). Different from Mexican bovine exports, Figure 1.9 shows that the United States (average share of 23%) is not the main destination for Mexican swine exports. The main destination is Japan (average share of 74%). However, the swine meat volume that Mexico exports to the United States (Figure 1.9) is larger than the bovine meat volume that Mexico exports to the United States (Figure 1.7). Nonetheless, Mexican imports (kg) from the United States are about 36 times bigger in volume (13 times bigger in nominal dollars according to Mexican Ministry of Economy (2008)) than Mexican exports (kg) to the United States (Figure 1.9).

The most imported chicken cut is boneless chicken, which has an average share of 47% (Figure 1.10). It is followed by chicken legs and thighs (34%), other chicken cuts and offal (16%), and whole chicken (3%). Mexican chicken imports for these four cuts averaged 214 million dollars from 2002 to 2007 (Mexican Ministry of Economy, 2008). Figure 1.11 shows that Mexican chicken imports from the United States on average account for about 92% of the total Mexican chicken imports.

On the export side, the most exported Mexican chicken cut is other chicken cuts and offal, which has an average share of 74% (Figure 1.10). It is followed by boneless chicken (13%), chicken legs and thighs (12%), and whole chicken (1%). From 2002 to 2007, Mexico exported an average of 540 thousand dollars per year (Mexican Ministry of Economy, 2008). Similar to Mexican swine exports, Figure 1.11 shows that the main destination for Mexican chicken exports is Hong Kong and Japan (average shares of 68% and 18% respectively). Consequently, Mexican chicken imports (kg) from the United States are far much larger than its exports (kg) to the United States (Figure 1.11). In addition, Mexican chicken imports tend to be more stable than its exports (Figure 1.10).

Finally, the Mexican export and import markets of bacon, ham and similar products are about 364 thousand kg (1.4 million dollars) and 47.7 million kg (70 million dollars) per year respectively (Figure 1.12). In addition, the United States has the highest average share (65%) of the total Mexican imports, while Japan has the highest average share (42%) of the total Mexican exports. Figure 1.12 also shows that Mexican ham and bacon imports tend to be stable, while exports tend to be volatile.

In summary, there is a high dependence in meat trade between the United States and Mexico. This suggests that both countries are very likely to be benefiting. On one side the United States benefits by matching meat cuts with consumers with high willingness to pay (therefore increasing the aggregate value of each animal), and on the other side Mexican consumers enjoy lower meat prices. Second, Mexican imports of bovine animal remains are larger than imports of bovine meat carcasses and half-carcasses and other cuts of bovine meat with bone in (Figure 1.6). Similarly, imports of swine remains are larger than imports of boneless swine meat and swine meat carcasses and half-carcasses (Figure 1.8). Likewise, imports of other chicken cuts and offal are larger than imports of whole chicken (Figure 1.10). Third, the United States is the main source of Mexican imports of beef, pork, chicken, and ham and bacon. However, the United States is only the main destination for Mexican beef and pork exports, but it is still a key destination for Mexican exports of chicken and ham and bacon. Fourth, Mexican imports of beef, pork, chicken, and ham and bacon are relatively stable, while Mexican exports are only relatively stable for beef and pork. That is, Mexican exports of chicken and ham and bacon are volatile.

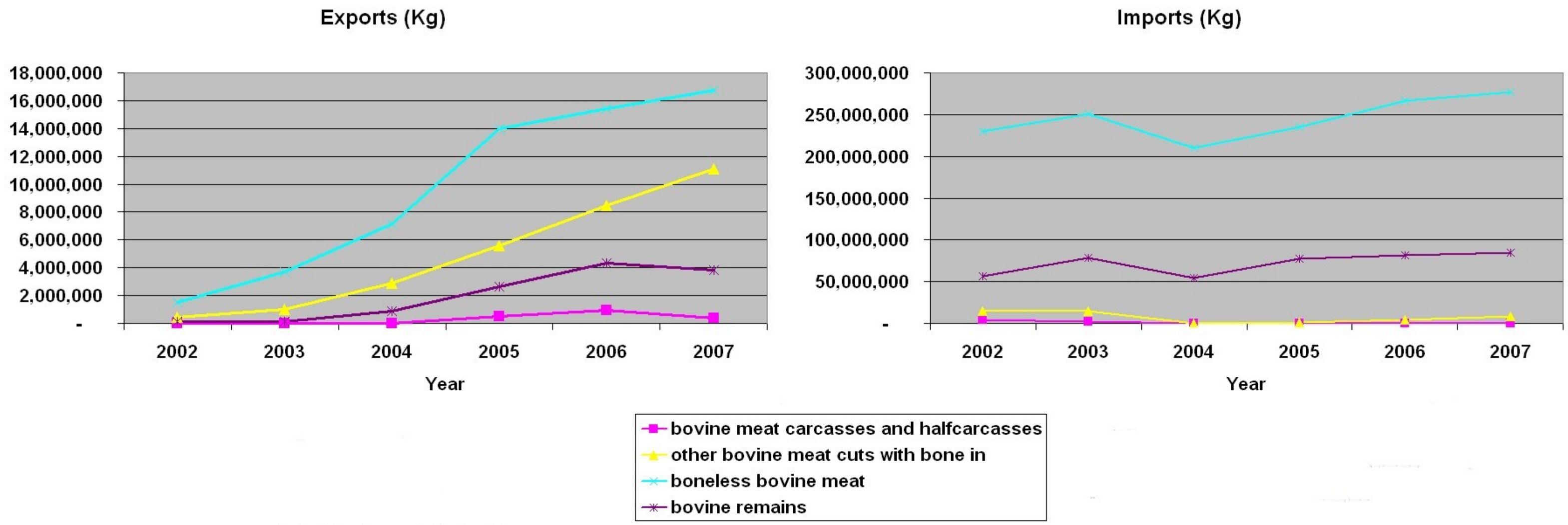

Figure 1.6: Mexican Exports and Imports of Bovine Meat by Cut (Kg).

Note: Series were computed from chapter 2 (meat and edible meat offal) of the Harmonized System. At the 8-digit level of disaggregation, bovine meat carcasses and half-carcasses includes commodities 02011001 and 02021001. Bovine meat other cuts with bone-in includes commodities 02012099 and 02022099. Boneless bovine meat includes commodities 02013001 and 02023001. Bovine remains include commodities 02061001, 02062101, 02062201 and 02062999. All years are calendar years (January to December) except for 2002, which was reported from April to December.

Source: Mexican Ministry of Economy, SIAVI Database, computed by author.

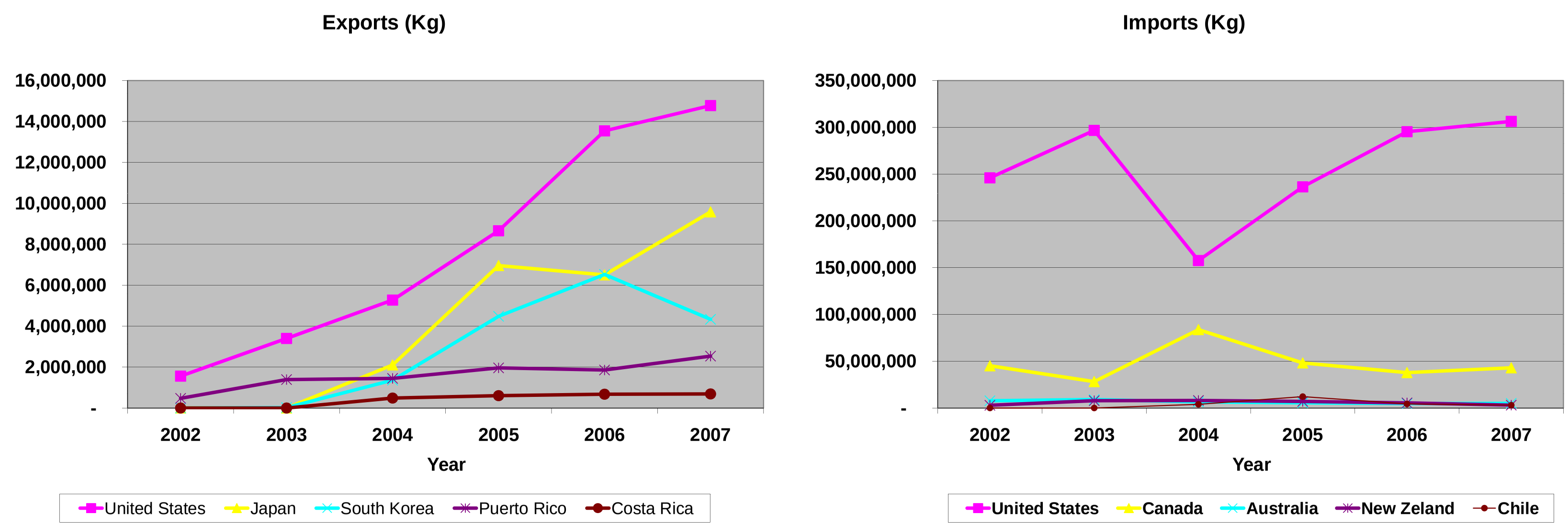

Figure 1.7: Mexican Exports and Imports of Bovine Meat (Top 5 Countries).

Note: Series were computed from chapter 2 (meat and edible meat offal) of the Harmonized System. At the 8-digit level of disaggregation, bovine meat carcasses and half-carcasses includes commodities 02011001 and 02021001. Bovine meat other cuts with bone-in includes commodities 02012099 and 02022099. Boneless bovine meat includes commodities 02013001 and 02023001. Bovine remains include commodities 02061001, 02062101, 02062201 and 02062999. All years are calendar years (January to December) except for 2002, which was reported from April to December.

Source: Mexican Ministry of Economy, SIAVI Database, computed by author.

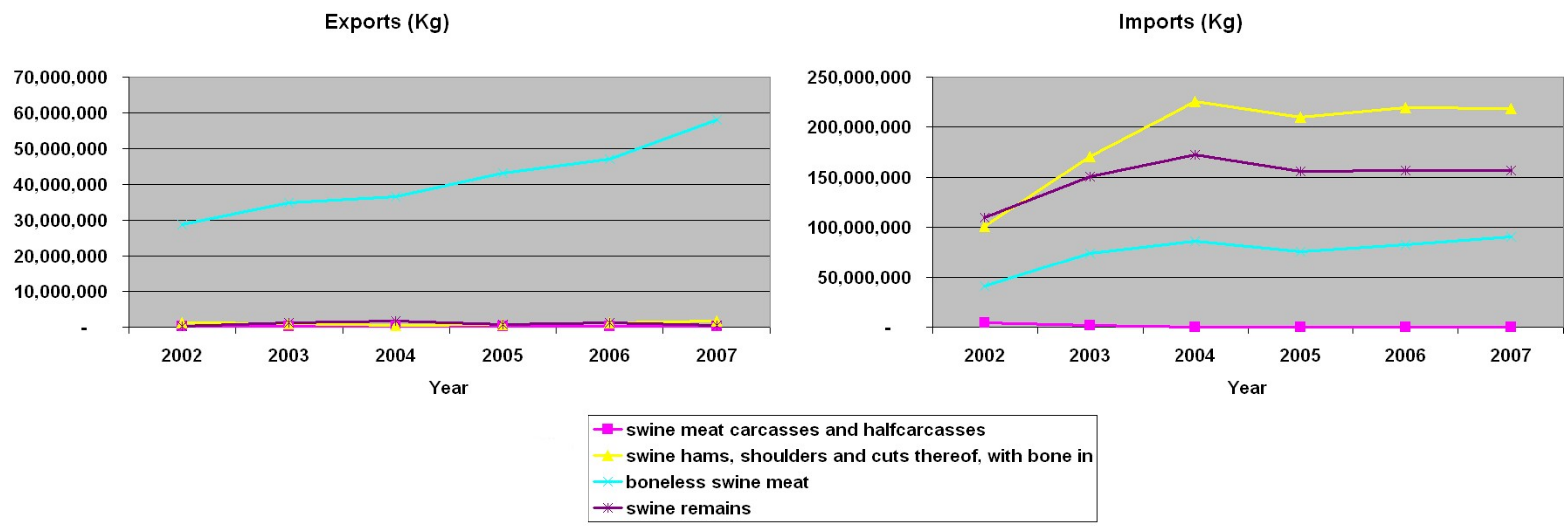

Figure 1.8: Mexican Exports and Imports of Swine Meat by Cut (Kg).

Note: Series were computed from chapter 2 (meat and edible meat offal) of the Harmonized System. At the 8-digit level of disaggregation, swine meat carcasses and half-carcasses include commodities 02031101 and 02032101. Swine hams, shoulder and cuts thereof, with bone-in include commodities 02031201 and 02032201. Boneless swine meat includes commodities 02031999 and 02032999. Swine remains include commodities 02063001, 02063099, 02064101, 02064901 and 02064999. All years are calendar years (January to December) except for 2002, which was reported from April to December.

Source: Mexican Ministry of Economy, SIAVI Database, computed by author.

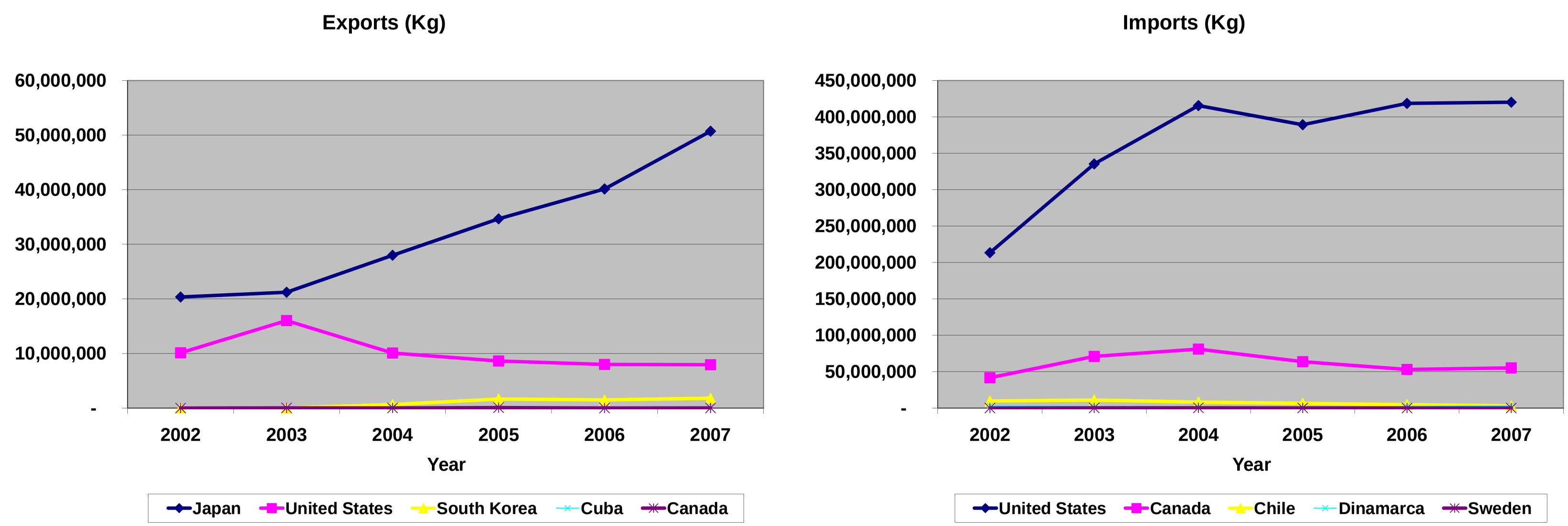

Figure 1.9: Mexican Exports and Imports of Swine Meat (Top 5 Countries).

Note: Series were computed from chapter 2 (meat and edible meat offal) of the Harmonized System. At the 8-digit level of disaggregation, swine meat carcasses and half-carcasses include commodities 02031101 and 02032101. Swine hams, shoulder and cuts thereof, with bone-in include commodities 02031201 and 02032201. Boneless swine meat includes commodities 02031999 and 02032999. Swine remains include commodities 02063001, 02063099, 02064101, 02064901 and 02064999. All years are calendar years (January to December) except for 2002, which was reported from April to December.

Source: Mexican Ministry of Economy, SIAVI Database, computed by author.

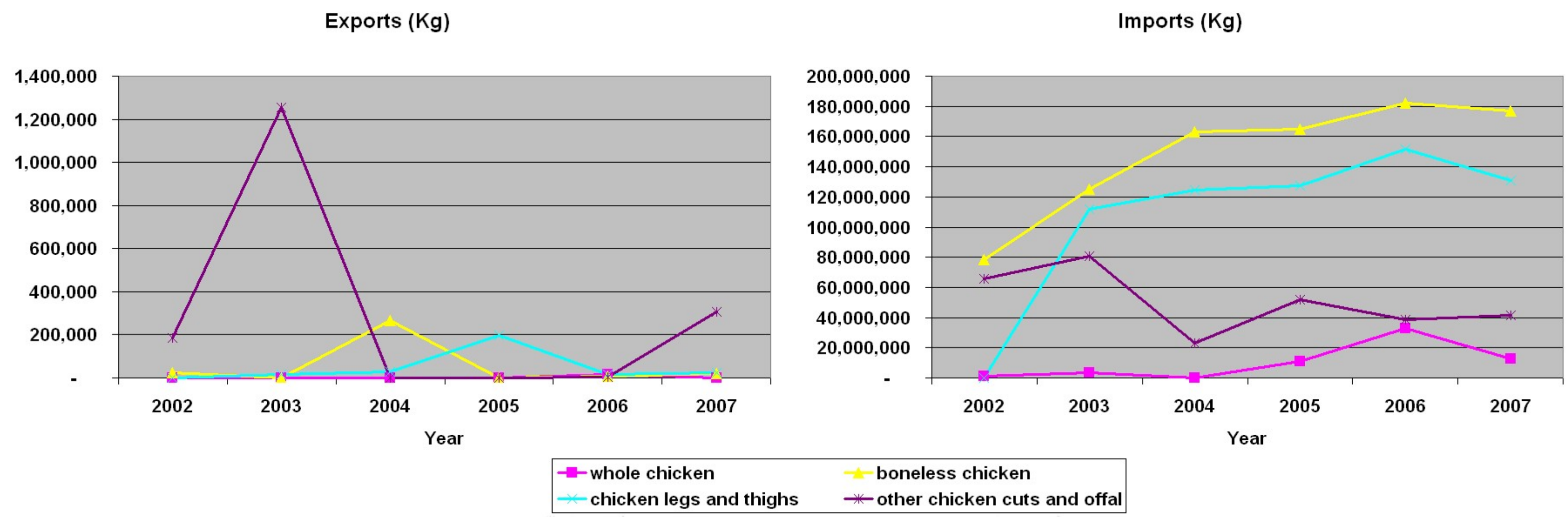

Figure 1.10: Mexican Exports and Imports of Chicken by Cut (Kg).

Note: Series were computed from chapter 2 (meat and edible meat offal) of the Harmonized System. At the 8-digit level of disaggregation, whole chicken include commodities 02071101 and 02071201. Boneless chicken includes commodities 02071301 and 02071401. Chicken legs and thighs include commodities 02071303 and 02071404. Other chicken cuts and offal include commodities 02071302, 02071399, 02071402, 02071403 and 02071499. All years are calendar years (January to December) except for 2002, which was reported from April to December.

Source: Mexican Ministry of Economy, SIAVI Database, computed by author.

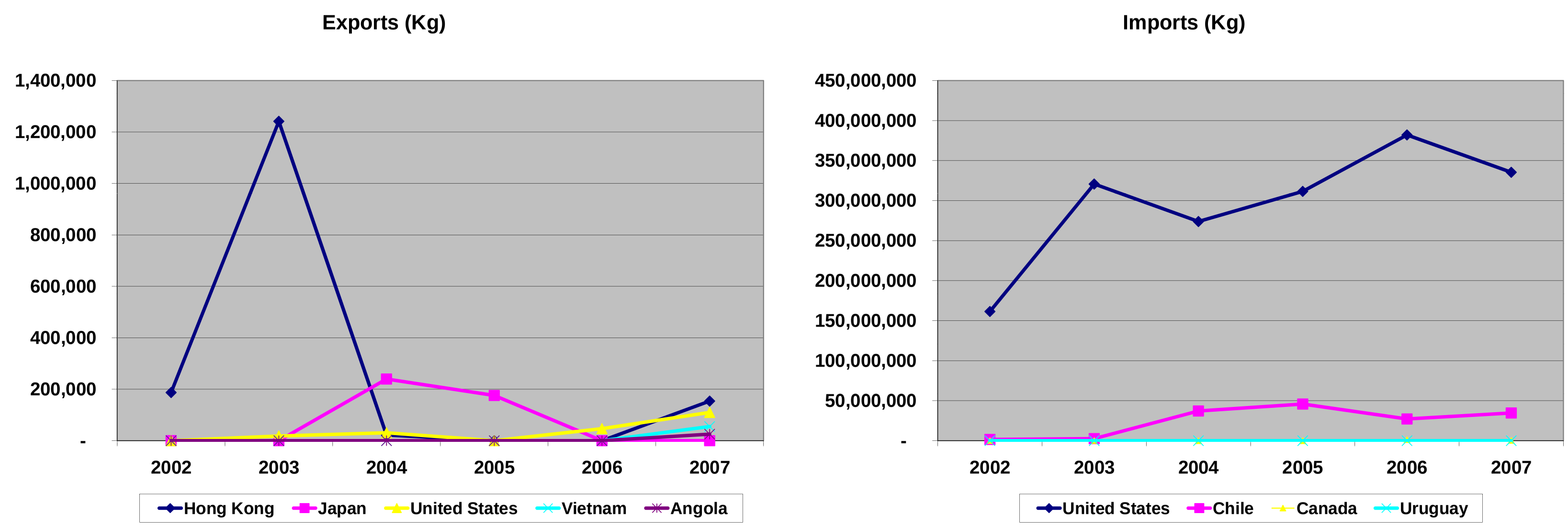

Figure 1.11: Mexican Exports and Imports of Chicken (Top 5 Countries).

Note: Series were computed from chapter 2 (meat and edible meat offal) of the Harmonized System. At the 8-digit level of disaggregation, whole chicken include commodities 02071101 and 02071201. Boneless chicken includes commodities 02071301 and 02071401. Chicken legs and thighs include commodities 02071303 and 02071404. Other chicken cuts and offal include commodities 02071302, 02071399, 02071402, 02071403 and 02071499. All years are calendar years (January to December) except for 2002, which was reported from April to December.

Source: Mexican Ministry of Economy, SIAVI Database, computed by author.

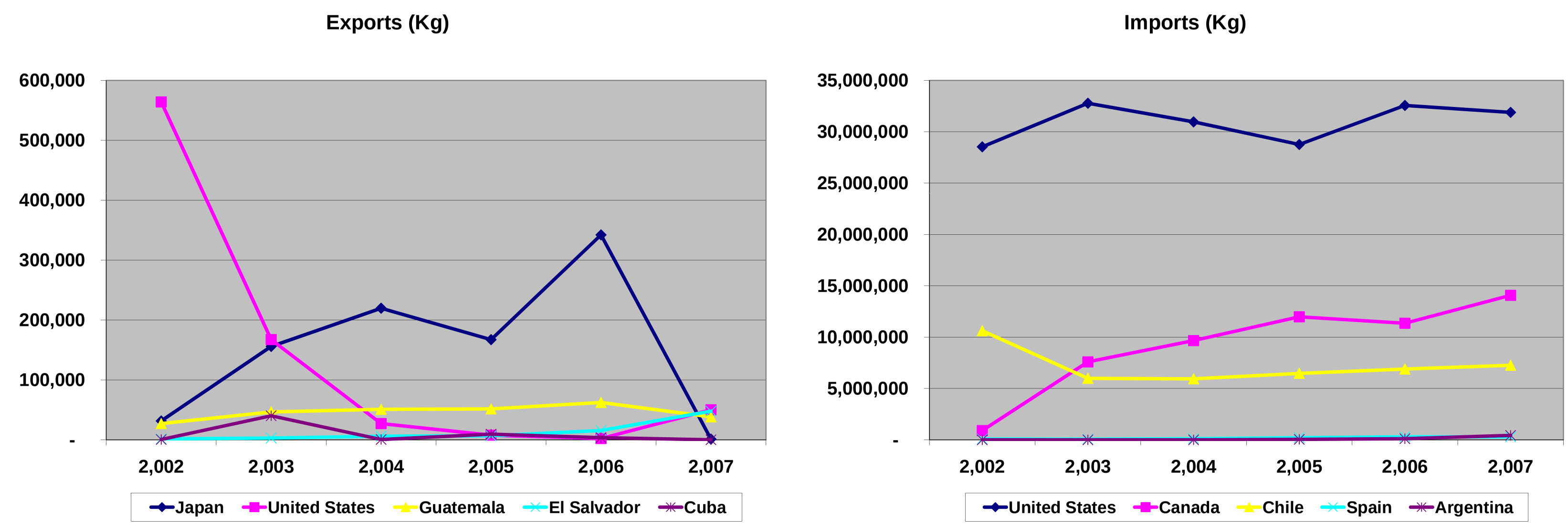

Figure 1.12: Mexican Exports and Imports of Bacon, Ham, and Similar Products (Top 5 Countries).

Note: Series were computed from chapter 2 (meat and edible meat offal) of the Harmonized System. At the 8-digit level of disaggregation, ham, bacon & similar products include commodities 02090001, 02090099, 02101101, 02101201, 02101999, 02102001, 02109903, and 02109999. All years are calendar years (January to December) except for 2002, which was reported from April to December.

Source: Mexican Ministry of Economy, SIAVI Database, computed by author.

CHAPTER II
LITERATURE REVIEW

The primary objective of this chapter is to review previous research on Mexican meat demand, relevant issues in consumer survey data, and how stratified samples and complex surveys are handled. Section 2.1 reviews meat demand studies in Mexico, and explains some of their drawbacks and how this study differs from them. Section 2.3 reviews censored expenditures, which is a frequently encountered problem in consumer survey data—the same nature of the data used in this study. To understand how other researchers have modeled and estimated adult equivalence scales, it is good to have knowledge of the censored expenditure problem. The literature reviewed in Section 2.4, which deals with adult equivalent scales, implicitly assumes that the reader is familiar with censored expenditures. Section 2.5 provides basic concepts related to missing data and then it explains how to handle missing data. Some of the techniques presented in Section 2.5 are implemented in Section 4.2.1. The models from Section 2.3 are used in Section 2.5 as examples of parametric models of item nonresponse on the dependent variable.

Finally, Section 2.6 deals with stratified sampling, complex surveys, and surveys weights in regression models. It also discusses the computation of standard errors of parameter estimates from regression models that use stratified samples. Section 2.6 is very important because the data used in this study applied a stratified sampling technique to collect information on household incomes and expenditures. Finally, Section 2.7 briefly explains the bootstrap, a general bootstrap algorithm, and different bootstrap sampling methods. In general, the bootstrap is a resampling technique that can be used to estimate standard errors of parameter estimates when other estimation techniques are inappropriate or not feasible.

2.1 Mexican Meat Demand Studies

There have been several studies performed on the Mexican meat market (e.g., López, 2008; Fernández, 2007; Malaga, Pan, and Duch, 2007; Erdil, 2006; Clark, 2006; Malaga, Pan, and Duch, 2006; Magaña Lemus, 2005; Dong, Gould, and Kaiser, 2004; Gould and Villarreal, 2002; Gould et al., 2002; Golan, Perloff, and Shen, 2001; González Sánchez, 2001; Sabates, Gould, and Villarreal, 2001; Dong and Gould, 2000; García Vega and García, 2000; Jiménez Gómez, 1996; García Vega, 1995; Heien, Jarvis, and Perali, 1989; Estrada Rosales, 1988; Ramírez Sosa, 1986; Chincilla Domínguez, 1985). In general, these studies can be classified into demand and price analysis, production and trade liberalization analysis, and/or consumer behavior analysis.

Studies that have analyzed Mexican meat *demand and prices* have usually considered broad meat commodity groups such as beef, pork, and chicken, but they have also considered food commodity groups such as cereal, meat, dairy, fat, fruit, vegetables, etc. (e.g., Erdil, 2006; Dong, Gould, and Kaiser, 2004; García Vega and García, 2000; Heien, Jarvis, and Perali, 1989; González Sánchez, 2001). However, none of the Mexican meat demand and price studies have formally tested Mexican consumers' separability of preferences. That is, Mexican studies have not yet investigated whether Mexican commodities can be partitioned into groups so that preferences within groups are described independently of the quantities in other groups (Deaton and Muellbauer, 1980, p. 122). Even when considering only meat commodity groups, tests on Mexican consumers' separability of preferences have not been done for fish and shellfish. Nonetheless, most of the studies have excluded fish and shellfish from the meat commodity groups. Only few studies on Mexican meat demand have included fish or seafood (e.g., Dong, Gould, and Kaiser, 2004; Gould et al., 2002; Golan, Perloff, and Shen, 2001).[1]

In addition, studies dealing with Mexican meat demand and prices usually encounter censored observations. The number of censored observations in Mexican meat

[1]In Australia, Alston and Chalfant (1987) found mixed results in terms of whether meat and other goods are separable in the household's utility function. In the United States, Moschini, Moro, and Green (1994) found evidence of separability between purchases of meat and other goods.

demand studies is often high (e.g., López, 2008; Gould et al., 2002; Golan, Perloff, and Shen, 2001; Sabates, Gould, and Villarreal, 2001; Dong and Gould, 2000; Heien, Jarvis, and Perali, 1989). In addition, censoring may occur on dependent variables, independent variables, or both. For example, price and quantity (and therefore expenditure) are usually censored. This generates a missing price and a zero quantity for those censored observations. To solve the problem of censored prices (i.e., observations with missing prices), researchers usually adopt a regression imputation approach (e.g., Malaga, Pan, and Duch, 2006) when prices are independent variables. The regression imputation approach is preferred over a substitution of the missing price with a simple average of non-missing prices (e.g., Golan, Perloff, and Shen, 2001, p. 545 and Dong, Shonkwiler, and Capps, 1998, p. 1099) because it provides more variability in the imputed variable. To solve the problem of censored quantities, researchers usually estimate a censored regression model (e.g., Malaga, Pan, and Duch, 2007; 2006; Dong, Gould, and Kaiser, 2004; Gould et al., 2002; Golan, Perloff, and Shen, 2001; Dong and Gould, 2000; Heien, Jarvis, and Perali, 1989) when quantities are the dependent variables. However, not all Mexican meat studies that encounter censored quantities estimate censored regression models. For instance, some researchers consider only the non-censored observations (i.e., a subset of the original sample) or they estimate their models as if the variables really take the values of zero (i.e., they ignore the censoring problem). In both cases, depending on the number of censored observations, this may lead to bias parameter estimates.[2]

Several censored regression models have been estimated for the Mexican meat market (censored NQUAIDS, censored QUAIDS, censored AIDS, double-hurdle, etc.). For example, Malaga, Pan, and Duch (2007) estimated a demand system by combining the two step censored approach of Shonkwiler and Yen (1999) and the Nonlinear Quadratic Almost Ideal Demand System (NQUAIDS) of Banks, Blundell, and Lewbel (1997). Malaga, Pan, and Duch (2006) used Heien and Wessells' (1990) two step procedure to estimate LA/AIDS and QUAIDS models, using Stone's price index.

[2]Section 2.3 discusses censored expenditures in more detail.

Dong, Gould, and Kaiser (2004) extended the Amemiya-Tobin approach to demand systems estimation using an AIDS specification. Gould et al. (2002) used a demand system approach. Golan, Perloff, and Shen (2001) use a generalized maximum entropy (GME) approach to estimate a nonlinear version of the AIDS with nonnegativity constraints. Dong and Gould (2000) developed a double-hurdle model of demand that accounted for unobserved prices of non-purchasing households, and adjusted for quality differences in poultry and pork for purchasing households. Finally, Heien, Jarvis, and Perali (1989) used an AIDS model, but reported Greene (1983) and Greene (1981) corrected elasticities.

It is worthwhile to mention that the use of the Heien and Wessells' (1990) two step procedure is not recommended. Shonkwiler and Yen (1999) explained and showed by the use of a Monte Carlo experiment that Heien and Wessells' (1990) estimator is inconsistent and performs poorly. In particular, "[a]s the censoring proportion increases, the [Heien and Wessells' (1990)] procedure produces significant parameter estimates in most cases but performs very poorly in that few 95% confidence intervals contain the true parameters" (Shonkwiler and Yen, 1999, p. 981). Finally, Malaga, Pan, and Duch (2007, p. 8) claimed that according to Tauchmann (2005) and Yen and Lin (2006); Shonkwiler and Yen (1999) procedure is inefficient. "The degree of the inefficiency depends on the degree of the correlation among the error terms" (Malaga, Pan, and Duch, 2007, p. 8) in the first step because univariate probit regressions rather than multivariate probit regressions are estimated. However, it needs to be clarified that if independent variables in different equations are not highly correlated and if error terms in different equations are highly correlated, then a quite large gain in efficiency can be obtained.[3] Therefore, Shonkwiler and Yen (1999) procedure is largely less efficient only if those two condition holds. That is, if independent variables in different equations are highly correlated and error terms in different equations are not highly correlated, then no large gain in efficiency is obtained by using multivariate

[3]See Zellner's (1962) proof on why SUR estimators are at least asymptotically more efficient than least squares equation-by-equation estimators.

probit regressions instead of univariate probit regressions.

Some Mexican studies have also been concerned with meat *production and trade liberalization*. For example, Malaga, Pan, and Duch (2007) and Malaga, Pan, and Duch (2006) investigated the effect of the North American Free Trade Agreement (NAFTA) on Mexican meat demand based on comparison of elasticity estimates for the years 1992, 1994, 1996, 1998, 2002, and 2004. Clark (2006) also compared elasticity estimates before (1970-1994) and after (1995-2004) NAFTA, and similar to García Vega (1995), she tested for structural change by using a slope shifter. On the contrary, Magaña Lemus (2005) analyzed and quantified the economic impact of liberalizing trade between the U.S. and Mexico by using a cost minimization approach that incorporated 2003 data from production, consumption and prices of chicken. In particular, Magaña Lemus (2005) analyzed two policy scenarios: the elimination of the Mexican tariff rate quota (TRQ) on U.S. leg quarters and the elimination of this TRQ as well as the removal of sanitary restrictions from nine Mexican states. Similarly, García Vega (1995) studied trade liberalization in the Mexican livestock, meat, and feedgrain sectors, and the overall liberalization effect through five simulation scenarios: liberalization of only cattle exports from Mexico, liberalization of only cattle imports by Mexico, liberalization of only meat imports by Mexico, liberalization of only feed imports by Mexico, and liberalization of exports and imports of cattle, meat, and feed simultaneously. In addition, García Vega (1995) analyzed the effects of changes in Mexican per capita incomes during the period of unilateral liberalization (1986-1991) on Mexican exports and imports of livestock, meat, and feedgrains.

Other Mexican studies have focused on analyzing *consumer behavior*. For example, Gould and Villarreal (2002) analyzed Mexican adult equivalence scales and weekly food, beef and pork expenditures in 1996. They focused on estimating commodity-specific (beef and pork) adult equivalence scales while endogenously determining commodity prices. Similarly, Gould et al. (2002) endogenously determined equivalence scales measures for meat and fish consumed at home in 1998. Likewise, Sabates, Gould, and Villarreal (2001) analyzed the impacts of household member counts versus endogenously determined equivalence scales at the per capita aggregated food expenditure level in 1996. In general, these studies found evidence that household composition (i.e., household members sizes and ages) is an important determinant of household expenditures. In particular, Sabates, Gould, and Villarreal (2001) explained that a simple count of household members does not provide the same information as the use of equivalence scales in explaining food purchase behavior. Finally, Gould et al. (2002) showed evidence that households adjust purchasing behavior (by achieving economies of scales) when there is a large number of adult equivalents. Gould and Villarreal (2002), Gould et al. (2002), and Sabates, Gould, and Villarreal (2001) all endogenously determined adult equivalent scales.[4] Other Mexican meat studies have incorporated household compositions by using a simple count or proportion of household members sizes and/or ages (e.g., Dong, Gould, and Kaiser, 2004; Gould et al., 2002; Golan, Perloff, and Shen, 2001; Dong and Gould, 2000; García Vega and García, 2000; Heien, Jarvis, and Perali, 1989).

There are also several studies on the Mexican meat market which have used the same data source that is used in this study, *Encuesta Nacional de Ingresos y Gastos de los Hogares (ENIGH) (2006).* However, these studies do not seem to be aware that the survey is complex.[5] Consequently, they have treated ENIGH as a simple random sample, instead of a stratified sample, without doing a preliminary examination (e.g., Malaga, Pan, and Duch, 2007; 2006; Dong, Gould, and Kaiser, 2004; Gould et al., 2002; Gould and Villarreal, 2002; Golan, Perloff, and Shen, 2001; Sabates, Gould, and Villarreal, 2001; Dong and Gould, 2000; García Vega and García, 2000; Heien, Jarvis, and Perali, 1989). Section 2.6 suggests that this may result in parameter estimates that may not be representative of the population or that may not capture potential differences among sub-populations Lohr (1999, pp. 221-254). Section 4.2.3 explains some practical consequences. Besides not treating the sample as a stratified sample, there are some studies on Mexican meat demand, which have used the same

[4]Section 2.4 further discusses adult equivalent scales.

[5]Complex surveys are discussed on Section 2.6.

data source, that have excluded from their analysis rural households (i.e., households located in cities or towns with a population of 14,999 or less). For example, Malaga, Pan, and Duch (2007; 2006) and Dong, Gould, and Kaiser (2004) only considered urban households (i.e., households located in cities or towns with a population of 15,000 people or more). They claimed they had to ignore rural households because of the problem of assigning a dollar value (i.e., an equivalent market price) to the meat produced at home. However, ENIGH *(Encuesta Nacional de Ingresos y Gastos de los Hogares (ENIGH), 2006)* does not record transactions of home-produced goods when the households do not make a living by selling home-produced goods. In addition, Malaga, Pan, and Duch (2007; 2006) and Dong, Gould, and Kaiser (2004) did not have an indicator in the data of how many rural households who produced meat at home were not included in data. That is, they excluded the rural households based on their belief that a large number of rural households consume meat produced at home. However, the urban households also have a chance of consuming home-produced goods. That is, the fact that you live in an urban or rural location does not eliminate the possibility of consuming home-produced goods. In addition, considering that urban locations are more populated, the number of urban households consuming home-produced goods may be larger than the number of rural households consuming home-produced goods. For this matter and because this study wants to obtain parameter estimates that are representative of the population, this study will not exclude any segment of the population. Finally, Gould et al. (2002) also limited their analysis to urban households; however, they clearly explained that their sample is not representative of Mexican households.

There are also differences in the number of geographical regions used in Mexican meat consumption studies. They range from three regions (e.g., Magaña Lemus, 2005) to ten regions (e.g., Dong and Gould, 2000; Heien, Jarvis, and Perali, 1989). Other Mexican meat studies have used five regions (López, 2008; Sistema de Información Agropecuaria de Consulta (SIACON), 2006), seven (Dong, Gould, and Kaiser, 2004), and eight (Gould and Villarreal, 2002; Gould et al., 2002). In addition, not all studies have incorporated urbanization level differences in meat consumption, but several studies have (López, 2008; Gould and Villarreal, 2002; Golan, Perloff, and Shen, 2001; Dong and Gould, 2000; Heien, Jarvis, and Perali, 1989). It is very important to incorporate differences among regions and urbanization levels when analyzing food consumption patterns in Mexico. Most Mexican meat demand studies have found significant differences (López, 2008; Dong, Gould, and Kaiser, 2004; Gould et al., 2002; Gould and Villarreal, 2002; Dong and Gould, 2000; Golan, Perloff, and Shen, 2001; García Vega and García, 2000; Heien, Jarvis, and Perali, 1989). For example, Dong, Gould, and Kaiser (2004, p. 1102) found "evidence of significant differences in food purchase patterns across regions", Gould and Villarreal (2002, p. 1081) anticipated regional differences "[g]iven the enormous regional differences in Mexico from an economic, cultural and climatic perspective," and García Vega and García (2000, p. 29) confirmed that "region was... one of the most significant variables used to explain the food consumption of the Mexicans."

Given that Mexico is very important for large meat exporters (such as the United States and Canada), the present study will fill in most of the gaps of what previous studies have not done.[6] This will allow for a more in-depth analysis of the Mexican meat market. For instance, the study will consider table cuts of meats (i.e., beefsteak; ground beef; pork steak; ground pork; chicken legs, thighs and breast; fish, etc.) rather than meat aggregates such as beef, pork, and chicken (e.g., López, 2008; Fernández, 2007; Malaga, Pan, and Duch, 2007; Clark, 2006; Malaga, Pan, and Duch, 2006; Gould and Villarreal, 2002; Gould et al., 2002; Golan, Perloff, and Shen, 2001; Sabates, Gould, and Villarreal, 2001; Dong and Gould, 2000; García Vega and García, 2000; García Vega, 1995; Heien, Jarvis, and Perali, 1989). In addition, it will not only present elasticity estimates at the table cut level (which are currently not available for Mexico), but also identify trends in consumption and imports. Additionally, it will explore regional and urbanization level differences in the consumption of table

[6]Marshallian and Hicksian price and expenditure elasticities reported in previous studies are summarized in Appendix B.

cuts of meats. On the other hand, the study is theoretically sound because it uses the entire target population rather than a segment of the target population that may not be representative (e.g., Malaga, Pan, and Duch, 2007; 2006; Dong, Gould, and Kaiser, 2004; Gould et al., 2002). It will also incorporate adult equivalence scales to compute the number of adult equivalents rather than ignoring them (e.g., Malaga, Pan, and Duch, 2007; 2006) or using a simple count or proportion of household members (e.g., Dong, Gould, and Kaiser, 2004; Gould et al., 2002; Golan, Perloff, and Shen, 2001; Dong and Gould, 2000; García Vega and García, 2000; Heien, Jarvis, and Perali, 1989). In addition, it will use a price imputation approach to account for censored prices, which is preferred over a substitution of the missing price with a simple average of non-missing prices (e.g., Golan, Perloff, and Shen, 2001; Dong, Shonkwiler, and Capps, 1998). It will use a consistent censored demand system estimated in two steps to account for censored quantities. It will use cross-sectional household survey data, which enables "better estimation of demand parameters and improvement of forecasts over those assuming average effects for all members of the population based on aggregate data" (Yen and Huang, 2002, p. 321). Finally it will incorporate estimation techniques from stratified sampling theory because the data sample is a stratified one.

2.2 Demand System Studies

In the previous section, Mexican meat demand studies were classified into demand and price analysis, production and trade liberalization analysis, and/or consumer behavior analysis. Demand systems are sets of demand equations that are estimated in a demand and price analysis. They are very popular for their ability to capture close interrelationships among commodities, which the single equation model fails to recognize.

Several studies have modeled Mexican meat demand using demand systems (López, 2008; Fernández, 2007; Malaga, Pan, and Duch, 2006; Clark, 2006; Erdil, 2006; Malaga, Pan, and Duch, 2006; Dong, Gould, and Kaiser, 2004; Gould et al., 2002;

Golan, Perloff, and Shen, 2001; González Sánchez, 2001; Dong and Gould, 2000; García Vega and García, 2000; García Vega, 1995; Heien, Jarvis, and Perali, 1989). Similarly, demand system models have been employed to analyze the U.S. meat demand (Asatryan, 2003; Medina, 2000; Brester and Schroeder, 1995; Capps et al., 1994; Hahn, 1995; Eales, 1994; Alston and Chalfant, 1993; Eales and Unnevehr, 1993; Brester and Wohlgenant, 1991; Moschini and Meilke, 1989; Thurman, 1989; Dahlgran, 1989; Wohlgenant, 1989; Hahn, 1988; Eales and Unnevehr, 1988; Chalfant, 1987; Thurman, 1987). There are also examples of meat demand studies in the United Kingdom, Great Britain, South Korea and Taiwan, Australia, Canada, and Japan (Fraser, 2000; Burton and Young, 1996; Capps et al., 1994; Cashin, 1991; Chalfant, Gray, and White, 1991; Hayes, Wahl, and Williams, 1990).

These models provide insight in determining a model specification, the meat cuts analyzed, and the methodological issues surrounding a meat demand and price analysis. Mexican meat demand studies also allow to compare and contrast previous elasticity estimates with this study's findings. Elasticity estimates presented in previous studies are reported in Appendix B.

2.3 Censored Expenditures

Censored expenditures are common in consumer survey data. Generally, the censoring is due to survey design and implementation or institutional constraints. *Censored expenditures* occur when the value is partially known. It is partially known because even though you do not have the actual value (it might be coded as zero or omitted) on the variable of interest (e.g., the dependent variable); you do have information on related variables (e.g., the independent variables). As it will be explained in Section 2.5, this is also referred as *item nonresponse* on the dependent variable. In literature, when information is missing on both dependent and independent variables, the dependent variable is referred as *truncated* (Wooldridge, 2006, p. 613; Pindyck and Rubinfeld, 1997, p. 325). Section 2.5 explains that when information is missing on both dependent and independent variables and there is no more information collected, it is also referred as *unit nonresponse*. A *truncated regression model* differs from a censored regression model in that in a truncated regression model any information about a certain segment of the population is not observed (Wooldridge, 2006, p. 613). In addition, truncated regression is a special case of a general problem known as *nonrandom sample selection* (Wooldridge, 2006, p. 616).

Wooldridge (2006, p. 609) explains *censored data* is an issue of data observability. Wooldridge (2006, p. 609) explains the use of a *censored regression model* when there is missing data on the response variable (the dependent variable) but there is information about when the variable is missing (above or below some known threshold). For instance, consider the example provided by Wooldridge (2006, p. 610) in which the value of a family's wealth is of interest. A censoring problem might occur, Wooldridge (2006) explains, when respondents are asked for their wealth, but people are allowed to respond with "more than $500,000." The actual wealth for those respondents whose wealth is less than $500,000 is observed, but not for those whose wealth is greater than $500,000. In this case, the censoring threshold is fixed for all families whose wealth is greater than $500,000.

However, the censoring threshold may also change depending on individual or family characteristics. For instance, consider another example provided by Wooldridge (2006, p. 611) where it is of interest to analyze the time in months until an inmate is arrested after being released from prison. By the end of the period in which you investigate if an inmate was arrested again after being released, not all of them would have been rearrested; therefore, the observations from the inmates not yet arrested would be censored. In other words, some felons may never be arrested again or they may be arrested after such a long time that there is a need to censor the number of days in order to analyze the data. In addition, in this case, the censoring time is different for each inmate. By providing an empirical application of the second example, Wooldridge (2006, p. 611) showed that applying Ordinary Least Squares (OLS) will result in coefficient estimates markedly different from those of a censoring regression model where coefficients and the variance of the error term are estimated by maximum likelihood. In his example, OLS coefficient estimates were all shrunk toward zero. Furthermore, Wooldridge (2006, p. 613) emphasized that an application of a censored regression model will be more reliable.

The second example provided by Wooldridge (2006, p. 611) is very similar to a problem encountered in this study with the Mexican survey data on household income and weekly expenditures. At the end of the period in which the interviewer recorded all items purchased by a household, there will be some items that have not been purchased, but are consumed by the household. Therefore, items not purchased during the week of the interview, which the household consumes, will be censored.

Pindyck and Rubinfeld (1997, p. 325) clarified that censoring occurs when "the dependent variable has been constructed on the basis of an underlying continuous variable for which there are a number of observations about which we do not have information." Pindyck and Rubinfeld (1997, p. 325) provide the following examples.

> Suppose, for example, that we are studying the wages of women. We know the actual wages of those women who are working, but we do not know the "reservation wage" (the minimum wage at which an individual will work) for those who are not. The latter group is simply recorded as not working. Or suppose that we are studying automobile purchasing behavior using a random survey of the population. For those who happened to buy a car, we can record their expenditure, but for those who did not we have no measure of the maximum amount they would have been willing to pay at the time of survey.

Pindyck and Rubinfeld (1997, p. 325) also explain that ordinary least-squares estimation of the censored regression model results in biased and inconsistent parameter estimates. They emphasized a maximum-likelihood estimator as a preferred alternative.

Pindyck and Rubinfeld's (1997, p. 325) examples provide insight into the data used in this study, the Mexican survey data on household income and weekly expenditures. For those households that happen to buy a particular item their expenditure is recorded, but for those who did not there is no measure of the maximum amount they would have been willing to pay at the time of the survey. As it will be explained later, the Mexican survey data on household income and weekly expenditures omit this transaction (i.e., does not make any record of items not purchased). Hence, expenditure on that particular item is censored.

Some researchers more specifically point out the importance of addressing the presence of censored food expenditures when working with weekly food expenditures. If weekly expenditures are reported at home and away from home, by the end of the survey period not all households will have purchased food away from home. Consequently, expenditures on food away from home will be censored in nature (Sabates, Gould, and Villarreal, 2001; Gould and Villarreal, 2002).[7] For example, when a purchase of food away from home is not reported, it is censored because it is not known if the household did not have a chance to buy it or because the household never buys it. In other words, when a purchase of food away from home is not reported by the interviewer, it is censored because this household may buy food away from home a week later after the interviewer left or the household may never buy it at all. Both Gould and Villarreal (2002) and Sabates, Gould, and Villarreal (2001) used the same data source used in this study, *Encuesta Nacional de Ingresos y Gastos de los Hogares (ENIGH) (2006)*. However, they used the 1996 survey while this study uses the 2006 survey.

2.4 Adult Equivalence Scales

Adult equivalence scales are measures that show how much an individual household member of a given age and sex contributes to household expenditures or consumption of goods relative to a standard household member. As explained by Deaton and Muellbauer (1986) adult equivalence scales assign different weights to household members according to their age and gender; whereas a simple count of household members, the most common practice, implicitly assumes each household member has the same marginal impact. The purpose of scales is to capture economies of size

[7] This is the same idea of the censored data problem mentioned above but this time distinguishing between at-home expenditures and away-from-home expenditures.

associated with larger households, the different impacts of children versus adults and to permit welfare comparisons across households of different size and composition (Lazear and Michael, 1980; Deaton and Muellbauer, 1986; Blaylock, 1991; Perali, 1993).

Deaton and Muellbauer (1986) note that equivalence scales can be determined from nutritional and psychological studies, sociological relationships, or the use of revealed consumption or purchase patterns. They note that the last approach appears to be the most reasonable but there continues to be a dilemma on how to use expenditure data to develop these scales (Brown and Deaton, 1972).

In Mexico, Gould et al. (2002), Gould and Villarreal (2002) and Sabates, Gould, and Villarreal (2001) have analyzed adult equivalence scales. Gould and Villarreal (2002) endogenously determined adult equivalence scales and allowed marginal impact to vary by age and gender. They accounted for censored meat expenditures for Mexican beef and pork purchases in 1996, and endogenously determined specific unit values and therefore product quality.

Gould and Villarreal (2002) reported estimates for income and adult equivalent elasticities, and marginal regional impacts. They showed that household composition is an important determinant of total household expenditures as well as product quality. They rejected the null hypothesis that the marginal impact of an additional household member on meat expenditures is invariant to the member's age or gender. They found a small but positive impact of the number of adult equivalents in the household on expenditures for beef and pork. They also discovered a negative impact of the number of adult equivalents in the household on endogenous unit values.

However, their study could not reject the null hypothesis that the female and male adult equivalent profiles are the same. Even more surprising, they realized that female adult equivalence scale consistently exceeds the male adult equivalence scale in consumption of beef for females of 40-65 years old. They attributed this result to the high participation of males in the labor force compared to adult females. Adult males working more time outside their home tend to purchase and consume more food away from home than adult females who stay at home. This result is similar to Sabates, Gould, and Villarreal (2001) who found that adult female equivalence scales in Argentina and Brazil were either no different or lower than adult male equivalence scales over the age of 40 years. Since the data they used in the analysis did not allow them to identify who purchased and consumed food away from home, Gould and Villarreal (2002) further examined this result by regressing the percentage of total food expenditures originating from food-away-from home purchases on household income, household size, percentage of adult males working full and part time, and percentage of adult females working full and part time. They obtained insignificant male adult impacts and significant female adult impacts.

Similarly, Sabates, Gould, and Villarreal (2001) analyzed the impacts of household member counts versus endogenously determined equivalence scales at the per capita aggregated food expenditure level. They estimated country specific expenditure functions to obtain parameter estimates and perform several non-nested hypothesis tests. For instance, hypothesis tests were elaborated to know whether male and female adult equivalent profiles are the same; or whether the use of a simple count of household members provides as much information as the use of adult equivalence scales in explaining food purchase behavior; or whether adult equivalence scales are the same across Argentina, Brazil and Mexico for the time periods of 1996-1997, 1995-1996, and 1996 respectively. In addition, they created interaction variables with income to calculate and report income and adult equivalent elasticities. Finally, Sabates, Gould, and Villarreal (2001) also compared the distribution of weekly per capita food expenditures based on the simple count of household members with the distribution of weekly per capita food expenditures based on the number of adult equivalence scales.

Sabates, Gould, and Villarreal (2001) found that adult male equivalent profiles are statistically different from adult female profiles. Male household members in general placed greater demands on household food supplies than female members. In particular, for both Argentina and Brazil the female adult equivalent value was below the male value; however, for Mexico, the male profile was greater than the female profile for up to age 35. After this age, the male and female profiles followed a similar pattern. The male profile in Mexico increased in adult equivalence scale values up to the mid-50s and then declined. They found the oldest male age category in Mexico has an adult equivalence scale value of 1.15 but it was not statistically different from 1. The female profiles for Argentina and Brazil were consistently less than 1. Similar to the male profile for Mexico, the male profile for Argentina and Brazil increased in adult equivalence scale values until the mid-50s and then declined.

Sabates, Gould, and Villarreal (2001) also found that a simple count of household members does not provide the same information as the use of equivalence scales in explaining food purchase behavior. Age and gender information has a statistical significant effect in food expenditures. Furthermore, Sabates, Gould, and Villarreal (2001) graphically showed and statistically proved that the distribution of weekly per capita food expenditures based on the simple count of household members is consistently above and statistically different than the distribution of weekly per capita food expenditures based on the number of adult equivalence scales. Therefore, using the former variable as a measure of poverty will result in a significant increase in the number of households below a defined poverty line.

In the United States, Tedford, Capps, and Havlicek (1986) developed a model to calculate adult equivalence scales, which they named after their last names as the TCH model. In their model, the life cycle was comprised of a sequence of developmental and transitional phases. Tedford, Capps, and Havlicek (1986) also compared adult scale parameter estimates for total food expenditure from their model with estimates from Blokland's (1976) and Buse-Salathe's (1978) models. In addition, they reported estimates of the income elasticity and household equivalence scale elasticity for food for the period 1977-1978. They considered geographical regions and whether household were located in central city or non-metropolitan area. Households that did not report relevant income or socio-demographic information were excluded from the analysis. In addition, Tedford, Capps, and Havlicek (1986) claimed that sample selection bias was not going to be a problem because the frequencies for the usable sample are quite similar to the frequencies for the overall sample.

Tedford, Capps, and Havlicek (1986) also presented different ways in which the life cycle can be delineated by ages or important events. They presented the view of Levinson et al. (1978) of the life cycle as a sequence of developmental and transitional periods and as a sequence of eras. They also presented the view of Duvall (1977) of the life cycle as a sequence of important events, and the National Research Council's recommendations of the different food energy allowances for males and/or females during the life cycle.

Based on the statistical significance of some key parameter estimates and the statistical significance from each other, Tedford, Capps, and Havlicek (1986) found that the Buse-Salathe's (1978) life-cycle-age-class specification was inconsistent with Blokland's (1976) specification. However, in the analysis of Tedford, Capps, and Havlicek (1986), despite differences in the age-class delineations and despite the fact that TCH model constitutes a more general specification than Buse-Salathe's (1978) model, the empirical findings of the scale parameters based on the TCH model were similar to those based on Buse-Salathe's (1978) model. Additionally, Buse-Salathe's (1978) model was also a more general specification than Blokland's (1976) model. Hence, the most general specification is found in the TCH model while the simplest specification is found in Blokland's (1976) model.

Tedford, Capps, and Havlicek (1986) also found that food expenditure behavior for males and females is generally different at various developmental and transitional stages of the life cycle. The TCH model even indicated that food expenditure behavior is different from males and females within the same developmental and transitional stages of the life cycle. They also found differences in household food expenditures by regions, seasons, and population density (city or non-metropolitan location).

Based on the life cycle pattern of the three models, Tedford, Capps, and Havlicek (1986) concluded that the adult equivalence scale specification by Blokland (1976) may be too restrictive. Second, the TCH and the Buse-Salathe's (1978) equivalence scales during the life cycle profile were reasonably similar, although noticeably differences resulted in the equivalence scales for females as well as for household members greater than sixty years of age.

In summary, Gould and Villarreal (2002), Sabates, Gould, and Villarreal (2001), Tedford, Capps, and Havlicek (1986) presented models where adult equivalence scales are determined endogenously within the model. All these models require the specification of an expenditure function which incorporates adult equivalence scales. Specifically, Gould and Villarreal (2002), and Sabates, Gould, and Villarreal (2001) used the Levinson's et al. (1978) sequence of transitional and developmental periods of the life cycle. Hence, adult equivalence scales were estimated by linking concepts from psychology, child development, and human development to economic concepts. Tedford, Capps, and Havlicek (1986) repeatedly remarked the explicit rationale and consistency of their TCH model with the life-cycle developmental concepts. However, although perhaps lacking some of this rationale and consistency, Tedford, Capps, and Havlicek (1986) also presented alternative models such as the Blokland's (1976) and Buse-Salathe's (1978) models and the National Research Council's recommendations on food energy allowances for males and/or females.

Despite the model used, it is always recommended to adjust for household size when working with household food expenditures. One way of adjusting for household size is by endogenously determining adult equivalence scales within the model and incorporating these scales in household food expenditures. However, a simpler way to adjust is by using exogenous measures of adult equivalence scales to compute per adult-equivalent food expenditures. It is also necessary that these scales are different for males and females because it has been statistically shown that male and female household members place different demands on household food supplies for at least certain age ranges (Gould and Villarreal, 2002; Sabates, Gould, and Villarreal, 2001; Tedford, Capps, and Havlicek, 1986). However, in the case of Mexico, Gould and Villarreal (2002) could not reject the null hypothesis that the female and male adult equivalent profiles are the same. Similarly, Sabates, Gould, and Villarreal (2001) found that adult female equivalence scales in Mexico are either no different or lower than adult equivalent scales over the age of 35 years. In addition, it is not advised to use the adult equivalence scale estimates from another country in Mexico nor the estimates of similar commodities because these scales change across countries (Sabates, Gould, and Villarreal, 2001) and across commodities (Gould and Villarreal, 2002).

Finally, it is observed that in general these adult equivalence scales tend to be smaller for female household members than male household members (Sabates, Gould, and Villarreal, 2001; Tedford, Capps, and Havlicek, 1986), but it might not always be the case specially when there is high participation of males in the labor force compared to adult females (Gould and Villarreal, 2002). In addition, these scales tend to be smaller than one for members younger or older than the standard adults (Gould and Villarreal, 2002; Sabates, Gould, and Villarreal, 2001; Tedford, Capps, and Havlicek, 1986).

2.5 Missing Data

The term missing data is generally used instead of nonresponse. When the nonresponse rate is not negligible, inference based upon only the respondents may be seriously flawed. Lohr (1999, p. 255) explains two types of nonresponse: unit nonresponse and item nonresponse. *Unit nonresponse* occurs when the entire observation unit is missing. For instance, the person provides no information for the survey. *Item nonresponse* occurs when some measurements are present for the observation unit but at least one item is missing. For instance, the person does not respond to a particular item in the questionnaire.

Lohr (1999, pp. 264–265) explains three different ways how the type of nonresponse (unit or item nonresponse) could be missing. Lohr (1999, p. 264) uses Little and Rubin's (1987) terminology of nonresponse classification.

> **Missing Completely at Random** If [the probability that a unit i is selected for the sample and it will respond] does not depend on [the vector of known information

about the unit i in the sample], [the response of interest], or the survey design, the missing data are missing completely at random (MCAR). Such a situation occurs if, for example, someone at the laboratory drops a test tube containing the blood sample of one of the survey participants—there is no reason to think that the dropping of the test tube had anything to do with the white blood cell count. If data are MCAR, the respondents are representative of the selected sample.

Missing at Random Given Covariates, or Ignorable Nonresponse If [the probability that a unit i is selected for the sample and it will respond] depends on [the vector of known information about the unit i in the sample] but not on [the response of interest], the data are missing at random (MAR); the nonresponse depends only on observed variables. We can successfully model the nonresponse, since we know the values of [the vector of known information about the unit i in the sample] for all sample units. Persons in the [National Crime Victimization Survey (NCVS)] would be missing at random if the probability of responding to the survey depends on race, sex, and age-all known quantities-but does not vary with victimization experience within each age/race/sex class. This is sometimes termed *ignorable nonresponse*: Ignorable means that a model can explain the nonresponse mechanism and that the nonresponse can be ignored after the model accounts for it, not that the nonresponse can be completely ignored and complete-data methods used.

Nonignorable Nonresponse If the probability of nonresponse depends on the value of a response variable and cannot be completely explained by values of the [vectors of known information about the unit i in the sample], then the nonresponse is *nonignorable*. This is likely the situation for the NCVS: It is suspected that a person who has been victimized by crime is less likely to respond to the survey than a nonvictim, even if they share the values of all known variables such as race, age, and sex. Crime victims may be more likely to move after a victimization and thus not be included in subsequent NCVS interviews. Models can help in this situation, because the nonresponse probability may also depend on known variables but cannot completely adjust for the nonresponse.

Lohr (1999, pp. 255–288) discusses four approaches to deal with nonresponse:

1. Ignoring the nonresponse (not recommended).

2. Preventing the nonresponse by designing a survey so that the nonresponse is low (highly recommended).

3. Taking a representative subsample of the nonrespondents and use it to make inferences about the other nonrespondents.

4. Using models to predict values for the nonrespondents. Among these models Lohr (1999, pp. 265–288) discusses weighting methods, imputation methods, and parametric models for nonresponse.

The main problem caused by the nonresponse is potential bias of population estimates. The bias results from estimating the population mean by using only the sample respondent mean, and the population mean in the nonrespondent group differs from the population mean in the respondent group. Lohr (1999, p. 258) shows that the bias is small if either (1) the mean of the population nonrespondents is close to the mean for the population respondents or (2) the proportion of the population nonrespondents to the entire population is small (i.e., there is little nonresponse). Since it not possible to know (1), the only alternative is to reduce the nonresponse rate.

Designing the survey such that the nonresponse is low refers to carefully studying the best way to collect the data. This includes being able to anticipate and prevent reasons for nonresponse as much as possible. Lohr (1999, pp. 260–262) provides and discusses a list of factors that need to be examined: survey content, time of survey, interviewers, data-collection method, questionnaire design, respondent burden, survey introduction, incentives and disincentives, and follow up.

Lohr (1999, p. 263) explains Hansen and Hurwitz's (1946) procedure to *subsample nonrespondents* and to use two-phase sampling (also called double sampling) for stratifying and then estimating the population mean or total. In this procedure, an estimate of the population mean is obtained from a portion of the sample average of the original respondents and a portion of the average of the subsampled nonrespondents. These portions are the percentages of the sample that responded and not responded respectively. Similarly, an estimate of the population total can be obtained from a portion of the sample units in the respondent stratum and a portion of the sampled units in the nonrespondent stratum.

Weighting methods for nonresponse refer to incorporating weights in calculating population estimates of interest or to the use of weights to adjust for the nonresponse. Some weighting methods are weighting-class adjustment methods, postratification using weights, and weights that are the reciprocal of the estimated probability of response. Lohr (1999, pp. 265–272) provides a discussion and additional references for these weighting methods. Lohr (1999, p. 272) also explains weighting adjustments are usually used for unit nonresponse, not for item nonresponse (which would require a different weight for each item).

Imputation methods refer to alternative ways in which a nonresponse is replaced. The word imputation refers to substituting a missing value for a replacement value. Imputation methods are commonly used for item nonresponse. Lohr (1999, pp. 272–278) explains deductive imputation, cell mean imputation, hot-deck imputation, regression imputation, cold-deck imputation, and multiple imputation. In particular, regression imputation uses a regression of the item of interest on variables observed for all cases to predict the missing value. However, Lohr (1999, p. 278) explains that "[v]ariances computed using the data together with the imputed values are always too small, partly because of the artificial increase in the sample size and partly because the imputed values are treated as though they were really obtained in the data collection." Lohr (1999, p. 278) refers to Rao (1996) and Fay (1996) for a discussion on methods for estimating the variances after imputation.

Finally, *parametric models for nonresponse* refer to models that estimate within the model the nonresponse by using information on both known values of the variable of interest and missing values of the variable of interest (i.e., the nonresponse). That is, a model for the complete data is developed and components are added to the model to account for the proposed nonresponse mechanism. Depending on how good the model describes the data, the estimates of the variances that result from fitting the model may be better or worse. Examples can be found in Wooldridge (2006, pp. 609–613) and Pindyck and Rubinfeld (1997, pp. 325–331) who explain a censoring model and a maximum likelihood model respectively to address item non-response on the dependent variable.

2.6 Stratified and Complex Samples

2.6.1 Stratified Sampling

Lohr (1999, pp. 23–24) explains three basic types of probability samples.

- A *simple random sample* (SRS) is the simplest form of probability sample. An SRS of size n is taken when every possible subset of n units in the population has the same chance of being the sample... In taking a random sample, the investigator is in effect mixing up the population before grabbing n units. The investigator does not need to examine every member of the population for the same reason that a medical technician does not need to drain you of blood to measure your red blood cell count. Your blood is sufficiently well mixed that any sample should be representative.
- In a *stratified random sample*, the population is divided into subgroups called strata. Then an SRS is selected from each stratum, and the SRSs in the strata are selected independently. The strata are often subgroups of interest to the investigator—for example, the strata might be different ethnic or age groups in a survey of people, different types of terrain in an ecological survey, or sizes of firms in a business survey. Element in the same stratum often tend to be more similar than randomly selected elements from the whole population, so stratification often increases precision.
- In a *cluster sample*, observation units in the population are aggregated into larger sampling units, called clusters. Suppose you want to survey Lutheran church members in Minneapolis but do not have a list of all church members in the city, so you cannot take an SRS of church members. However, you do have a list of all the Lutheran churches. You can then take an SRS of the churches and then subsample all or some church members in the selected churches. In this case, the churches form the clusters, and the church members are the observation units.

All these three methods involve random selection of units to be in the sample. The key difference among them is in the level at which the random selection of units takes place. For instance, in an SRS, the observation units are randomly sampled from the population of observation units; in a stratified random sample, the strata are first selected and then the observation units within each stratum are randomly sampled; in a cluster sample, the clusters are first randomly selected from the population of all clusters and then all or some of the observation units are sampled. To illustrate this further, Lohr (1999, p. 24) provides a very useful example. Suppose you want to estimate the number of journal publications that professors at your university have. In an SRS, construct a list of all professors in your sample and randomly select n of them and ask them for the number of journal publications. In a stratified sample, classify faculty by college (agricultural sciences and natural resources, architecture, arts and sciences, business, education, engineering, human sciences, mass communications, etc.) and then take an SRS of faculty in the agricultural sciences and natural resources, another SRS of faculty in architecture, and so on. Finally, in a cluster sample, randomly select 10 of the 50 academic departments in the university and ask each professor in each selected department for his/her number of journal publications. Cameron and Trivedi (2005, p. 816) explain that the prefix "simple" in "random sample" is added because more systematic sampling methods still usually have a random element.

Lohr (1999, p. 95) further explains stratified random sampling. In stratified random sampling the strata do not overlap, and they constitute the whole population so that each sampling unit belongs to exactly one stratum. Lohr (1999, pp. 95–96) provides the following reasons to use stratified sampling:

1. To be protected from the possibility of obtaining a really bad sample that is not representative of the population.

2. To obtain data of known precision for subgroups. These subgroups should be the strata, which coincide with the domain of the study.

3. To reduce cost and increase ease of administration.

4. To obtain more precise (having lower variance) estimates for the whole popula-

tion.

The sampling weight in stratified sampling is given by $w_{hj} = (N_h/n_h)$ (Lohr, 1999, p. 103), where $N = N_1 + N_2 + \ldots + N_H$ is the total number of units in the entire population, H is the number of "layers" (also called strata), N_h is the population units in the h^{th} stratum, and n_h is number of observations randomly sampled from the population units in stratum h. The sampling weight w_{hj} can be thought of as the number of units in the population represented by the sample unit j in stratum h or simply the sample member (h, j).[8] Additionally, Lohr (1999, p. 103) explains the probability of selecting the j^{th} unit in the h^{th} stratum to be in the sample is $\pi_{hj} = n_h/N_h$, which is also the sampling fraction in the h^{th} stratum. Hence, the sampling weight is the reciprocal of the probability of selection. That is, $w_{hj} = 1/\pi_{hj}$. Then, the sum of the sampling weights equals the population size. That is, $N = \sum_{h=1}^{H} \sum_{j \in \mathcal{S}_h} w_{hj}$, where $\mathcal{S}_h$ is the set of n_h units in the SRS for stratum h. "[If] each sampled unit 'represents' a certain number of units in the population,... the whole sample 'represents' the whole population" (Lohr, 1999, p. 103).[9]

It is very important that a statistician does not ignore the weights in a stratified sampling. A statistician who designs a survey to be analyzed using weights has implicitly visualized a model for the data. A sample is usually stratified and subpopulations oversampled precisely because researchers believe there will be differences among the subpopulations. Such differences also need to be included in the model. "A data analyst who ignores stratification variables and dependence among observations is not fitting a good model to the data but is simply being lazy" (Lohr, 1999, p. 229).

Lohr (1999, p. 229) recommends incorporating weights in calculating quantities such as means, medians, quantiles, totals, and ratios. One way to estimate these

[8] As it will be discussed in Section 4.1, ENIGH calls the sampling weight the "expansion factor" (i.e., the number of households that a particular household represents nationally).

[9] As it will be mentioned in Section 4.2, according to ENIGH—Síntesis Metodológica (2006), the results obtained from ENIGH survey can be generalized to the entire Mexican population.

quantities is by incorporating the stratification variables (Lohr, 1999, pp. 95–130). Another way to estimate these quantities (but not their standard errors) is by constructing an empirical distribution for the population from the sampling weights. In a simple example where sampling weights were incorporated into an empirical mass function, (Lohr, 1999, p. 234) showed that "[t]he statistics calculated using weights are much closer to the population quantities".

Wooldridge (2002, p. 551) explains that there are a variety of selection mechanisms that result in *nonrandom samples* (also called *selected samples*). Some of these are due to sample design, while others are due to the behavior of the units being sampled, including nonresponse on survey questions and attrition from social programs (i.e., in panel data where people leave the sample entirely and usually do not reappear in later years).

Wooldridge (2002, p. 590) explains *stratified samples* are a form of nonrandom samples. In stratified samples different subsets of the population are sampled with different frequencies. Two common kinds of stratification are discussed by Wooldridge (2002, pp. 590–591): standard stratified sampling (SS sampling) and variable probability sampling (VP sampling).

> In *SS sampling*, the population is first partitioned into J groups, $\mathcal{W}_1$, $\mathcal{W}_2$, ... , $\mathcal{W}_J$, which are assumed to be nonoverlapping and exhaustive. We let $\mathbf{w}$ denote the random variable representing the population of interest... For $j = 1, \ldots, J$, draw a random sample of size N_j from stratum j. For each j, denote this random sample by $\{\mathbf{w}_{ij}$: $i = 1, 2, \ldots, N_j\}$. The strata samples sizes N_j are nonrandom. Therefore, the total sample size, $N = N_1 + \ldots + N_J$, is also nonrandom. A randomly drawn observation from stratum j, $\mathbf{w}_{ij}$, has distribution $\mathrm{D}(\mathbf{w}|\mathbf{w} \in \mathcal{W}_j)$. Hence, the observations within a stratum are identically distributed but observations across strata are not.

Notice that Wooldridge's (2002) definition of SS sampling is the same as Lohr (1999) definition of stratified random sampling. Now, consider Wooldridge's (2002, p. 591) explanation of variable probability sampling (VP sampling).

> [In *VP sampling*,] an observation is drawn at random from the population. If the observation falls into stratum j, it is kept with probability p_j. Therefore, random draws

Table 2.1: Variable Probability Sampling (VP Sampling).

Repeat the following steps N times
1. Draw an observation $\mathbf{w}_i$ at random from the population.
2. If $\mathbf{w}_i$ is in stratum j, toss (a biased) coin with probability p_j of turning up heads. Let $h_{ij} = 1$ if the coin turns up heads and zero otherwise.
3. Keep observation i if $h_{ij} = 1$; otherwise, omit it from the sample.

Source: Wooldridge (2002, p. 591).

> from the population are discarded with varying frequencies depending on which stratum they fall into. This kind of sampling is appropriate when information on the variable or variables that determine the strata is relatively easy to obtain compared with the rest of the information. Survey data sets, including interviews to collect panel or longitudinal data, are good examples. Suppose we want to oversample individuals from, say, lower income classes. We can first ask an individual her or his income. If the response is in income class j, this person is kept in the sample with probability p_j, and then the remaining information, such as education, work history, family background, and so on can be collected; otherwise, the person is dropped without further interviewing.

It is important to notice that in VP sampling the observations within a stratum are discarded randomly. Wooldridge (1999) discusses why VP sampling is equivalent to the procedure in Table 2.1.

2.6.2 Complex Surveys

Usually large surveys involve the use of the three different types of probability samples (SRS, stratified random sampling, and cluster sampling) at different stages of the survey. For example, survey that are stratified with several stages of clustering are referred to as *complex surveys* (Lohr, 1999, p. 221). Equivalently, Cameron and Trivedi (2005, p. 41) refer to *stratified multistage cluster samples* as *complex surveys*. Cameron and Trivedi (2005, p. 41) discuss the following advantage and disadvantage of complex surveys:

- **Advantage**: It is cost effective because it reduces geographical dispersion; therefore, it is possible to oversample certain subpopulations. On the contrary, a random sample may produce too few observation of certain subpopulations.

- **Disadvantage**: Stratified sampling will reduce interindividual variation, which allows greater precision.

Cameron and Trivedi (2005, p.41) also explain that *multistage surveys* sequentially partition the population into the following categories:

1. **Strata**: Nonoverlapping subpopulations that exhaust the population.
2. **Primary sampling units** (PSUs): Nonoverlapping subsets of the strata.
3. **Secondary sampling units** (SSUs): Sub-units of the PSU, which may in turn be partitioned and so on.
4. **Ultimate sampling unit** (USU): The final unit chosen for interview, which could be a household or a collection of households (a segment).

Notice that when clusters are used in any or all of the SSUs or USUs, the multistage survey will be a complex survey. As an example of a multistage survey, "the strata may be the various states or provinces in a country, the PSU may be regions within the state or province, and the USU may be a small cluster of households in the same neighborhood" (Cameron and Trivedi, 2005, p. 41). In addition, Cameron and Trivedi (2005, p. 41) also explain *two-stage-sampling*. In the first stage, the surveyed PSUs are drawn at random. In the second stage, the USU is drawn at random from the selected PSUs. If more stages were added, additional intermediate sampling units such as SSUs will appear. Cameron and Trivedi (2005, p. 41) explain:

> A consequence of these sampling methods is that different households will have different probabilities of being samples. The sample is then unrepresentative of the population. Many surveys provide sampling weights that are intended to be inversely proportional to the probability of being sample, in which case these weights can be used to obtain unbiased estimators of population characteristics.

The purpose in complex surveys is to provide a population summary when population parameters may vary across strata (Cameron and Trivedi, 2005, p. 853). "[A] weighted estimator is used and is viewed as an estimate of the census parameter"

(Cameron and Trivedi, 2005, p. 853). Consequently, demand parameters and elasticities in this study can be interpreted as population estimates.

2.6.3 Survey Weights and Regression in Stratified or Complex Samples

Whether sampling weights should be used in regression have been widely debated (Brewer and Mellor, 1973; DuMouchel and Duncan, 1983; Fuller, 1984; Pfeffermann and Homes, 1985; Devaney and Fraker, 1989; Kott, 1991; Lohr and Liu, 1994; Wooldridge, 2002, pp. 590–598; Cameron and Trivedi, 2005, pp. 811–859). Cameron and Trivedi (2005, p. 813 and p. 819) explain the consequences of stratified and cluster samples for regression modeling:

- First, weighted estimators that adjust for differences in sampling rates may be necessary if the goal of analysis is prediction of population behavior.
- Second, such weighting is unnecessary if interest lies in regression of y on $\mathbf{x}$, provided the conditional model for y given $\mathbf{x}$ is correctly specified and *stratification* is not on the dependent variable. [However, in many applications the conditional model for y give $\mathbf{x}$ is incorrectly specified.] Examples include cases with omitted regressors or situations when $E[y|\mathbf{x}]$ is nonlinear in $\mathbf{x}$ or $E[y_i|\mathbf{x}_i] = \mathbf{x}_i'\boldsymbol{\beta}_i$ where some components of $\boldsymbol{\beta}_i$ are correlated with $\mathbf{x}$.
- Third, if samples are determined in part by the value of the dependent variable, such as an oversample of low-income people when income is the dependent variable, weighted estimation is necessary.
- Fourth, clustering at minimum leads to standard error estimates that appreciably understate the true standard errors and can even lead to inconsistent parameter estimates unless adjustment is made for clustering using methods similar to those... for panel data analysis.

It is important to recognize that the rationale for weighting in complex surveys is different from that of weighted least squares (WLS). Lohr (1999, pp. 360–361) explains the use of WLS will provide the same parameter estimate, but the weights in complex surveys come from sampling design, not from an assumed covariance structure. Consequently, the estimated variance of the coefficients in not the WLS variance, but a different one (Lohr, 1999, p. 361). Lohr (1999, p. 355) explains "[i]f you use weights w_i in weighted least squares estimation, you will obtain the same point estimates...; however, in complex surveys, the standard errors and hypothesis tests the software provides will be incorrect and should be ignored." Kott (1990) explains the standard errors are incorrect because the rationale for weighted regression analysis is different from that in generalized least squares (GLS) theory. "As a result, GLS-based estimated standard errors—like those derived using SAS and most conventional regression programs—are meaningless in this context" (Kott, 1990). Consequently, Devaney and Fraker (1990, p. 732) "encourage all researchers to note carefully Kott's warning regarding the limitations of standard regression packages when applied to sample survey data."

2.6.4 Standard Errors of Parameter Estimates from Regressions in Stratified or Complex Samples

Lohr (1999, pp. 347–378) explains that even though there is debate whether the sample sampling weights are relevant for inference in regression (Lohr, 1999, p. 363), the data structure needs to be taken into account in either approach. She explains two things can happen in complex surveys (Lohr, 1999, pp. 352–253):

1. Observations may have different probabilities of selection, π_i. If the probability of selection is related to the response variable y_i, then an analysis that does not account for the different probabilities of selection may lead to biases in the estimated regression parameters.
2. Even if the estimators of the regression parameters are approximately design unbiased, the standard errors given by SAS or SPSS will likely be wrong if the survey design involves clustering. Usually, with clustering, the design effect (deff) for regression coefficients will be greater than 1.

2.6.4.1 Stratification Based on Exogenous Variables

Cameron and Trivedi (2005, p. 820) explain:

- If one takes a structural or analytical approach and assumes that the model of

$E[y|\mathbf{x}]$ is correctly specified, there is no need to use sample weights. Results can be used to analyze effects of changes in $\mathbf{x}$ on $E[y|\mathbf{x}]$.

- If one instead takes a descriptive or data summary approach then weights should be used. Regression is then interpreted as estimating census coefficients.

If the first approach is adopted and the model of $E[y|\mathbf{x}]$ is correctly specified, Wooldridge (2002, p. 596) explains the standard unweighted estimator on the stratified sample is consistent and asymptotically normal. In addition, Wooldridge (1999) shows that the usual asymptotic variance estimators are valid when stratification is based on $\mathbf{x}$ and the stratification problem is ignored. In this case the usual conditional maximum likelihood analysis holds, and in the case of regression the usual heteroskedasticity robust variance matrix estimator can be used (Wooldridge, 1999, p. 597). In addition, "[w]hen a generalized conditional information matrix equality holds, and stratification is based on $\mathbf{x}$, Wooldridge (1999) shows that the unweighted estimator is more efficient than the weighted estimator" (Wooldridge, 2002, p. 597). Nonetheless, Cameron and Trivedi (2005, p. 821) caution, "[e]ven if the parameters are consistently estimated using unweighted estimation, weighting must be used in subsequent impact calculations if one wishes to predict population impacts, rather than sample impacts."

However, Wooldridge (2002, p. 594) and Wooldridge (2001, pp. 464–465) provide formulas for calculating the asymptotic variance matrix of weighted least squares estimator under standard stratified sampling (SS sampling) and variable probability sampling (VP sampling). These formulas are useful when the generalized conditional information matrix equality does not hold or when the model of $E[y|\mathbf{x}]$ is not correctly specified. The formulas are explained below.

In VP sampling, Wooldridge (2002, p. 594) shows that in estimating the following linear model by weighted least squares (WLS),

$$(2.1)\quad y = \mathbf{x}\boldsymbol{\beta}_0 + u, \quad E(\mathbf{x}'u) = \mathbf{0},$$

where $\mathbf{x}$ is a $(1 \times K)$ vector of explanatory variables, y is a scalar response variable, and u is a scalar disturbance variable; the asymptotic variance estimator is

$$\left(\sum_{i=1}^{N_0} p_{j_i}^{-1}\mathbf{x}_i'\mathbf{x}_i\right)^{-1}\left(\sum_{i=1}^{N_0} p_{j_i}^{-2}\hat{u}_i^2\mathbf{x}_i'\mathbf{x}_i\right)\left(\sum_{i=1}^{N_0} p_{j_i}^{-1}\mathbf{x}_i'\mathbf{x}_i\right)^{-1}, \tag{2.2}$$

where $\hat{u}_i = y_i - \mathbf{x}_i\hat{\boldsymbol{\beta}}_w$ is the residual after WLS estimation, $p_{j_i}^{-1}$ the weight attached to observation i in the estimation, j_i the stratum for observation i, the number of observations falling into stratum j is denoted by N_j, the number of data points that are actually available for estimation is $N_0 = N_1 + N_2 + \ldots + N_J$, and N is the number of times the population is sampled. Wooldridge (2002, p. 592) explains that if N is fixed, then N_0 is a random variable. It is not known what each N_j would be prior to sampling. Wooldridge (2002, p. 593) explains that in practice, the $p_{j_i}^{-1}$ are the sampling weights reported with other variables in stratified samples. Additionally, Wooldridge (2002, p. 594) explains that this asymptotic variance matrix estimator is simply White's (1980) heteroskedastic-consistent covariance matrix estimator applied to the stratified sample, where all variables for observation i are weighted by $p_{j_i}^{-1/2}$ before performing the regression. This estimator has also been suggested by Hausman and Wise (1981). Additionally, Wooldridge (2002, p. 594) remarks that it is important to remember that the asymptotic variance matrix estimator above is not due to potential heteroskedasticity in the underlying population model. Even if $E(u^2|\mathbf{x}) = \sigma_0^2$, the estimator in Equation (2.1) is generally needed because of the stratified sampling. Wooldridge (2002, p. 594) explains this estimator works in the presence of heteroskedasticity of arbitrary and unknown form in the population, and it is routinely computed by many regression packages.

The weights in SS sampling are different from those in the VP sampling. In SS sampling the weights are (Q_{j_i}/H_{j_i}) rather than $p_{j_i}^{-1}$, where j_i denotes the stratum for observation i, $Q_j = \mathrm{P}(w \in \mathcal{W}_j)$ denotes the population frequency for stratum j (it is assumed that Q_j are known), and $H_j = N_j/N$ denotes the fraction of observations in stratum j. Additionally, the formula for the asymptotic variance is different.

In SS sampling, Wooldridge (2001, pp. 464–465) shows that in estimating the linear model in Equation (2.1) above, the weighted estimator is consistent for $\boldsymbol{\beta}_0$.

Additionally, if the stratification is exogenous and $\mathrm{E}(u|\mathbf{x}) = 0$, the asymptotic variance matrix estimator of $\hat{\boldsymbol{\beta}}_w$ can be written as

$$\left(\sum_{i=1}^{N}(Q_{j_i}/H_{j_i})\mathbf{x}_i'\mathbf{x}_i\right)^{-1}\left(\sum_{i=1}^{N}(Q_{j_i}/H_{j_i})^2\hat{u}_i^2\mathbf{x}_i'\mathbf{x}_i\right)\left(\sum_{i=1}^{N}(Q_{j_i}/H_{j_i})\mathbf{x}_i'\mathbf{x}_i\right)^{-1}, \tag{2.3}$$

which is again simply White's (1980) heteroskedasticity-consistent covariance matrix estimator applied to the stratified sample, where all variables for observation j are weighted by $(Q_{j_i}/H_{j_i})^{-1/2}$ before performing the regression.

Wooldridge (2002, pp. 595–596) comments that if the population frequencies Q_j are known in VP sampling, he recommends using as weights $Q_j/(N_j/N_0)$ rather than p_j^{-1}. His recommendation is based on his findings in Wooldridge (1999). Additionally, Wooldridge (2002, p. 596) explains that when the sampling weights Q_{j_i}/H_{j_i} or $p_{j_i}^{-1}$ and the stratum are given, the weighted M-estimator under SS or VP sampling is fairly straightforward, but it is not likely to be efficient. It is possible to do better with conditional maximum likelihood (Imbens and Lancaster, 1996).

Nonetheless, whether the model of $E[y|\mathbf{x}]$ can be correctly specified is a judgment call. If the weighted and unweighted estimates have the same probability limit, then it is correctly specified. Cameron and Trivedi (2005, p. 821) explain the test of the difference between the weighted least squares estimator, $\hat{\boldsymbol{\beta}}_W$, and the simple linear homoscedatic estimator (i.e., the usual least squares estimator), $\hat{\boldsymbol{\beta}}$, proposed by DuMouchel and Duncan (1983) will test for correct model specification in the case of linear regression. One caveat is that "the null hypothesis of this test assumes that the element errors are iid" (Kott, 1991, p. 110). However, the test is very popular (see Cameron and Trivedi, 2005, p. 821; Kott, 1991, p. 110) and frequently used (see Devaney and Fraker, 1990; 1989).

DuMouchel and Duncan (1983, p. 538) recommend the data passes this test before one accepts the simple linear homoscedastic model and uses the estimator $\hat{\boldsymbol{\beta}}$ over $\hat{\boldsymbol{\beta}}_W$. The hypotheses tested are

$$\begin{aligned} &H_0 : \boldsymbol{\Delta} = E(\hat{\boldsymbol{\Delta}}) = E(\hat{\boldsymbol{\beta}}_W - \hat{\boldsymbol{\beta}}) = 0, \\ &H_a : \mathbf{Y} = \mathbf{X}\boldsymbol{\alpha} + \mathbf{Z}\boldsymbol{\gamma} + \boldsymbol{\epsilon}, \end{aligned} \tag{2.4}$$

where $\hat{\boldsymbol{\beta}} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{Y}$, $\hat{\boldsymbol{\beta}}_W = (\mathbf{X}'\mathbf{W}\mathbf{X})^{-1}\mathbf{X}'\mathbf{W}\mathbf{Y}$, $\mathbf{W}$ is a $(n \times n)$ diagonal matrix whose i^{th} diagonal element is the sample weight w_i, $\mathbf{Y}$ is a $(n \times 1)$ vector of observations in the dependent variable, $\mathbf{X}$ is a $(n \times p)$ matrix of observations in the independent variables, the columns of $\mathbf{Z}$ are further (perhaps unobserved) predictors that should have been included in the regression but were not, $\boldsymbol{\epsilon}$ is a random error with $E(\boldsymbol{\epsilon}) = 0$ and $\text{var}(\boldsymbol{\epsilon}) = \sigma^2 \mathbf{I}_n$, and $\boldsymbol{\alpha}$ and $\boldsymbol{\gamma}$ are vector of parameters. Equivalently, the hypotheses above can be written as

$$\begin{aligned} &H_0 : \mathbf{Y} = \mathbf{X}\boldsymbol{\alpha} + \boldsymbol{\epsilon}, \\ &H_a : \mathbf{Y} = \mathbf{X}\boldsymbol{\alpha} + \mathbf{Z}\boldsymbol{\gamma} + \boldsymbol{\epsilon}, \end{aligned} \tag{2.5}$$

or

$$\begin{aligned} &H_0 : \text{Simple linear homoscedastic model}, \\ &H_a : \text{Omitted predictor model}. \end{aligned} \tag{2.6}$$

"If [the simple linear] model is rejected, we conclude that $\hat{\boldsymbol{\beta}}$ and $\hat{\boldsymbol{\beta}}_W$ have different expectations" (DuMouchel and Duncan, 1983, p. 539). Therefore, $E[y|\mathbf{x}]$ is incorrectly specified. "The rationale for preferring unweighted to weighted regression is also rejected unless some other variables $\mathbf{Z}$ can be found that leads one to accept an extended model" (DuMouchel and Duncan, 1983, p. 539).

DuMouchel and Duncan (1983, pp. 538–539) explain two F tests for these hypotheses. The first way tests for $\boldsymbol{\Delta} = 0$, involves the use of an ANOVA table and requires several computations. The second way, which is equivalent to the first way, test for $\boldsymbol{\gamma} = 0$ in the following regression model estimated by ordinary least squares,

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\alpha} + \mathbf{W}\mathbf{X}\boldsymbol{\gamma} + \boldsymbol{\epsilon}. \tag{2.7}$$

This implies creating a new variable $\mathbf{Z} = \mathbf{W}\mathbf{X}$ and performing an F test for $\boldsymbol{\gamma} = 0$. DuMouchel and Duncan (1983, p. 539) explain two methods for performing the F test for $\boldsymbol{\gamma} = 0$. The following F test statistic follows "Method A" in DuMouchel and Duncan (1983, p. 539),

$$F_{p,(n-p)} = \frac{(\text{ESS}_R - \text{ESS}_{UR})/p}{\text{ESS}_{UR}/(n-p)}, \tag{2.8}$$

where $\text{ESS}_R = (\mathbf{Y} - \mathbf{X}\hat{\boldsymbol{\alpha}})'(\mathbf{Y} - \mathbf{X}\hat{\boldsymbol{\alpha}})$ and $\text{ESS}_{UR} = (\mathbf{Y} - \mathbf{X}\hat{\boldsymbol{\alpha}} - \mathbf{Z}\hat{\boldsymbol{\gamma}})'(\mathbf{Y} - \mathbf{X}\hat{\boldsymbol{\alpha}} - \mathbf{Z}\hat{\boldsymbol{\gamma}})$.

Therefore, reject H_0 if $F > F^*_{p,(n-p)}(\theta)$ with at most $\theta 100\%$ probability of Type I error. The quantity $F^*_{p,(n-p)}(\theta)$ is a critical value from an F distribution with p degrees of freedom in the numerator, $(n-p)$ degrees of freedom in the denominator, and θ level.[10]

Kott (1991, p. 109) explained that when the simple linear homoscedastic model is preferred over the weighted least squares estimator, the sampling design is said to be *noninformative*. Consequently, some researchers (e.g., Gardner, 2007, p. 26) refer to *informative weighting* when H_0 is rejected and *noninformative weighting* when fail to reject H_0.

2.6.4.2 Stratification Based on Endogenous Variables

Stratification based on endogenous variables occur, for example, when low-income people are purposely oversampled and income is the dependent variable (Cameron and Trivedi, 2005, p. 822). In this case, the least squares estimators are inconsistent (Cameron and Trivedi, 2005, p. 822). Other common examples of endogenous stratification include *truncated regression*, *choice-based sampling*, and *on-site sampling*. In general, the survey design in these examples will lead to a sample distribution that will differ from the population distribution. Cameron and Trivedi (2005, pp. 822–829) discuss appropriate methods for these examples.

Cameron and Trivedi (2005, pp. 829–845) also discuss methods when the assumption of independence of sampled observations is relaxed. In particular, Cameron and Trivedi (2005, pp. 829–845) present models similar to panel data analysis (cluster-specific random effects estimator and cluster-specific fix effects estimator) for controlling for dependence on unobservables within a cluster.

Wooldridge (2002, pp. 558–590) also explains how to deal with nonrandom samples on the basis of the response variable, how to do nonrandom sample corrections with a probit or tobit model under exogenous or endogenous explanatory variables, and

[10] I.e., $\theta = \Pr_{\nu_1,\nu_2}\left(F > F^*_{\nu_1,\nu_2}(\theta)\right)$.

how to deal with other nonrandom sample issues.

2.6.4.3 Use of Statistical Software

Lohr (1999, p. 355) recommends, "[i]n practice, use professional software designed for estimating regression parameters in complex surveys. If you do not have access to such software, use any statistical regression package that calculates weighted least squares estimates. If you use weights w_i in weighted least squares estimation, you will obtain the same point estimates...; however, in complex surveys, the standard errors and hypothesis tests the software provides will be incorrect and should be ignored."

Lohr (1999, p. 364) explains that statistical software such as SAS, S-PLUS, BMDP, or SPSS will not use weights when estimating standard errors and performing hypothesis tests; however, SUDAAN (Shah, Barnwell, and Bieler., 1995), PC CARP (Fuller et al., 1989), and WesVarPC (Brick, Broene, and Severynse, 1996) will. Lohr (1999, p. 364) cautions that "[b]lindly running your data through software, without understanding what the software is estimating, can lead to misinterpreted results."

Lohr (1999, p. 361) explains SUDAAN and PC CARP both use linearization to calculate the estimated variances of parameter estimates. OSIRIS (Lepkowski, 1982) and WesVarPC use replication methods to estimate variances. More information on these software packages can be found in Lohr (1999, pp. 313–315).

Other packages mentioned by Lohr (1999, p. 314) include Stata, CENVAR, CLUSTERS, Epi Info, and VPLX. In addition, Lohr (1999, p. 314) explains, Cohen (1997), Lepkowski and Bowles (1996), Carlson, Johnson, and Cohen (1993) evaluate PC-based packages for analysis of complex survey data.

Kott (1990) recommends two regression packages for complex samples: PC CARP (Fuller et al., 1986) and SURREGR (Holt, 1977). Cameron and Trivedi (2005, p. 857) recommend the package SUDAAN (2009), which as SURREGR, it is developed by the Research Triangle Institute.

2.6.4.4 Other Methods

Lohr (1999, pp. 289–318) also explains several methods for estimating variances of estimated totals and other statistics from complex surveys. She explains linearization (Taylor Series) methods, random group and resampling methods (balanced repeated replication (BRR), the Jacknife, and the Bootstrap) for calculating variances of non-linear statistics. In addition, she also explains the calculation of generalized variance functions (GVF) and how to construct confidence intervals.

Lohr (1999, p. 314) explains *linearization methods* have been widely used to find variance estimates in complex surveys. The main disavantage of linearization methods is that derivatives needs to be calculated for each statistic of interest; therefore, complicates programs for estimating variances. The *random group method* is easy to compute, but it has the disadvantage of needing several random groups in order to have a stable estimate of the variance (Lohr, 1999, p. 314). "[T]he number of random groups... is limited by the number of PSU's sampled in a stratum" (Lohr, 1999, p. 314). *Resampling methods* have the advantage of avoiding partial derivatives by computing estimates for subsamples of the sample; therefore, requiring less programming time (Lohr, 1999, p. 314). However, they have the disadvantage of requiring more computing time. "They have been shown to be equivalent to linearization for large samples when the characteristic of interest is a smooth function of population totals" (Lohr, 1999, p. 314). The *BBR* method "is usually used only for two-PSU-per-stratum designs or for designs that can be reformulated into two PSU per strata" (Lohr, 1999, p. 314). Finally, *GVF* are easy to use but has the following disadvantage: "Unless you can calculate the variance using one of the other methods, you cannot be sure that your statistic follows the model used to develop the GVF" (Lohr, 1999, p. 314). For more information on these methods refer to Lohr (1999, pp. 298–318).

2.6.5 Summary

The use of sampling weights (whether for inference or not) in regression have been widely debated. Cameron and Trivedi (2005, p. 813) summarize occasions when sample weights may be necessary. If stratification is based on exogenous variables, weighting is unnecessary if the simple linear homoscedastic model holds. If stratification is based on endogenous variables, weighting is necessary. However, the use of weights in complex surveys is different from weighted least squares (WLS). WLS is consistent but the standard errors of the parameter estimates obtained from WLS are incorrect. In addition, WLS can be used to test whether the conditional model for y given $\mathbf{x}$ is correctly specified, provided stratification is on exogenous variables. This test was first proposed by DuMouchel and Duncan (1983) for the case of linear regression. Furthermore, Wooldridge (2002, p. 594) and Wooldridge (2001, pp. 464–465) provide the asymptotic variance matrix estimators of $\hat{\boldsymbol{\beta}}_W$ for variable probability sampling and standard stratified sampling respectively. Those formulas are not the usual variance matrices provided by statistical softwares. However, the formulas are used when stratification is based on exogenous variables and the generalized conditional information matrix equality explained by Wooldridge (2002, p. 597) and the conditional model for y given $\mathbf{x}$ do not hold. If stratification is based on exogenous variables and these latter two conditions hold, Wooldridge (1999) showed that the unweighted estimator is more efficient than the weighted estimator.

In practice, the use of statistical software designed for estimating regression parameters in complex surveys will provide standard errors which are adjusted by the sample weights. However, if statistical software designed for complex surveys is not available, there are several methods that can be used (linearization methods, random group methods, resampling methods, BBR methods, and GVF), which are explained by Lohr (1999, pp. 298–318). After all, several statistical softwares designed for complex surveys use these methods.

2.7 The Bootstrap

The bootstrap was first proposed by Efron (1979). Then, further theory was presented by Singh (1981), Bickel and Freedman (1981), and Efron (1982). Efron and Tibshirani (1993) provided a good introductory statistics treatment. Other studies, mentioned in the literature reviewed, include Freedman (1984), Sitne (1990), Hall (1992), Dixon (1993), Hjorth (1994), Brownstone and Kazimi (1998), and Mackinnon (2002).

Cameron and Trivedi (2005, p. 355) explain that "bootstrap methods for statistical inference... have the attraction of providing a simple way to obtain standard errors when the formulae from asymptotic theory are complex." There is a wide range of bootstrap methods, but Cameron and Trivedi (2005, p. 357) classify them into two broad approaches. "First, the simplest bootstrap methods can permit statistical inference when conventional methods such as standard error computation are difficult to implement. Second, more complicated bootstraps can have the additional advantage of providing asymptotic refinements that can lead to a better approximation in finite samples."

Lohr (1999, p. 306) explains the bootstrap for an simple random sample (SRS) with replacement. The bootstrap for an SRS with replacement is expected to reproduce properties of the whole population. Lohr (1999, p. 306) provides the following example. Suppose $\mathcal{S}$ is an SRS of size n. The sample $\mathcal{S}$ is treated as if it were a population, and resamples from $\mathcal{S}$ are taken. If the sample really is similar to the population—if the empirical probability mass function (epmf) of the sample is similar to the probability mass function of the population—then samples generated from the epmf should behave like samples taken from the population.

Lohr (1999, p. 307) further explains that after a B total of SRSs with replacement are taken from $\mathcal{S}$ (i.e., B resamples), the bootstrap distribution of the parameter of interest is calculated. Then, this distribution may be used to calculate a confidence interval directly. A 95% confidence interval is calculated by finding the 2.5 percentile and 97.5 percentile of the bootstrap distribution of the parameter of interest.

The bootstrap for an SRS can also be without replacement (Lohr, 1999, p. 307). Gross (1980) discusses some properties of with-replacement and without-replacement bootstrap distributions. When the original SRS is without replacement, Gross (1980) proposes creating N/n copies of the sample to form a "pseudopopulation" (where N denotes the population size), and then drawing a B total of SRSs without replacement from the pseudopopulation. When n/N is small, the with-replacement and without-replacement bootstrap distribution should be similar (Lohr, 1999, p. 307).

Bootstrap methods for statistical inference in the context of stratified samples have also been studied. For example, Rao and Wu (1988) explain rescaling bootstrap methods for a stratified random sample, Sitter (1992) describes and compares three bootstrap methods for complex surveys, and Shao and Tu (1995) summarize theoretical results for the bootstrap in complex survey samples.

Cameron and Trivedi (2005, p. 358) summarize key bootstrap methods for an estimator $\hat{\boldsymbol{\theta}}$ and associated statistics based on an iid sample $\{\mathbf{w}_1, \mathbf{w}_2, \ldots, \mathbf{w}_n\}$, where usually $\mathbf{w}_i = (y_i, \mathbf{x}_i)$ and $\hat{\boldsymbol{\theta}}$ is a smooth estimator that is $\sqrt{N}$ consistent and asymptotically normally distributed.[11] For notational simplicity, Cameron and Trivedi (2005, pp. 359–361) generally presented results for scalar θ. For vector $\boldsymbol{\theta}$ in most instances the replacement of θ by θ_j, the j^{th} component of $\boldsymbol{\theta}$ is required. Statistics of interest include the usual regression output: the estimate $\hat{\theta}$; standard errors $s_{\hat{\theta}}$; t-statistic $t = \frac{(\hat{\theta}-\theta_0)}{s_{\hat{\theta}}}$, where θ_0 is the null hypothesis value; the associated critical value or p-value for this statistic; and confidence interval.

A general *bootstrap algorithm* is presented by Cameron and Trivedi (2005, p. 360):

> 1. Given data $\mathbf{w}_1, \mathbf{w}_2, \ldots, \mathbf{w}_N$ draw a bootstrap sample [of] size N using a [bootstrap sampling] method given [below] and denote this new sample $\mathbf{w}_1^*, \mathbf{w}_2^*, \ldots, \mathbf{w}_N^*$.
>
> 2. Calculate an appropriate statistic using the bootstrap sample. Examples include (a) the estimate $\hat{\theta}^*$ of θ, (b) the standard error $s_{\hat{\theta}^*}$ of the estimate $\hat{\theta}^*$, and (c) a t-statistic $t^* = \frac{(\hat{\theta}^*-\hat{\theta})}{s_{\hat{\theta}^*}}$ centered at the original estimate $\hat{\theta}$. Here $\hat{\theta}^*$ and $s_{\hat{\theta}^*}$ are

[11]Cameron and Trivedi (2005, p. 358) use N to denote the bootstrap sample size. If it is desired to use N to denote the population size and n the bootstrap sample size, then N needs to be replaced by n in the proceeding discussion related to Cameron and Trivedi (2005).

calculated in the usual way but using the new bootstrap sample rather than the original sample.

3. Repeat steps 1 and 2 B independent times, where B is a large number, obtaining B bootstrap replications of the statistic of interest, such as $\hat{\theta}_1^*, \hat{\theta}_2^*, \ldots, \hat{\theta}_B^*$ or $t_1^*, t_2^*, \ldots, t_B^*$.

4. Use these B bootstrap replications to obtain a bootstrapped version of the statistic.

The following *bootstrap sampling methods* are explained by Cameron and Trivedi (2005, p. 360):

- **Empirical distribution function (EDF) bootstrap or nonparametric bootstrap.**

  The simplest bootstrapping method is to use the empirical distribution of the data, which treats the sample as being the population. The $\mathbf{w}_1^*, \mathbf{w}_2^*, \ldots, \mathbf{w}_N^*$ are obtained by sampling with replacement from $\mathbf{w}_1, \mathbf{w}_2, \ldots, \mathbf{w}_N$. In each bootstrap sample so obtained, some of the original data points will appear multiple times whereas others will not appear at all... [This method] is also called a **paired bootstrap** since in single equation regression models $\mathbf{w}_i = (y_i, \mathbf{x}_i)$, so here both y_i and $\mathbf{x}_i$ are resampled.

- **Parametric bootstrap.**

  Suppose the conditional distribution of the data is specified, say $y|\mathbf{x} \sim F(\mathbf{x}, \boldsymbol{\theta}_0)$, and an estimate $\hat{\boldsymbol{\theta}} \xrightarrow{P} \boldsymbol{\theta}_0$ is available. Then in step 1 we can instead form a bootstrap sample by using the original $\mathbf{x}_i$ while generating y_i by random draws from $F(\mathbf{x}_i, \hat{\boldsymbol{\theta}})$. This corresponds to regressors fixed in repeated samples, [see Cameron and Trivedi (2005, Section 4.4.5)]. Alternatively, we may first resample $\mathbf{x}_i^*$ from $\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_N$ and then generate y_i from $F(\mathbf{x}_i^*, \hat{\boldsymbol{\theta}})$, $i = 1, 2, \ldots, N$. Both... examples... can be applied in fully parametric models.

- **Residual bootstrap.**

  For regression model with additive iid error, say $y_i = g(\mathbf{x}_i, \boldsymbol{\beta}) + u_i$, we can form fitted residuals $\hat{u}_1, \hat{u}_2, \ldots, \hat{u}_N$, where $\hat{u}_i = y_i - g(\mathbf{x}_i, \hat{\boldsymbol{\beta}})$. Then in step 1 bootstrap from these residuals to get a new draw of residuals, say $(\hat{u}_1^*, \hat{u}_2^*, \ldots, \hat{u}_N^*)$, leading to

> a bootstrap sample $(y_1^*, \mathbf{x}_1), (y_2^*, \mathbf{x}_2), \ldots, (y_N^*, \mathbf{x}_N)$, where $y_i^* = g(\mathbf{x}_i, \hat{\boldsymbol{\beta}}) + u_i^*$. [The residual bootstrap] uses information intermediate between the nonparametric and parametric bootstrap. It can be applied if the error term has distribution that does not depend on unknown parameters.

In this study, the first bootstrap sampling method is used. According to Cameron and Trivedi (2005, p. 361), "the paired bootstrap... appl[ies] to a wide range of non-linear models, and rel[ies] on weak distributional assumptions." However, according to Cameron and Trivedi (2005, p. 361), the other bootstraps generally provide better approximations (see Horowitz, 2001, p. 3185).

Particularly, this study uses the %BOOT macro developed by SAS Online Support. "The %BOOT macro does elementary nonparametric bootstrap analyses for simple random samples, computing approximate standard errors, bias-corrected estimates, and confidence intervals assuming a normal sampling distribution" (SAS Institute Inc., 2008, p. 1). Additionally, this study resamples observations and the %BOOT macro executes a macro loop that generates and analyzes the resamples one at time. Moreover, with the %BOOT macro "[e]ither method of resampling for regression models (observations or residuals) can be used regardless of the form of the error distribution. However, residuals should be resampled only if the errors are independent and identically distributed and if the functional form of the model is correct within a reasonable approximation. If these assumptions are questionable, it is safer to resample observations" (SAS Institute Inc., 2008, p. 8). Finally, the default size of each resample used by the %BOOT macro is equal to the size of the input dataset from which the rample is being taken. For detailed information about the %BOOT macro refer to SAS Online Support.

CHAPTER III
CONCEPTUAL FRAMEWORK

This chapter explains the censored demand system that is applied in the study. Section 3.1 begins by discussing the advantages of a complete demand system and the theoretical restrictions that are usually imposed. Section 3.4 presents the consistent two-step procedure that is used to estimate the censored model. However, this censored demand system is not derived from a specific utility function; therefore, it does not impose the theoretical restrictions. Instead, it accounts for censored observations, which is critical for analyzing Mexican meat demand at the table cut level. It is also widely accepted by applied economists and the scientific community in peer-reviewed publications, and it is very flexible and practical. For instance, it allows for incorporating estimation techniques used in stratified sampling theory, which is necessary when using the data source employed in this study.

Given that the two-step procedure make use of limited dependent variables, Section 3.2 reviews the logic behind the functional forms needed when working with these variables. Section 3.3 develops the probit model, which is not only one example but also the model applied in the first step of the two-step estimation procedure. Section 3.3.1 explains how to interpret its parameter estimates and Section 3.3.2 discusses its maximum-likelihood estimation procedure.

3.1 Demand System Models

Developments in demand theory suggest new models that are able to capture close interrelationships among commodities. Stone (1954) is credited for the first empirical application of a complete demand system approach. He is the first to form a bridge between the conventional (i.e., the "ad-hoc" single demand equation estimation) and the modern demand analysis.

In the modern approach, a complete demand system is a set of demand equations derived from well-behaved utility functions which describe the allocation of expenditures among alternative commodities. This demand system approach provides information on the degree and nature of the interrelatedness of the demand functions, makes assumptions regarding the interaction of commodities and the nature of utility functions, and presents a formal attempt to incorporate theoretical restrictions into the model to insure consumer behavior is consistent with theory.

For instance, given a strong correlation in the demand for table cuts of meats (e.g., beefsteak; ground beef; pork steak; ground pork; chicken legs, thighs and breasts; fish, etc.), demand systems can be used to capture interrelationships and jointly estimate their demand parameters. Basically, changes in prices in one commodity simultaneously affect the quantity demanded of the other commodities and the total expenditure allocation. Therefore, a demand system approach recognizes that a change in consumption of one meat cut will be balanced by changes in the consumption of the other meat cuts and total meat expenditure.

The theoretical restrictions, which are incorporated into the model, consist on imposing conditions in the Marshallian (which are obtained by maximizing a utility function subject to a budget constraint) and Hicksian (which are derived from the cost minimization principle) demand equations. Specifically, they must satisfy four properties: (a) adding-up, (b) homogeneity, (c) symmetry, and (d) negativity.

The property or restriction of *adding-up* implies that the sum of expenditures on alternative commodities within a demand system (from both Marshallian and Hicksian demands) must be equal to the total expenditure on the commodities in that system. That is, the following equation must hold,

$$\sum_{i=1}^{M} p_i\, q_i^c(\mathbf{p}, U) = \sum_{i=1}^{M} p_i\, q_i(\mathbf{p}, m) = m, \tag{3.1}$$

where p_i = price of commodity i, q_i^c = Hicksian or compensated demand of commodity i, q_i = Marshallian or uncompensated demand of commodity i, U = utility, m = total expenditure. The Engel aggregation condition is derived from the adding-up property.

The property of *homogeneity* of degree zero in prices and total expenditure for Marshallian demands implies that, for any positive constant $\lambda > 0$, changing prices and expenditures by λ will not affect the quantities demanded. The property of homogeneity of degree 0 in prices for Hicksian demands implies that for any positive constant $\lambda > 0$, changing all the prices by λ will not affect the quantities demanded. It is expressed in equation form as

$$q_i^c(U, \lambda\mathbf{p}) = \lambda^0\, q_i^c(U, \mathbf{p}) = q_i(\lambda m, \lambda\mathbf{p}) = \lambda^0\, q_i(m, \mathbf{p}). \tag{3.2}$$

The *symmetry* property of the cross-price derivatives of the Hicksian demands is implied by Young's theorem. This means that, in a Hicksian constant utility demand system, the effect of the price of commodity j on the demand for commodity i is equal to the effect of the price of commodity i on the demand for commodity j, or

$$\frac{\partial q_i^c(U, \mathbf{p})}{\partial p_j} = \frac{q_j^c(U, \mathbf{p})}{\partial p_i}, \quad \text{for}\, i \neq j. \tag{3.3}$$

The *negativity* condition of Hicksian demands implies that the own-price derivatives will be negative because the Slutzky matrix of elements $\frac{\partial q_i^c}{\partial p_j} = s_{ij}$ is negative semidefinite, a condition derived from the concavity of well-behaved cost functions.

A demand system approach usually incorporates the first three restrictions into one model to ensure that it is consistent with consumer behavior theory. Some of the advantages of a demand system approach are:

- It usually imposes the neoclassical restrictions, which reduces to a large extent the number of parameters to be estimated. This is critical when dealing with annual time series data, where there are often relatively few observations per parameter.

- It becomes useful (in a econometric sense) when the theoretical restrictions are appropriately imposed. For instance, it allows for gains in estimation efficiency and it is likely to alleviate to a large degree the problem of multicollinearity among prices, income, and other exogenous factors.

- It captures changes in socioeconomic and demographic characteristics that may lead to reallocation of expenditure among the consumption categories.

- It simultaneously incorporates changes in consumption of the commodities being analyzed.
- It obtains a realistic description of consumer behavior under varying conditions.

Unfortunately, even when a demand system approach is selected, the following drawbacks still exit.

- It requires a relatively large sample size.
- It works with a large number of coefficients, which reduces the number of degrees of freedom and might make the model difficult to estimate.
- It does not provide information about the "true" functional form of the demand functions.

Modern demand theory has also developed demand systems that deal with censored observations.[1] Unlike complete demand systems, these systems of equations are most of the time not derived from specific utility functions. Hence, it is often not possible to impose any of the theoretical restrictions. Instead, they are primarily focused on accounting for censored observations.

Several censored regression models that have been estimated in the Mexican meat market were briefly mentioned in Section 2.1. "The [Heien and Wessells' (1990)] estimator [was the] favorite choice for empirical analysts for nearly a decade" (Shonkwiler and Yen, 1999, p. 981) until Shonkwiler and Yen (1999) proposed their consistent two-step estimation procedure with limited dependent variables. They explained that their procedure is preferred over Hein and Wessells (1990) because the latter is based on a set of unconditional mean expressions for the censored dependent variables which are inconsistent. In particular, "[a]s the censoring proportion increases, the [Heien and Wessells' (1990)] procedure produces significant parameter estimates in most cases but performs very poorly in that few 95% confidence intervals contain the true parameters" (Shonkwiler and Yen, 1999, p. 981).

[1] Section 2.3 discusses censored observations.

3.2 Limited Dependent Variable Models

Wooldridge (2006, p. 582) explains a *limited dependent variable* is generally a dependent variable whose range of values is substantively restricted. For example, a binary variable takes only two values, zero and one.[2] Wooldridge (2006, p. 582) provides other examples of limited dependent variables such as participation percentage in a pension plan must be between zero and 100, the number of times an individual is arrested in a given year is a nonnegative integer, and college grade point average is between zero and 4.0 at most colleges. Similarly, Wooldridge (2006, p. 582) explains, many economic variables are limited in that they must be positive but not all of them need special treatment. Generally, when a variable takes on many different values, a special econometric model is rarely needed; but when it takes on a small number of discrete values a special econometric model is very often necessary.

When a variable is binary (e.g., zero-one variable), *binary response models* are needed. Using a *linear probability model* often leads to predicted values[3] that are less than zero or greater than one and to partial effects of explanatory variables (when the explanatory variables have not been transformed by applying logarithm) that are constant (Wooldridge, 2006, p. 583). In addition, the error term of the linear probability model is heteroscedastic (see Griffiths, Hill, and Judge, 1992, p. 739; Pindyck and Rubinfeld, 1997, p. 300; and Wooldridge, 2006, p. 256). Because the error term is heteroscedastic, the Gauss-Markov Theorem does not longer applies, which means the linear probability model is not longer the best linear unbiased model (Griffiths, Hill, and Judge, 1992, p. 739), but it is still consistent and unbiased (Pindyck and Rubinfeld, 1997, p. 300). The error term being heteroscedastic have also implications, even in large samples, for the usual t and F statistics (Wooldridge, 2006, p. 256). Additionally, the error term being heteroscedastic have implication on estimates of the standard errors.

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[2] Zero and one reflect two choices or events, e.g. yes or no, good or bad, rain or not rain, etc.

[3] Predicted values and/or fitted values can be interpreted as the probability that the binary variable takes the value of one. Clearly, values less than zero or greater than one do not make sense.

Even though researchers have tried to address these drawbacks, in some occasions the results are not very satisfying. For example, let the predicted value equal to zero when the model predicts it to be less than zero and equal to one when the model predicts it to be greater than one. Pindyck and Rubinfeld (1997, p. 301) explain:

> This is not very satisfying, however, because we might predict an occurrence with a probability of 1 when it is possible that it might not occur, or we might predict an occurrence with a probability of 0 when it might actually occur. While the estimation procedure may well yield unbiased estimates, the prediction obtained from the estimation process are clearly biased.

In addition, correcting for heteroscedasticity by using weighted least-squares estimation (see Pindyck and Rubinfeld, 1997, pp. 300-301 and Wooldridge, 2006, pp. 284-295) or by using heteroskedasticity-robust inference (see Wooldridge, 2006, pp. 272-278) does not guarantee that the predicted values will lie in the (0,1) interval. Furthermore, an alternative approach to deal with predicted values outside the (0,1) interval consists of reestimating the parameters corresponding to the dependent variables subject to the constraint that the predicted values must be greater than or equal to zero but less than or equal to one (Pindyck and Rubinfeld, 1997, p. 301). However, there is no guarantee that the estimates will be unbiased (Pindyck and Rubinfeld, 1997, p. 301). For other problems with the use of the linear probability model when the dependent variable is binary, and other issues when correcting for heteroscedasticity, refer to Pindyck and Rubinfeld (1997, pp. 298-304). However, "[i]t turns out that, in many applications, the usual OLS statistics are not far off, and it is still acceptable in applied work to present a standard OLS analysis of linear probability model" (Wooldridge, 2006, p. 256).

However, a more satisfying approach is to transform the linear probability model such that the predicted values will always be in the (0, 1) interval (Pindyck and Rubinfeld, 1997, p. 304). That is, the predicted values obtained from information on the dependent variables, which may be real numbers from minus infinity to infinitive, have to be transformed into probabilities, which are real numbers between zero and one. In addition, it is desired to have the property that increases in any of the dependent variables will be transformed into increases or decreases of the dependent variable (a variable whose values are a real number between zero and one) (Pindyck and Rubinfeld, 1997, p. 304). Since these two desirable properties are present in a cumulative probability function, it makes sense to use a cumulative probability function to transform the model. The most commonly used cumulative probability functions are the normal and the logistic. The *probit model* is associated with the use of the cumulative normal probability function and the *tobit model* is associated with the use of the cumulative logistic probability function.

3.3 The Probit Model for Binary Response

In this section, the probit model for a binary response variable (a "dummy" dependent variable) is developed following Griffiths, Hill, and Judge (1992). The probit model is a sophisticated binary response model and it is a nonlinear model in parameters.

Consider a household decision maker, t, choosing whether or not to buy a certain meat cut, i, for the household consumption of the week.[4] Assuming that the household derives utility from each of the outcomes the decision maker takes, then the decision maker will take the alternative that provides the household the greater utility. For household t, the alternative chosen is observed and a zero-one or discrete (dummy) variable $d_i(t)$ is defined as the outcome,

$$(3.4)\quad d_i(t) = \begin{cases} 1, & \text{if household } t \text{ buys meat cut } i, \\ 0, & \text{if household } t \text{ does not buys meat cut } i. \end{cases}$$

The variable $d_i(t)$ is a discrete random variable because it is not possible to predict with certainty the outcome that a randomly selected household will have.

[4]The use of $t = 1, 2, \ldots, T$ implies here cross-sectional data (e.g., a sample of households). However, it could also apply to time series data or other data samples.

In terms of a latent or unobserved variable, $d_i^*(t)$, Equation (3.4) can written as

$$(3.5)\quad d_i^*(t) = I_i(t) + v_i(t), \qquad d_i(t) = \begin{cases} 1 & \text{if} \quad d_i^*(t) > 0, \\ 0 & \text{if} \quad d_i^*(t) \leq 0, \end{cases}$$

where $I_i(t)$ is defined as a "utility index" (see Griffiths, Hill, and Judge, 1992, p. 740 and pp. 757-760) and $v_i(t)$ is a random random error. Thus, when the sum of the utility index and the random error is positive, household t buys meat cut i; however, when this sum is negative, household t does not buy meat cut i.

For an arbitrary household t,

$$I_i(t) = \alpha_{i1} + \alpha_{i2} z_{i2}(t) + \ldots + \alpha_{iK_1} z_{iK_1}(t).$$

For simplicity, the household subscript t is dropped so that

$$\begin{aligned} (3.6)\quad I_i &= \alpha_{i1} + \alpha_{i2} z_{i2} + \ldots + \alpha_{iK_1} z_{iK_1} \\ &= \mathbf{z_i}' \boldsymbol{\alpha}_i, \end{aligned}$$

where $\mathbf{z}_i' = \begin{pmatrix} 1 & z_{i2} & \ldots & z_{iK_1} \end{pmatrix}$ is a $(1 \times K_1)$ vector of explanatory variables, $\boldsymbol{\alpha}_i = \begin{pmatrix} \alpha_{i1} & \alpha_{i2} & \ldots & \alpha_{iK_1} \end{pmatrix}'$ is a $(K_1 \times 1)$ vector of parameters and $I_i \in R$ (i.e., the value of I_i lies over the real number line). In this case, the utility index measures the household's "propensity" to buy meat cut i. Note that increases in any of the dependent variables will increase or decrease I_i. In addition, the larger the value of I_i, the greater the utility household t receives from choosing option $d_i = 1$. Thus, as the value of I_i increases, the greater the probability that household t chooses the option $d_i = 1$, $P(d_i = 1|\mathbf{z}_i)$. This latter relationship between I_i and $P(d_i = 1|\mathbf{z}_i)$ is called strictly increasing or monotonic. Hence, to capture the relationship between I_i and $P(d_i = 1|\mathbf{z}_i)$, a function is needed that, in addition to satisfy the previous two properties, will depict how the probability $P(d_i = 1|\mathbf{z}_i)$ vary between zero and one as I_i varies between minus infinity and infinity. Any cumulative distribution function (cdf) meets these objectives. The probit model makes use of the standard normal cumulative probability function as follows:

$$(3.7)\quad P(d_i = 1|\mathbf{z}_i) = \Phi(I_i) = \Phi(\alpha_{i1} + \alpha_{i2} z_{i2} + \ldots + \alpha_{iK} z_{iK}) = \Phi(\mathbf{z}_i' \boldsymbol{\alpha}_i),$$

where $\Phi(I_i)$ is the standard normal cumulative distribution function (cdf) evaluated at I_i. The cdf is given by

$$(3.8)\quad \Phi(I_i) = P[v \le I_i] = \int_{-\infty}^{I_i} \phi(v)dv = \int_{-\infty}^{I_i} (2\pi)^{-1/2}\, e^{-v^2/2}\, dv,$$

where v is a standard normal random variable. Note that as $I_i \to -\infty$, $\Phi(I_i) \to 0$ and as $I_i \to \infty$, $\Phi(I_i) \to 1$.

Note that d_i in Equation (3.4) can be rewritten as

$$(3.9)\quad d_i = \begin{cases} 1, & \text{with probability} \quad P(d_i = 1|\mathbf{z}_i), \\ 0, & \text{with probability} \quad P(d_i = 0|\mathbf{z}_i), \end{cases} \qquad 0 \le P(d_i|\mathbf{z}_i) \le 1.$$

In addition, since d_i is a discrete random variable, it has a Bernoulli probability mass function. That is,

$$(3.10)\quad g(d_i|\mathbf{z}_i) = P(d_i = 1|\mathbf{z}_i)^{d_i}[1 - P(d_i = 1|\mathbf{z}_i)]^{1-d_i}, \qquad d_i = 0, 1.$$

Therefore, the mean and variance of the discrete random variable d_i are[5]

$$(3.11)\quad E(d_i|\mathbf{z}_i) = 1\, P(d_i = 1|\mathbf{z}_i) + 0\, P(d_i = 0|\mathbf{z}_i) = P(d_i = 1|\mathbf{z}_i),$$

$$\begin{aligned}(3.12)\quad \mathrm{var}(d_i|\mathbf{z}_i) &= E[d_i - E(d_i)]^2 = E[d_i - P(d_i = 1|\mathbf{z}_i)]^2 \\ &= [1 - P(d_i = 1|\mathbf{z}_i)]^2 P(d_i = 1|\mathbf{z}_i) + [0 - P(d_i = 1|\mathbf{z}_i)]^2[1 - P(d_i = 1|\mathbf{z}_i)] \\ &= P(d_i = 1|\mathbf{z}_i)[1 - P(d_i = 1|\mathbf{z}_i)].\end{aligned}$$

Then, Equation (3.11) and Equation (3.5) implies that

$$\begin{aligned}(3.13)\quad E(d_i|\mathbf{z}_i) &= P(d_i = 1|\mathbf{z}_i) = P(d_i^* > 0|\mathbf{z}_i) = P[v > -I_i|\mathbf{z}_i] \\ &= 1 - P[v \le -I_i|\mathbf{z}_i] = 1 - \Phi(-I_i) = \Phi(I_i),\end{aligned}$$

where $P[v \le -I_i|\mathbf{z}_i] = \Phi(-I_i)$ if and only if it is assumed that v is independent of $\mathbf{z}_i$ and has a standard normal cumulative distribution function (see Wooldridge, 2006, p. 585).

[5]To find the variance, it is easier to let $P_i = P(d_i = 1|\mathbf{z}_i)$ and then compute $\mathrm{var}(d_i|\mathbf{z}_i) = E[d_i - E(d_i)]^2 = E[d_i - P_i]^2 = \sum_{d_i=0,1} [d_i - P_i]^2 g(d_i|\mathbf{z}_i) = [1 - P_i]^2 P_i + [0 - P_i]^2[1 - P_i] = P_i[1 - P_i]$.

The above probit statistical model, which is explained in Griffiths, Hill, and Judge (1992, pp. 736-760), has a relationship to economic utility theory. Griffiths, Hill, and Judge (1992, pp. 757-760) explain this relationship and the underlying economic principles.

3.3.1 Interpreting the Probit Model

In binary response models, interest lies in the effect of z_{ik} on the response probability $P(d_i = 1|\mathbf{z}_i)$, see Equation (3.7). When z_{ik} is a roughly continuous variable, the partial effect of z_{ik} on $P(d_i = 1|\mathbf{z}_i)$ is given by

$$\frac{\partial P(d_i = 1|\mathbf{z}_i)}{\partial z_{ik}} = \frac{\partial \Phi(\mathbf{z}_i'\boldsymbol{\alpha}_i)}{\partial z_{ik}} = \phi(\mathbf{z}_i'\boldsymbol{\alpha}_i)\frac{\partial(\mathbf{z}_i'\boldsymbol{\alpha}_i)}{\partial z_{ik}} = \phi(\mathbf{z}_i'\boldsymbol{\alpha}_i)\alpha_{ik}, \tag{3.14}$$

where $\phi(\mathbf{z}_i'\boldsymbol{\alpha}_i) = (2\pi)^{-\frac{1}{2}}e^{-\frac{1}{2}(\mathbf{z}_i'\boldsymbol{\alpha}_i)^2}$ is the standard normal probability density function evaluated at $\mathbf{z}_i'\boldsymbol{\alpha}_i$ and α_{ik} is the k^{th} parameter of the vector $\boldsymbol{\alpha}_i$. Griffiths, Hill, and Judge (1992, pp. 742-743) observe that:

1. Because $\phi(\mathbf{z}_i'\boldsymbol{\alpha}_i)$ is the standard normal probability density function evaluated at $\mathbf{z}_i'\boldsymbol{\alpha}_i$, then $\phi(\mathbf{z}_i'\boldsymbol{\alpha}_i)$ is always positive. This means the partial effect of z_{ik} on $P(d_i = 1|\mathbf{z}_i)$ has always the sign of α_{ik}. That is, if $\alpha_{ik} > 0$, an increase in z_{ik} increases $P(d_i = 1|\mathbf{z}_i)$; and if $\alpha_{ik} < 0$, an increase in z_{ik} decreases $P(d_i = 1|\mathbf{z}_i)$.

2. The magnitude of the partial effect of z_{ik} on $P(d_i = 1|\mathbf{z}_i)$ is determined by the product of the magnitudes of $\phi(\mathbf{z}_i'\boldsymbol{\alpha}_i)$ and α_{ik}. Since ϕ is the standard normal probability density function, the maximum value of $\phi(\mathbf{z}_i'\boldsymbol{\alpha}_i) \approx 0.40$ occurs when $\mathbf{z}_i'\boldsymbol{\alpha}_i = 0$. Additionally, $\phi(\mathbf{z}_i'\boldsymbol{\alpha}_i) \to 0$ when $\mathbf{z}_i'\boldsymbol{\alpha}_i \to -\infty$ or $\mathbf{z}_i'\boldsymbol{\alpha}_i \to \infty$. Thus, the closer $\mathbf{z}_i'\boldsymbol{\alpha}_i$ to zero is, the greater the value of $\phi(\mathbf{z}_i'\boldsymbol{\alpha}_i)$ and the greater the partial effect of z_{ik} on $P(d_i = 1|\mathbf{z}_i)$ has. Similarly, the farther away from zero $\mathbf{z}_i'\boldsymbol{\alpha}_i$ is, the smaller the value of $\phi(\mathbf{z}_i'\boldsymbol{\alpha}_i)$ and the smaller the partial effect of z_{ik} on $P(d_i = 1|\mathbf{z}_i)$ has.[6]

[6] Since Φ is the standard normal cumulative distribution function, a similar argument can be made by using the relationship between Φ and ϕ. It is known that $\Phi(\mathbf{z}_i'\boldsymbol{\alpha}_i) = 0.5$ when $\mathbf{z}_i'\boldsymbol{\alpha}_i = 0$; $\Phi(\mathbf{z}_i'\boldsymbol{\alpha}_i) \to 0$ when $\mathbf{z}_i'\boldsymbol{\alpha}_i \to -\infty$; and $\Phi(\mathbf{z}_i'\boldsymbol{\alpha}_i) \to 1$ when $\mathbf{z}_i'\boldsymbol{\alpha}_i \to \infty$. Thus, the closer to 0.5 the value

However, when z_{ik} is a binary explanatory variable (i.e., a dummy dependent variable), Wooldridge (2006, pp. 585-586) explains that the partial effect from changing z_{ik} from zero to one on $P(d_i = 1|\mathbf{z}_i)$, holding all other variables fixed, is

$$(3.15) \quad \frac{\partial P(d_i = 1|\mathbf{z}_i)}{\partial z_{ik}} =$$
$$\Phi(\alpha_{i1} + \alpha_{i2}z_{i2} + \ldots + \alpha_{i(k-1)}z_{i(k-1)} + \alpha_{ik} + \alpha_{i(k+1)}z_{i(k+1)} + \ldots + \alpha_{iK_1}z_{iK_1})$$
$$-\Phi(\alpha_{i1} + \alpha_{i2}z_{i2} + \ldots + \alpha_{i(k-1)}z_{i(k-1)} + \alpha_{i(k+1)}z_{i(k+1)} + \ldots + \alpha_{iK_1}z_{iK_1}).$$

Note that Equation (3.15) the partial effect of z_{ik} on $P(d_i = 1|\mathbf{z}_i)$ also depends on the sign of α_{ik}. For example, if $\alpha_{ik} > 0$ then $\Phi(\alpha_{i1}+\alpha_{i2}z_{i2}+\ldots+\alpha_{ik}+\ldots+\alpha_{iK}z_{iK}) > \Phi(\alpha_{i1} + \alpha_{i2}z_{i2} + \ldots + \alpha_{i(k-1)}z_{i(k-1)} + \alpha_{i(k+1)}z_{i(k+1)} + \ldots + \alpha_{iK}z_{iK})$ and $\frac{\partial P(d_i=1|\mathbf{z}_i)}{\partial z_{ik}} > 0$. Similarly, if $\alpha_{ik} < 0$ then $\Phi(\alpha_{i1} + \alpha_{i2}z_{i2} + \ldots + \alpha_{ik} + \ldots + \alpha_{iK}z_{iK}) < \Phi(\alpha_{i1} + \alpha_{i2}z_{i2} + \ldots + \alpha_{i(k-1)}z_{i(k-1)} + \alpha_{i(k+1)}z_{i(k+1)} + \ldots + \alpha_{iK}z_{iK})$ and $\frac{\partial P(d_i=1|\mathbf{z}_i)}{\partial z_{ik}} < 0$. However, to find the magnitude of the partial effect of z_{ik} on $P(d_i = 1|\mathbf{z}_i)$ it is necessary to calculate Equation (3.15).

Wooldridge (2006, p. 586) also generalizes Equation (3.15) for cases when z_{ik} is a discrete variable (e.g., the number of household members). When z_{ik} is a discrete variable, the partial effect from changing z_{ik} from c_k to c_k+1 on $P(d_i = 1|\mathbf{z}_i)$, holding all other variables constant, is

$$(3.16) \quad \frac{\partial P(d_i = 1|\mathbf{z}_i)}{\partial z_{ik}} =$$
$$\Phi(\alpha_{i1} + \alpha_{i2}z_{i2} + \ldots + \alpha_{i(k-1)}z_{i(k-1)} + \alpha_{ik}(c_k + 1) + \alpha_{i(k+1)}z_{i(k+1)} + \ldots + \alpha_{iK}z_{iK})$$
$$-\Phi(\alpha_{i1} + \alpha_{i2}z_{i2} + \ldots + \alpha_{i(k-1)}z_{i(k-1)} + \alpha_{ik}c_k + \alpha_{i(k+1)}z_{i(k+1)} + \ldots + \alpha_{iK}z_{iK}).$$

Finally, Wooldridge (2006, p. 586) explains how to handle simple functional forms similar to Equation (3.6). In other words, how to handle transformations of the explanatory variables in Equation (3.6). Wooldridge (2006, p. 586) provides the

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of $\Phi(\mathbf{z}_i'\boldsymbol{\alpha}_i)$ is, the greater the value of $\phi(\mathbf{z}_i'\boldsymbol{\alpha}_i)$ and the greater the partial effect of z_{ik} on $P(d_i = 1|\mathbf{z}_i)$ has. Similarly, the closer to zero or one the value of $\Phi(\mathbf{z}_i'\boldsymbol{\alpha}_i)$ is, the smaller the value of $\phi(\mathbf{z}_i'\boldsymbol{\alpha}_i)$ and the smaller the partial effect of z_{ik} on $P(d_i = 1|\mathbf{z}_i)$ has.

following example. In the binary response model,

$$P(d_i = 1|\mathbf{z}_i) = \Phi(\mathbf{z}_i'\boldsymbol{\alpha}_i) = \Phi\left(\alpha_{i1} + \alpha_{i2}z_{i2} + \alpha_{i3}z_{i2}^2 + \alpha_{i4}\log(z_{i3}) + \alpha_{i5}z_{i4}\right),$$

the partial effect of z_{i2} on $P(d_i = 1|\mathbf{z}_i)$ is $\frac{\partial P(d_i=1|\mathbf{z}_i)}{\partial z_{i2}} = \phi(\mathbf{z}_i'\boldsymbol{\alpha}_i)(\alpha_{i2} + 2\alpha_{i3}z_{i2})$ and the partial effect of z_{i3} on $P(d_i = 1|\mathbf{z}_i)$ is $\frac{\partial P(d_i=1|\mathbf{z}_i)}{\partial z_{i2}} = \phi(\mathbf{z}_i'\boldsymbol{\alpha}_i)\left(\alpha_{i4}\,\frac{1}{z_{i3}}\right)$. Models with interactions among explanatory variables can be handled similarly.

3.3.2 Maximum Likelihood Probit Parameter Estimation

Griffiths, Hill, and Judge (1992, p. 744) explain maximum likelihood estimation of the unknown parameters of the Probit model is indispensable because of the discrete nature of the outcome variable $d_i(t)$, and the nonlinear relation (in parameters) between the choice probability (probability that household t chooses option $d_i = 1$) and the explanatory variables $z_{ik}(t)$.

Griffiths, Hill, and Judge (1992, p. 744) explain the fist step toward maximum likelihood estimation of the unknown parameters $\boldsymbol{\alpha}_i$ of the probit model is to specify the probability density functions of the observable random variables $d_i(t)$. These are

$$g[d_i(t)|\mathbf{z}_i(t)] = P_i(t)^{d_i(t)}[1 - P_i(t)]^{1-d_i(t)}, \qquad d_i(t) = 0, 1, \qquad t = 1, \ldots, T, \tag{3.17}$$

where $P_i(t) = P[d_i(t) = 1|\mathbf{z}_i(t)] = \Phi[\mathbf{z}_i'(t)\boldsymbol{\alpha}_i]$, see Equation (3.7), have been introduced for simplicity, and T is the total number of households (i.e., the sample size or total number of observations).

Now, maximum likelihood estimation assumes the T observations are independent, which implies that the joint probability density function of the T random variables $d_i(t)$ is the product of its probability density functions $g[d_i(t)|\mathbf{z}_i(t)]$. That is, the joint probability density function of the random variables $d_i(1), d_i(2), \ldots, d_i(T)$ is

$$\begin{aligned} (3.18)\quad & g[d_i(1), \ldots, d_i(T)|\mathbf{z}_i(1), \ldots, \mathbf{z}_i(T)] \\ &= \prod_{t=1}^{T} g[d_i(t)|\mathbf{z}_i(t)] = \prod_{t=1}^{T} P_i(t)^{d_i(t)}[1 - P_i(t)]^{1-d_i(t)} \\ &= \prod_{t=1}^{T} \{\Phi[\mathbf{z}_i'(t)\boldsymbol{\alpha}_i]\}^{d_i(t)}\{1 - \Phi[\mathbf{z}_i'(t)\boldsymbol{\alpha}_i]\}^{1-d_i(t)}. \end{aligned}$$

Griffiths, Hill, and Judge (1992, p. 744) explain that if the parameters $\boldsymbol{\alpha}_i$ were known, Equation (3.18) could be used to calculate the probability that any set of T choice outcomes occurs. For example, if $\boldsymbol{\alpha}_i$ were known, then $P[d_i(1) = 1, \ldots, d_i(t-1) = 1, d_i(t) = 0, d_i(t+1) = 1, \ldots, d_i(T) = 1 | \mathbf{z}_i(1), \ldots, \mathbf{z}_i(T)] = g[d_i(1) = 1, \ldots, d_i(t-1) = 1, d_i(t) = 0, d_i(t+1) = 1, \ldots, d_i(T) = 1 | \mathbf{z}_i(1), \ldots, \mathbf{z}_i(T)]$ can be calculated directly from Equation (3.18). However, in practice $\boldsymbol{\alpha}_i$ is unknown. The idea of maximum likelihood is to choose estimates of $\boldsymbol{\alpha}_i$ that maximize the probability of obtaining the sample that is observed. To obtain the maximum likelihood estimates of the probit model, the parameters $\boldsymbol{\alpha}_i$ are considered unknown and the sample outcomes $d_i(t)$ and $\mathbf{z}_i(t)$ are considered known in Equation (3.18). Hence, considering the unknown parameters $\boldsymbol{\alpha}_i$ as variables and the known variables $d_i(t)$ and $\mathbf{z}_i(t)$ as constants, the joint probability density function, Equation (3.18), becomes a function of $\boldsymbol{\alpha}_i$ and it is called the *likelihood function*. It is written as

$$(3.19)\quad L(\boldsymbol{\alpha}_i) = \prod_{t=1}^{T} \{\Phi[\mathbf{z}_i'(t)\boldsymbol{\alpha}_i]\}^{d_i(t)} \{1 - \Phi[\mathbf{z}_i'(t)\boldsymbol{\alpha}_i]\}^{1-d_i(t)}$$

where $\Phi[\mathbf{z}_i'(t)\boldsymbol{\alpha}_i]$ is the standard normal cumulative distribution function (cdf) evaluated at $\mathbf{z}_i'(t)\boldsymbol{\alpha}_i$. To find the values of $\boldsymbol{\alpha}_i$ that maximize the likelihood function, usually you will take the partial derivative of $L(\boldsymbol{\alpha}_i)$ with respect to $\boldsymbol{\alpha}_i$, set it equal to zero and solve for $\boldsymbol{\alpha}_i$. However, if you adopt this procedure you will realize that the partial derivatives lead to complicated expressions which do not have easy algebraic expressions.

To make this process easier, economists maximize the *log-likelihood function* instead. The log-likelihood function is obtained by taking the logarithm or the natural logarithm to Equation (3.19). This gives

$$(3.20)\quad l(\boldsymbol{\alpha}_i) = \log L(\boldsymbol{\alpha}_i) = \sum_{t=1}^{T} \{d_i(t) \log \Phi[\mathbf{z}_i'(t)\boldsymbol{\alpha}_i] + [1 - d_i(t)] \log (1 - \Phi[\mathbf{z}_i'(t)\boldsymbol{\alpha}_i])\}$$

Now, taking the partial derivative of $l(\boldsymbol{\alpha}_i)$ with respect to $\boldsymbol{\alpha}_i$ and setting it equal to zero gives

$$(3.21)\quad \frac{\partial l(\boldsymbol{\alpha}_i)}{\partial \boldsymbol{\alpha}_i} = \sum_{t=1}^{T} \left\{ d_i \frac{\phi[\mathbf{z}_i'(t)\boldsymbol{\alpha}_i]}{\Phi[\mathbf{z}_i'(t)\boldsymbol{\alpha}_i]} + [1 - d_i(t)] \frac{-\phi[\mathbf{z}_i'(t)\boldsymbol{\alpha}_i]}{1 - \Phi[\mathbf{z}_i'(t)\boldsymbol{\alpha}_i]} \right\} \mathbf{z}_i(t) = 0,$$

where $\frac{\partial[\mathbf{z}_i'(t)\boldsymbol{\alpha}_i]}{\partial \boldsymbol{\alpha}_i} = [\mathbf{z}_i'(t)]' = \mathbf{z}_i(t)$, $\phi[\mathbf{z}_i'(t)\boldsymbol{\alpha}_i] = (2\pi)^{-\frac{1}{2}} e^{-\frac{1}{2}[\mathbf{z}_i'(t)\boldsymbol{\alpha}_i]^2}$, and $\Phi[\mathbf{z}_i'(t)\boldsymbol{\alpha}_i]$ is given in Equation (3.8). Clearly, Equation (3.21) leads to no easy algebraic expression and it is difficult to solve for $\boldsymbol{\alpha}_i$.

As explained by Griffiths, Hill, and Judge (1992, p. 745), modern computer software uses numerical optimization methods to find the values of $\boldsymbol{\alpha}_i$ that maximize the log-likelihood function. For more information on numerical optimization methods for the probit model refer to Judge et al. (1988, pp. 791-793). Once the values of $\boldsymbol{\alpha}_i$ that maximizes Equation (3.21) are found, they are called maximum likelihood estimates ($\hat{\boldsymbol{\alpha}}_i$).

3.4 Two-Step Censored Demand System Estimation

In this section, Shonkwiler and Yen's (1999) consistent censored demand system is presented. The model is preferred over Heien and Wessells' (1990) censored demand system and enjoys some of the advantages mentioned in Section 3.1, but it does not incorporate the theoretical restrictions of adding-up, homogeneity, symmetry, and negativity because it is not derived from a specific utility function. Most importantly, the model is designed to take into account censored observations, which is critical in this study for analyzing the Mexican meat demand at the disaggregated level. It is also widely accepted by applied economists and the scientific community in peer-reviewed publications, and it is very flexible and practical, which allows for incorporating estimation techniques used in stratified sampling theory.

For an arbitrary observation from the i^{th} equation, $i = 1, 2, \ldots, M$, the censored system of equations with limited dependent variables, proposed by Shonkwiler and

Yen (1999), is written as follows:

$$
\begin{aligned}
(3.22)\quad y_i &= d_i y_i^*, \\
y_i^* &= \mathbf{x}_i'\boldsymbol{\beta}_i + \epsilon_i, \\
d_i &= \begin{cases} 1 & \text{if} \quad d_i^* > 0, \\ 0 & \text{if} \quad d_i^* \leq 0, \end{cases} \\
d_i^* &= \mathbf{z}_i'\boldsymbol{\alpha}_i + v_i,
\end{aligned}
$$

where y_i and d_i are (1×1) observed dependent variables, y_i^* and d_i^* are (1×1) corresponding latent or unobserved variables, $\mathbf{z}_i' = (\ 1 \quad z_{i2} \quad \ldots \quad z_{iK_1}\ )$ and $\mathbf{x}_i' = (\ 1 \quad x_{i2} \quad \ldots \quad x_{iK_2}\ )$ are $(1 \times K_1)$ and $(1 \times K_2)$ vector of explanatory variables respectively, $\boldsymbol{\alpha}_i = (\ \alpha_{i1} \quad \alpha_{i2} \quad \ldots \quad \alpha_{iK_1}\ )'$ and $\boldsymbol{\beta}_i = (\ \beta_{i1} \quad \beta_{i2} \quad \ldots \quad \beta_{iK_2}\ )'$ are $(K_1 \times 1)$ and $(K_2 \times 1)$ vector of parameters respectively, and ϵ_i and v_i are (1×1) random errors.

Shonkwiler and Yen (1999, p. 973) explain that if it is assumed that for each i the error terms $(\ \epsilon_i \quad v_i\ )'$ are distributed as bivariate normal with $\text{cov}(\epsilon_i, v_i) = \delta_i$; then, the unconditional mean of y_i is[7]

$$(3.23)\quad \mathrm{E}(y_i|\mathbf{x}_i, \mathbf{z}_i) = \Phi(\mathbf{z}_i'\boldsymbol{\alpha}_i)\mathbf{x}_i'\boldsymbol{\beta}_i + \delta_i\phi(\mathbf{z}_i'\boldsymbol{\alpha}_i).$$

Then, using Equation (3.23), the system in Equation (3.22) can be written as

$$(3.24)\quad y_i = \Phi(\mathbf{z}_i'\boldsymbol{\alpha}_i)\mathbf{x}_i'\boldsymbol{\beta}_i + \delta_i\phi(\mathbf{z}_i'\boldsymbol{\alpha}_i) + \xi_i, \quad i = 1, \ldots, M,$$

where $\xi_i = y_i - \mathrm{E}(y_i|\mathbf{x}_i, \mathbf{z}_i)$ and $\mathrm{E}(\xi_i) = 0$.

Shonkwiler and Yen (1999) suggest the following two-step procedure for the system in Equation (3.24). First, obtain maximum-likelihood probit estimates $\hat{\boldsymbol{\alpha}}_i$ of $\boldsymbol{\alpha}_i$ for $i = 1, 2, \ldots, M$ using the binary dependent variable $d_i = 1$ if $y_i > 0$ and $d_i = 0$ otherwise. That is, estimate the following probit models (Equation (3.7)) by maximum likelihood:

$$(3.25)\quad P(d_i = 1|\mathbf{z}_i) = \Phi(\alpha_{i1} + \alpha_{i2}z_{i2} + \ldots + \alpha_{iK_1}z_{iK_1}) = \Phi(\mathbf{z}_i'\boldsymbol{\alpha}_i), \quad i = 1, \ldots, M.$$

[7]This study follows Shonkwiler and Yen's (1999) terminology.

Second, calculate $\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)$ and $\phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)$ and estimate $\boldsymbol{\beta}_1, \boldsymbol{\beta}_2, \ldots, \boldsymbol{\beta}_M, \delta_1, \delta_2, \ldots, \delta_M$ in the system

$$(3.26)\quad y_i = \Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\mathbf{x}_i'\boldsymbol{\beta}_i + \delta_i\phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i) + \xi_i, \quad i = 1, \ldots, M,$$

by maximum likelihood (ML) or seemingly unrelated regression (SUR) procedure,[8] where

$$(3.27)\quad \xi_i = \epsilon_i + [\Phi(\mathbf{z}_i'\boldsymbol{\alpha}_i) - \Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)]\mathbf{x}_i'\boldsymbol{\beta}_i + \delta_i[\phi(\mathbf{z}_i'\boldsymbol{\alpha}_i) - \phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)].$$

Su and Yen (2000) explain that differentiating the unconditional mean (Equation(3.23)) with respect to a common variable in $\mathbf{x}_i$ and $\mathbf{z}_i$, say x_{ij}, where $z_{ik} = x_{ij}$ and $k = 1$ or 2 or … or K_1, $j = 1$ or 2 or … or K_2, gives

$$(3.28)\quad \frac{\partial \mathrm{E}(y_i|\mathbf{x}_i, \mathbf{z}_i)}{\partial x_{ij}} = \Phi(\mathbf{z}_i'\boldsymbol{\alpha}_i)\beta_{ij} + \mathbf{x}_i'\boldsymbol{\beta}_i\phi(\mathbf{z}_i'\boldsymbol{\alpha}_i)\alpha_{ij} - \delta_i(\mathbf{z}_i'\boldsymbol{\alpha}_i)\phi(\mathbf{z}_i'\boldsymbol{\alpha}_i)\alpha_{ij}.$$

However, when x_{ij} is a common binary explanatory variable (i.e., a common dummy dependent variable), similar to the procedure explained by (Wooldridge, 2006, pp. 585-586), the partial effect from changing x_{ij} from zero to one on $\mathrm{E}(y_i|\mathbf{x}_i, \mathbf{z}_i)$, holding all other variables fixed, is

$$(3.29)\quad \frac{\partial \mathrm{E}(y_i|\mathbf{x}_i, \mathbf{z}_i)}{\partial x_{ij}} =$$
$$\begin{aligned}
&\Phi(\alpha_{i1} + \alpha_{i2}z_{i2} + \ldots + \alpha_{i(j-1)}z_{i(j-1)} + \alpha_{ij} + \alpha_{i(j+1)}z_{i(j+1)} + \ldots + \alpha_{iK_1}z_{iK_1}) \\
&\times \left[\beta_{i1} + \beta_{i2}x_{i2} + \ldots + \beta_{i(j-1)}x_{i(j-1)} + \beta_{ij} + \beta_{i(j+1)}x_{i(j+1)} + \ldots + \beta_{iK_2}x_{iK_2}\right] \\
&-\Phi(\alpha_{i1} + \alpha_{i2}z_{i2} + \ldots + \alpha_{i(j-1)}z_{i(j-1)} + \alpha_{i(j+1)}z_{i(j+1)} + \ldots + \alpha_{iK_1}z_{iK_1}) \\
&\times \left[\beta_{i1} + \beta_{i2}x_{i2} + \ldots + \beta_{i(j-1)}x_{i(j-1)} + \beta_{i(j+1)}x_{i(j+1)} + \ldots + \beta_{iK_2}x_{iK_2}\right] \\
&+\delta_i \left[\phi(\alpha_{i1} + \alpha_{i2}z_{i2} + \ldots + \alpha_{i(j-1)}z_{i(j-1)} + \alpha_{ij} + \alpha_{i(j+1)}z_{i(j+1)} + \ldots + \alpha_{iK_1}z_{iK_1})\right. \\
&\qquad \left. -\phi(\alpha_{i1} + \alpha_{i2}z_{i2} + \ldots + \alpha_{i(j-1)}z_{i(j-1)} + \alpha_{i(j+1)}z_{i(j+1)} + \ldots + \alpha_{iK_1}z_{iK_1})\right].
\end{aligned}$$

Furthermore, Su and Yen (2000) explain, the elasticities can be derived from Equation (3.28). For example, the elasticities of commodity i with respect to price

[8] For an applied review on seemingly unrelated regressions see López (2008).

p_j, total meat expenditure m, and demographic variable r_l are (e.g., see Yen, Kan, and Su, 2002), respectively,

$$
\begin{aligned}
(3.30)\quad e_{ij} &= \frac{\partial \mathrm{E}(y_i|\mathbf{x}_i, \mathbf{z}_i)}{\partial p_j}\frac{p_j}{\mathrm{E}(y_i|\mathbf{x}_i, \mathbf{z}_i)}, \\
(3.31)\quad e_{i} &= \frac{\partial \mathrm{E}(y_i|\mathbf{x}_i, \mathbf{z}_i)}{\partial m}\frac{m}{\mathrm{E}(y_i|\mathbf{x}_i, \mathbf{z}_i)}, \\
(3.32)\quad e_{il} &= \frac{\partial \mathrm{E}(y_i|\mathbf{x}_i, \mathbf{z}_i)}{\partial r_l}\frac{r_l}{\mathrm{E}(y_i|\mathbf{x}_i, \mathbf{z}_i)}.
\end{aligned}
$$

Then, these elasticities can be evaluated using parameter estimates and sample means of explanatory variables.[9] As explained by Su and Yen (2000, p. 736), the elasticity of commodity i with respect to demographic variable r_l is "not strictly defined... [but] allow convenient assessment of the significance of corresponding variables in a complex functional relationship." In other words, in a complex functional form, the statistical significance of an artificial elasticity allows to assess the statistical significance of the corresponding binary variable. Finally, the compensated or Hicksian elasticities of commodity i with respect to price p_j can be obtained from Slutsky equation in elasticity form. That is,

$$(3.33)\quad e_{ij}^{c} = e_{ij} + e_i\left(\frac{p_j\,\mathrm{E}(y_j|\mathbf{x}_j, \mathbf{z}_j)}{m}\right).$$

[9]Provided that the data sample used in this study (ENIGH) is a stratified sample, means of explanatory variables are computed incorporating the variables strata and weight (see SAS Institute Inc., 2004, pp. 4313–4362).

CHAPTER IV
METHODS AND PROCEDURES

This chapter starts by explaining the Mexican database on household income and expenditures that is used in this study. In particular, Section 4.1 explains what type of information is contained in the database, the sampling methods used to collect the data, how the data is collected, and the activities performed to preserve the quality of the data. It also discusses how the Mexican database is divided into seven datasets. Section 4.2.1 explains the variables that are used and the variables that are created or transformed. It also reports the difficulties that emerge as the data is prepared for the model used in this study. Section 4.2.2 specifies the two step estimation procedure of the censored demand system proposed in Section 3.4. Then, Section 4.2.3 explains and provides examples of the importance of analyzing ENIGH 2006 as a stratified sampling. Finally, Section 4.2 illustrates the importance and some of the uses of the demand elasticities estimated in Section 4.2.2.

4.1 Data

The data used in the study depends on what is being estimated and analyzed. To estimate parameters and elasticities, Mexican data on household income and expenditures was obtained from *Encuesta Nacional de Ingresos y Gastos de los Hogares (ENIGH) (2006)*, which is a nation-wide survey encompassing Mexico's 31 states and the Federal District (a territory which belongs to all states). To illustrate the importance and use of the demand elasticity estimates, additional data was employed from the International Monetary Fund (IMF) and the Food and Agricultural Policy Research Institute (FAPRI).

ENIGH is a cross-sectional data sample and it is published by a Mexican governmental institution (*Instituto Nacional de Estadística, Geografía e Informática* (INEGI)). ENIGH is published since 1977 (e.g., see Heien, Jarvis, and Perali, 1989) and it is also available for the years 1984, 1989, 1992 (e.g., see Malaga, Pan, and Duch, 2007; 2006; Golan, Perloff, and Shen, 2001), 1994 (e.g., see Malaga, Pan, and Duch, 2007; 2006; Dong and Gould, 2000), 1996 (e.g., see Malaga, Pan, and Duch, 2007; 2006; García Vega and García, 2000), 1998 (e.g., see Malaga, Pan, and Duch, 2007; 2006; Dong, Shonkwiler, and Capps, 1998), 2000, 2002 (e.g., see Malaga, Pan, and Duch, 2007; 2006), 2004 (e.g., see Malaga, Pan, and Duch, 2007; 2006) and 2006 (e.g., see López, 2008). However, this study only uses the 2006 survey, which was conducted from August to November.

ENIGH nation-wide Mexican household survey contains information about house infrastructure, appliances and services as well as household members demographic and socio-demographic characteristics and occupational activities. The information from each survey is recorded into seven datasets (Concentrated, Households, Members, Income, Expenditures, Financial Transactions, and No Monetary Transactions). Appendix C provides a comparison of the number of observations in each dataset from 1984 to 2006 as well as a description of each dataset. In ENIGH 2006, the observation unit for the Concentrated, Households, Expenditures, and Financial Transactions datasets is the household, while the observation unit for the Members and Incomes datasets is the household member. For the No Monetary Transactions dataset the observation unit is the household or the household member. In particular, ENIGH 2006 contains information about household incomes, and quantities and prices of goods purchased.

It is important to analyze ENIGH as a stratified sample, which is different from a random sample. In stratified sampling the population is divided into subgroups (strata), which are often of interest to the investigator, and a simple random sample is taken from each stratum (Lohr, 1999, p. 24). According to ENIGH—*Síntesis Metodológica (2006)*, ENIGH's sampling methods are probabilistic, multi-staged, stratified, and conglomerated. According to *Encuesta Nacional sobre la Dinámica de las Relaciones en los Hogares (ENDIREH)— Síntesis Methodológica (2006)*, the sampling method is *probabilistic* because the sampling units have a probability of being selected, which is known and different from zero. Additionally, the sampling method is *multi-staged* because the sampling units are selected in multiple stages. It is *stratified* because the target population is divided into groups with similar characteristics, which form the strata. Finally, it is *conglomerated* because the sampling units (households) are made up from the observation units (household members). However, as mentioned before, for some datasets the observation unit is the household. For example, the Members dataset contains information on household members' age, gender, marital status, etc., but the Expenditures dataset only contains information on food expenditures for the household unit.

Results obtained from the survey can be generalized to the entire population (ENIGH—*Síntesis Metodológica, 2006*). ENIGH chooses households for interview and excludes from the analysis diplomatic foreign homes and homes maintained by companies for business-related purposes. Additionally, ENIGH is based on the international recommendations of the United Nations (UN) and the International Labour Organization (ILO). Furthermore, it is articulated to the Mexican governmental institutions and surveys accomplished by INEGI.

In order to collect the data, ENIGH performs direct interviews to each household during one week, usually from August to November (e.g., Appendix, Table C.1). The workforce is organized into interviewers, supervisors, and state project managers. Two instruments are used to collect the data: a questionnaire and a journal. The questionnaire is designed to collect the data concerning the house infrastructure, the members and their household identification, and members' socio-demographic characteristics. In addition, for household members older than 12 years old, the questionnaire will capture occupational activities and related characteristics as well as income and expenditures. On the other hand, the journal is designed to collect at-home and away-from-home expenditures on food, drinks, cigarettes and public transportation. During the first day of interview, expenditures on food, drinks, cigarettes and public transportation are recorded in the journal by the interviewer in order to train the interviewee. The journal remains with, and is filled by, the interviewee for the next six days of the week (INEGI, personal communication). Hence, data on food, drinks, cigarettes and public transportation is recorded in the Expenditure dataset (see Appendix, Table C.2) only when the household makes a purchase.[1] However, the interviewer will visit the household each day until the end of the week of interview in order to continue training the interviewee and make sure expenditures on food, drinks, cigarettes and public transportation are correctly being recorded by the interviewee in the journal (INEGI, personal communication). In the first day of interview, food that already belonged to the household, before the interviewer arrived, is recorded in the journal only if the food was acquired the day before the interviewer arrived (INEGI, personal communication). Finally, ENIGH does not record consumption transactions of "home-produced goods" when the households do not make a living by selling home-produced goods (INEGI, personal communication).

To assure the quality of the data during the collection period, the following supervising activities are performed: a) registering the questionnaire and journal by an id number, which contains the year, state, stage, consecutive number and type of home; b) controlling the number of homes in the framework; c) verifying the nonresponse; d) observing directly the interview and supervisor; and e) applying a re-interview questionnaire to completed interviews. After the data is collected, it is carefully entered into the database, which is then electronically validated. In case of omitted item observations, incomplete observations, errors or inconsistent information, the data is verified via phone or by returning to the collection field. When it is not possible to have a 100% response rate, a nonresponse rate is reported. In ENIGH 2006, there was a nonresponse rate of 10.55%.

Finally, to perform the forecasts and simulation analysis, additional data was obtained from the International Monetary Fund (2008), International Financial Statis-

[1]This way of collecting information generates the censoring problem of Section 2.3. Additionally, although ENIGH will not record meat cuts that the household did not buy during the week of the interview, if Section 2.5's terminology is used, there will be item nonresponse in some variables (e.g., price, quantity, expenditure, etc.), but it is possible to still recover other variables (e.g., the "expansion factor", stratum, household size, etc.).

tics (IFS) Online Database; FAPRI (2008); and FAPRI (2009b). Data on Mexican Gross Domestic Product (GDP), Mexican GDP deflator, Mexican population, exchange rate (pesos/dollar), and U.S. GDP deflator for the period 2006-2008 was obtained from International Monetary Fund (2008), IFS Online Database. Data on Mexican real GDP growth projection, Mexican population growth projection, Mexican nominal exchange rate growth projection, U.S. GDP deflator growth projection, and Mexican GDP deflator growth projection for the year 2007 and the period 2008-2018 was obtained from FAPRI (2008) and (2009b) respectively.

4.2 Two-Step Censored Demand System Estimation

4.2.1 Procedures

As explained in Section 2.4, adult equivalence scales are used to compute the number of adult equivalents per household by taking into account how much an individual household member of a given age and sex contributes to household expenditures or consumption of goods relative to a standard household member. This study computes the number of adult equivalents per household so that household meat consumptions can be comparable. For instance, meat consumption in different households cannot be directly compared without computing per capita meat consumption because a bigger households will naturally have a tendency to consume more meat than smaller households. Not adjusting meat consumption and expenditures by adult equivalents presents a problem when estimating quantity consumed (quantity demanded) as a function of prices and total expenditure. For example, suppose there is one household which purchases certain amount of beef, and a bigger household who not only pays a higher price but also purchases more beef.[2] If a comparison of these two households is made without adjusting by adult equivalents, a price and a quantity increase will be observed as we move from the first to the second household, which

[2]An alternative example is obtained if a household which purchases certain amount of beef is considered and it is compared to a smaller household who not only pays a lower price but also purchases less beef.

economically does not make much sense.[3] On the other hand, if it is adjusted by the number of adult equivalents (i.e., compute per adult-equivalent beef consumption) and a comparison of these two households is made (same example), a price increase will always be accompanied with a quantity decrease as long as the increase in household size is greater than the increase in the quantity of beef purchased.[4] In other words, adjusting by adult equivalents reduces the likelihood of the inconsistency that price increases are accompanied with quantity increases or that price decreases are accompanied with quantity decreases.

Therefore, this study uses the National Research Council's recommendations of the different food energy allowances for males and/or females during the life cycle as reported by Tedford, Capps, and Havlicek (1986) (Table 4.1) to obtain the number of adult equivalents and compute per capita meat consumption per household in kilograms per week (i.e., per adult-equivalent consumption per week) and per capita nominal meat expenditure variables in Mexican pesos (i.e., per adult-equivalent nominal meat expenditure per week). However, Table 4.1 assumes males and females have the same food energy standard. This is consistent with Gould and Villarreal's (2002) findings discussed in Section 2.4. Gould and Villarreal (2002) could not reject the null hypothesis that the female and male adult equivalent profiles are the same in Mexico. In addition, Section 2.4 discussed that similar findings have been found in other South American countries (e.g., Sabates, Gould, and Villarreal, 2001).

There are other ways to adjust for household size. However, computing the number of adult equivalents is preferred to ignoring (e.g., Malaga, Pan, and Duch, 2006; 2007) or using a simple count or proportion (e.g., Dong, Gould, and Kaiser, 2004; Golan, Perloff, and Shen, 2001) of household members. It is preferred because it reduces the number of parameters to be estimated and studies seem to indicate that there might

[3] Price increases should be accompanied with quantity decreases, assuming homogeneous households and *ceteris paribus*.

[4] For the alternative example of a smaller household who pays a lower price and also purchases less beef, it will be observed that a price decrease will always be accompanied with a quantity increase as long as the decrease in household size is greater than the decrease in quantity of beef purchased.

Table 4.1: National Research Council's Recommendations of Different Food Energy Allowances for Males and/or Females During the Life Cycle.

National Research Council (NRC) Food Energy Standard (FES)	
Age	FES
0-1	0.32
1-2	0.41
3-5	0.60
6-8	0.80
9-11	0.94
12-14	1.05
15-22	1.11
23-50	1.00
51-90	0.89

Source: Tedford, Capps, and Havlicek (1986, p. 324).

be gains in estimation efficiency.

This study also considers five regions and two urbanization variables to incorporate differences in meat consumption among regions and urbanization levels. The five regions considered in this study are the Northeast, Northwest, Central-West, Central, and Southeast region (NE, NW, CW, C, and SE respectively). The Northeast region of Mexico consists of the states of Chihuahua, Cohahuila de Zaragoza, Durango, Nuevo León, and Tamaulipas. The Northwest region of Mexico consists of the states of Baja California, Sonora, Baja California Sur, and Sinaloa. The Central-West region of Mexico consists of the states of Zacatecas, Nayarit, Aguascalientes, San Luis Potosí, Jalisco, Guanajuato, Querétaro Arteaga, Colima, and Michoacán de Ocampo. The Central region of Mexico consists of the states of Hidalgo, Estado de México, Tlaxcala, Morelos, and Puebla, and Distrito Federal. Finally, the Southeast region of Mexico consists of the states of Veracruz de Ignacio de la Llave, Yucatán, Quintana Roo, Campeche, Tabasco, Guerrero, Oaxaca, and Chiapas (see also Appendix, Figure C.5 and Figure C.6). These are the major geographical regions used in SIACON-SIAP-SAGARPA (2006), which is is the same governmental institution that performs

ENIGH.[5] As explained in Section 2.1, other Mexican meat demand studies have used from three to ten regions. Similarly, this study follows SIACON-SIAP-SAGARPA (2006) and uses their two definitions of urbanization variables. That is, stratum 1 and stratum 2 are the urban sector, and stratum 3 and stratum 4 are the rural sector. The urban households are located within a population of 15,000 people or more while the rural households are located within a population of 14,999 people or less (see also Appendix, Table C.3).

Another issue that arises in ENIGH (2006) is that of censored observations. For instance, this study consider eighteen table cuts of meats, which are beefsteak (beefsteak and milanesa); ground beef (hamburger patty and ground beef); other beef cuts (brisket, tore shank, rib cutlet, strips for grilling, meat for stewing/boiling, and meat cut with bone); beef offal (head, udder, heart, liver, marrow, rumen/belly, etc.); pork steak; pork leg and shoulder (chopped leg, middle leg, clear plate, Boston shoulder, and picnic shoulder); ground pork; other pork (pork chops, upper leg, spareribs, and smoked pork chops); chorizo (a pork sausage highly seasoned especially with chili powder and garlic); ham, bacon and similar products from beef and pork (ham, bologna, embedded pork, salami, and bacon); beef and pork sausages; other processed beef and pork (shredded meat, pork skin/chicharron, crushed and dried meats, stuffing, smoked/dried meat, etc.); chicken legs, thighs and breasts (with bone and boneless); whole chicken; chicken offal (wings, head, neck, gizzard, liver, etc.); chicken ham and similar products (chicken sausages, ham, nuggets, bologna, etc.); fish (whole catfish, whole carp, whole tilapia, fish fillet, tuna, salmon, codfish, smoked fish, dried fish, fish nuggets, sardines, young eel, manta ray, ell, fish/crustaceous eggs, etc.); and shellfish (fresh shrimp, clam, crab, oyster, octopus, and processed shrimp).[6] However, the way in which ENIGH records food consumption and the fact that households are

[5]SIACON-SIAP-SAGARPA (2006) used in their analysis ENIGH (2000), ENIGH (2002) and ENIGH (2004).

[6]Table C.7 in the Appendix also explains the eighteen table cuts of meats considered in this study.

interviewed for only one week have some data implications.

Censored observations are produced because ENIGH reports food consumption only when households make a purchase and because the collection period from each household is only one week. For example, from a total of $20,875$ households that participated in the survey, $3,966$ households did not consume any meat cut at all during the week of the interview. In this study, only households that are meat consumers are analyzed. Consequently, the 3,966 households that did not consume at least one meat (including at-home and away-from-home expenditures on meat) during the one week of interview, are not considered meat consumers. Therefore, meat consumers are those households that consume at least one meat cut per week (at home or away from home) during the week of interview. That is, if none of the household members (average household size is 4.14 members per household) consumed at least one meat cut during one week (at home or away from home), the household is not a meat consumer.

There are two sources of data censoring in ENIGH 2006. First, censoring occurs because some households that participated in the survey did not consume any meat cut at all during the week of interview as explained in the previous paragraph (i.e., 3,966 households). Second, censoring occurs because some households did not purchase all meat cuts during the week of interview. Censoring generates a missing price and a zero quantity for the meat cuts that the households did not buy during the week of interview. Price is censored because for the meat cuts that the household did not buy during the week of interview, the price that households would have been willing to pay is not known. Quantity is censored because for the meat cuts that the households did not buy during the week of interview, it is not known whether the household did not have a chance to buy or if they never buy those meat cuts. Table 4.3 reports the average per capita consumption per week of the 18 meat cuts considered in this study when including and excluding the zero observations.

To solve the problem of censored quantities (i.e., observations with zero quantities) this study used a censored regression model. In particular, this study will incorporate estimation techniques from stratified sampling with the two-step estimation of a censored system of equations proposed by Shonkwiler and Yen (1999) and later illustrated by Su and Yen (2000). However, estimating standard errors of parameter estimates in complex surveys is different and more difficult than estimating standard errors of parameter estimates in simple random samples. Estimating them in the same manner is incorrect (Lohr, 1999, pp. 289–318 and 347–378). Consequently, this study will estimate them by using the nonparametric bootstrap procedure (see Cameron and Trivedi, 2005, p. 360 or SAS Institute Inc., 2008 or López, 2008, p. 108).

To solve the problem of censored prices (i.e., observations with missing prices), similar to Malaga, Pan, and Duch (2007; 2006), a regression imputation approach was adopted for each of the eighteen meat cuts considered in this study. In particular, non-missing prices of each meat cut was regressed as function of a constant, total income, dummy variables for the education level of the household decision maker, regional dummy variables, stratum dummy variables, the number of adult equivalent, a dummy variable for car, and a dummy variable for refrigerator.[7] When analyzing the Mexican meat market, it is not unusual to incorporate a dummy variable for refrigerator (e.g. Dong, Gould, and Kaiser, 2004; Gould and Villarreal, 2002; Gould et al., 2002; Sabates, Gould, and Villarreal, 2001; Dong and Gould, 2000). Finally, a price imputation approach is preferred over a substitution of the missing price with the corresponding simple average of non-missing prices within each Mexican state and strata (e.g., Golan, Perloff, and Shen, 2001, p. 545 and Dong, Shonkwiler, and Capps, 1998, p. 1099).[8]

Table 4.2 shows the number of non-missing and missing observations, as well as the average prices in 2006 Mexican pesos per kilogram (pesos/kg) of the eighteen

[7]Each regression used the SURVEYREG procedure and incorporated the variables strata and weight as documented in SAS Institute Inc. (2004, pp. 4363–4418).

[8]If you adopt the latter procedure, using four strata and Mexico's 31 states plus the Federal District will only provide 128 different values for price imputation and using two strata will only provide 64 different values.

meat cuts considered in this study before and after price imputation.[9] The mean before price imputation uses only non-missing observations to compute the average while mean after price imputation uses both non-missing and imputed (originally missing) observations. Finally, the high number of censored observations is common in household surveys where meat is analyzed at the disaggregated level (see Taylor, Phaneuf, and Piggott, 2008) and even when meat is analyzed at the aggregated level (see López, 2008; Gould et al., 2002; Golan, Perloff, and Shen, 2001; Sabates, Gould, and Villarreal, 2001; Dong and Gould, 2000; Dong, Shonkwiler, and Capps, 1998; Heien, Jarvis, and Perali, 1989).

[9] Average prices also incorporate the variables strata and weight, and were computed using the SURVEYMEANS procedure (see SAS Institute Inc., 2004, pp. 4313–4362).

Table 4.2: Number of Non-Missing and Missing Observations and Average Prices.

p_i	Num. Non-Missing	Num. Missing	Before p_i Imputed Mean (Pesos/Kg)	Before p_i Imputed Std. Err. of Mean	After p_i Imputed Mean (Pesos/Kg)	After p_i Imputed Std. Err. of Mean
Beef						
p_1	6,348	10,561	61.3642	0.2572	60.8785	0.1059
p_2	2,938	13,971	55.6279	0.4059	56.2014	0.0780
p_3	2,795	14,114	52.0036	0.6439	51.4183	0.1199
p_4	734	16,175	36.8413	1.0864	35.8138	0.1046
Pork						
p_5	892	16,017	50.3311	0.6043	50.3466	0.0417
p_6	1,506	15,403	47.0965	0.5020	46.9521	0.0519
p_7	366	16,543	48.6391	0.9688	47.9718	0.0515
p_8	2,168	14,741	46.8656	0.5416	46.7112	0.0816
Processed Beef & Pork						
p_9	3,175	13,734	50.7869	0.9072	51.2935	0.1824
p_{10}	4,156	12,753	50.5261	0.4528	48.7871	0.1385
p_{11}	2,384	14,525	31.2680	0.5327	31.4529	0.0849
p_{12}	2,626	14,283	72.5129	1.1257	73.8783	0.2174
Chicken						
p_{13}	5,057	11,852	35.2406	0.2458	34.6859	0.0969
p_{14}	5,716	11,193	28.5982	0.2876	28.1278	0.0953
p_{15}	760	16,149	22.4321	0.8949	24.8824	0.0924
Processed Chicken						
p_{16}	2,593	14,316	46.7430	0.5581	46.0728	0.1000
Seafood						
p_{17}	3,970	12,939	48.7240	0.5964	47.9096	0.1596
p_{18}	713	16,196	81.5472	2.2547	87.1642	0.1806

Note: p_i, $i = 1, 2, \ldots, 18$, where 1 = Beefsteak, 2 = Ground Beef, 3 = Other Beef, 4 = Beef Offal, 5 = Pork Steak, 6 = Pork Leg & Shoulder, 7 = Ground Pork, 8 = Other Pork, 9 = Chorizo, 10 = Ham, Bacon & Similar Products from Beef & Pork, 11 = Beef & Pork Sausages, 12 = Other Processed Beef & Pork, 13 = Chicken Legs, Thighs & Breasts, 14 = Whole Chicken, 15 = Chicken Offal, 16 = Chicken Ham & Similar Products, 17 = Fish, 18 = Shellfish. Average exchange rate in 2006 is U.S. \$1 = 10.90 Pesos (Banco de México, 2008).

Source: ENIGH 2006 Database, computed by author.

Table 4.3: Per Capita Consumption of Meat Cuts Per Week.

q_i	Num. of Non-Zero Obs.	Num. of Zero Obs.	Excluding Zero Obs. Mean (Kg/Cap.)	Excluding Zero Obs. Std. Err. of Mean	Including Zero Obs. Mean (Kg/Cap.)	Including Zero Obs. Std. Err. of Mean
			Beef			
q_1	6,348	10,561	0.2689	0.0040	0.1078	0.0022
q_2	2,938	13,971	0.2089	0.0052	0.0369	0.0012
q_3	2,795	14,114	0.3170	0.0093	0.0562	0.0020
q_4	734	16,175	0.3249	0.0168	0.0151	0.0011
			Pork			
q_5	892	16,017	0.2231	0.0095	0.0109	0.0007
q_6	1,506	15,403	0.2699	0.0083	0.0205	0.0519
q_7	366	16,543	0.1755	0.0090	0.0038	0.0003
q_8	2,168	14,741	0.2839	0.0240	0.0388	0.0035
			Processed Beef & Pork			
q_9	3,175	13,734	0.1265	0.0038	0.0239	0.0009
q_{10}	4,156	12,753	0.1340	0.0031	0.0352	0.0017
q_{11}	2,384	14,525	0.1787	0.0050	0.0264	0.0010
q_{12}	2,626	14,283	0.1363	0.0048	0.0221	0.0010
			Chicken			
q_{13}	5,057	11,852	0.4100	0.0065	0.1458	0.0032
q_{14}	5,716	11,193	0.4480	0.0073	0.1403	0.0032
q_{15}	760	16,149	0.4719	0.0563	0.0251	0.0035
			Processed Chicken			
q_{16}	2,593	14,316	0.1969	0.0056	0.0293	0.0011
			Seafood			
q_{17}	3,970	12,939	0.2762	0.0075	0.0676	0.0023
q_{18}	713	16,196	0.2783	0.0169	0.0113	0.0009

Note: q_i, $i = 1, 2, \ldots, 18$, where 1 = Beefsteak, 2 = Ground Beef, 3 = Other Beef, 4 = Beef Offal, 5 = Pork Steak, 6 = Pork Leg & Shoulder, 7 = Ground Pork, 8 = Other Pork, 9 = Chorizo, 10 = Ham, Bacon & Similar Products from Beef & Pork, 11 = Beef & Pork Sausages, 12 = Other Processed Beef & Pork, 13 = Chicken Legs, Thighs & Breasts, 14 = Whole Chicken, 15 = Chicken Offal, 16 = Chicken Ham & Similar Products, 17 = Fish, 18 = Shellfish.

Source: ENIGH 2006 Database, computed by author.

4.2.2 Model Specification

As explained in Section 3.4, this study uses the two-step estimation of a censored demand system proposed by Shonkwiler and Yen (1999), but incorporates stratification variables into the estimation procedure. Interest lies in estimating a censored system of eighteen equations ($M = 18$), where 1 = beefsteak, 2 = ground beef, ... , 18 = shellfish. Each equation contains $K_1 + K_2 = 25 + 25 = 50$ regression coefficients and a data sample of $T = 16,909$ observations for each equation.

The i^{th} equation of the t^{th} household, in the censored system, can be written as (see Section 3.4)

$$q_i(t) = \Phi[\mathbf{z}_i'(t)\boldsymbol{\alpha}_i]\mathbf{x}_i'(t)\boldsymbol{\beta}_i + \delta_i\phi[\mathbf{z}_i'(t)\boldsymbol{\alpha}_i] + \xi_i(t), \quad i = 1, \ldots, 18, \tag{4.1}$$

where $q_i(t)$ is a (1×1) observed dependent variable; $\Phi[\mathbf{z}_i'(t)\boldsymbol{\alpha}_i]$ is the standard normal cumulative distribution function (cdf) evaluated at $\mathbf{z}_i'(t)\boldsymbol{\alpha}_i$, which is a (1×1) scalar; $\phi[\mathbf{z}_i(t)'\boldsymbol{\alpha}_i]$ is the standard normal probability density function (pdf) evaluated at $\mathbf{z}_i'(t)\boldsymbol{\alpha}_i$, which is a (1×1) scalar;

$$\begin{aligned} \mathbf{z}_i'(t) &= \begin{pmatrix} 1 & z_{i2}(t) & \ldots & z_{iK_1}(t) \end{pmatrix} \\ &= \begin{pmatrix} 1 & p_1(t) & \ldots & p_{18}(t) & m(t) & NE(t) & NW(t) & CW(t) & C(t) & urban(t) \end{pmatrix} \end{aligned}$$

is $(1 \times K_1) = (1 \times 25)$ vector of explanatory variables;

$$\begin{aligned} \mathbf{x}_i'(t) &= \begin{pmatrix} 1 & x_{i2}(t) & \ldots & x_{iK_2}(t) \end{pmatrix} \\ &= \begin{pmatrix} 1 & p_1(t) & \ldots & p_{18}(t) & m(t) & NE(t) & NW(t) & CW(t) & C(t) & urban(t) \end{pmatrix} \end{aligned}$$

is $(1\times K_2) = (1\times 25)$ vector of explanatory variables; $\boldsymbol{\alpha}_i = (\ \alpha_{i1} \quad \alpha_{i2} \quad \ldots \quad \alpha_{iK_1}\ )'$ is a $(K_1 \times 1) = (25 \times 1)$ vector of parameters; $\boldsymbol{\beta}_i = (\ \beta_{i1} \quad \beta_{i2} \quad \ldots \quad \beta_{iK_2}\ )'$ is a $(K_2 \times 1)$ $= (25\times 1)$ vector of parameters; and $\xi_i(t)$ is a (1×1) random error. More specifically, $q_1(t)$, $q_2(t)$, ... , $q_{18}(t)$ are (1×1) observations on per capita consumption in kilograms (kg) of beefsteak, ground beef, ... , and shellfish respectively; $p_1(t)$, $p_2(t)$, ... , $p_{18}(t)$ are (1×1) observations on the nominal price in Mexican pesos per kilogram (nominal pesos/kg) of beefsteak, ground beef, ... , and shellfish respectively; $m(t)$ is a (1×1)

observation on total per capita expenditure on all meat cuts (beefsteak, ground beef, . . . , and shellfish) in Mexican pesos (nominal pesos); NE(t), NW(t), CW(t), C(t), and SE(t) are (1×1) observations from regional dummy (or zero-one) variables taking the value of "1" if the observation belongs to the Northeast, Northwest, Central-West, Central or Southeast region respectively, "0" otherwise; and *urban*(t) and *rural*(t) are (1×1) observations from urbanization level dummy variables, which take the value of "1" if the observation belong to the urban or rural sector respectively, "0" otherwise. Additionally, notice that the baseline is the rural population of the Southeast region. In other words, the omitted observations are SE(t) and *rural*(t). This is necessary to avoid perfect multicollinearity. That is, the SE(t) and *rural*(t) observations are omitted in order to avoid a perfect linear relation between the observations NE(t), NW(t), CW(t), C(t), SE(t) and the scalar 1, which corresponds to the intercept. Similarly, the vector *rural*(t) is omitted in order to avoid a perfect linear relation between the observations *urban*(t), *rural*(t) and the scalar 1, which corresponds to the intercept. In addition, note that $\mathbf{z}_i(t) = \mathbf{z}_j(t) = \mathbf{x}_i(t) = \mathbf{x}_j(t)$ for all $i, j = 1, 2, \ldots, 18$. Finally, Table 4.4 provides a description of the dependent and independent variables used in the estimation of the censored demand system.

Table 4.4: Variables Used in the Censored Demand System Estimation.

Variable	**Description**
q_i	Per adult-equivalent consumption in kilograms (kg) per week of meat cut i, $i = 1, 2, \ldots, 18$, where 1 = beefsteak, 2 = ground beef, 3 = other beef, 4 = beef offal, 5 = pork steak, 6 = pork leg and shoulder, 7 = ground pork, 8 = other pork, 9 = chorizo, 10 = ham, bacon and similar products from beef and pork, 11 = beef and pork sausages, 12 = other processed beef and pork, 13 = chicken legs, thighs and breasts, 14 = whole chicken, 15 = chicken offal, 16 = chicken ham and similar products, 17 = fish, and 18 = shellfish.
p_i	Nominal price in Mexican pesos per kilogram (nominal pesos/kg) of meat cut i, $i = 1, 2, \ldots, 18$, where 1 = beefsteak, 2 = ground beef, 3 = other beef, 4 = beef offal, 5 = pork steak, 6 = pork leg and shoulder, 7 = ground pork, 8 = other pork, 9 = chorizo, 10 = ham, bacon and similar products from beef and pork, 11 = beef and pork sausages, 12 = other processed beef and pork, 13 = chicken legs, thighs and breasts, 14 = whole chicken, 15 = chicken offal, 16 = chicken ham and similar products, 17 = fish, and 18 = shellfish.
m	Per adult-equivalent expenditure in Mexican pesos (nominal pesos) per week.
urban	Dummy variable for urban households. This variable equals “1” if household location is within a population of 15,000 people or more, and “0” otherwise.
rural	Dummy variable for rural households. This variable equals “1” if household location is within a population of 14,999 people or less, and “0” otherwise.
NE	Dummy variable for the Northeast region of Mexico. This variable equals “1” if the observation belongs to the Northeast region, “0” otherwise. This region consists of the states of Chihuahua, Cohahuila de Zaragoza, Durango, Nuevo León, and Tamaulipas.
NW	Dummy variable for the Northwest region of Mexico. This variable equals “1” if the observation belongs to the Northwest region, “0” otherwise. This region consists of the states of Baja California, Sonora, Baja California Sur, and Sinaloa.
CW	Dummy variable for the Central-West region of Mexico. This variable equals “1” if the observation belongs to the Central-West region, “0” otherwise. This region consists of the states of Zacatecas, Nayarit, Aguascalientes, San Luis Potosí, Jalisco, Guanajuato, Querétaro Arteaga, Colima, and Michoacán de Ocampo.

continued on next page ⇒

Table 4.4: *Continued*

Variable	**Description**
C	Dummy variable for the Central region of Mexico. This variable equals "1" if the observation belongs to the Central region, "0" otherwise. This region consists of the states of Hidalgo, Estado de México, Tlaxcala, Morelos, Puebla, and Distrito Federal.
SE	Dummy variable for the Southeast region of Mexico. This variable equals "1" if the observation belongs to the Southeast region, "0" otherwise. This region consists of the states of Veracruz de Ignacio de la Llave, Yucatán, Quintana Roo, Campeche, Tabasco, Guerrero, Oaxaca, and Chiapas.
wgt	Sampling weight variable. That is, the number of households that the interviewed household represents nationally.
str	Stratum variable. This variable equals "1" if household location is within a population of 100,000 people or more, "2" if household location is within a population between 15,000 and 99,999 people, "3" if household location is within a population between 2,500 people and 14,999 people, and "4" if household location is within a population of less than 2,500 people.

Now, expanding Equation (4.1) gives

$$
\begin{aligned}
\underset{(1\times 1)}{q_i(t)} &= \Phi\left(\begin{pmatrix} 1 & p_1(t) & \ldots & p_{18}(t) & m(t) & NE(t) & NW(t) & CW(t) & C(t) & urban(t) \end{pmatrix}_{(1\times 25)} \begin{pmatrix} \alpha_{i1} \\ \alpha_{i2} \\ \vdots \\ \alpha_{i25} \end{pmatrix}_{(25\times 1)}\right) \\
&\quad \times \begin{pmatrix} 1 & p_1(t) & \ldots & p_{18}(t) & m(t) & NE(t) & NW(t) & CW(t) & C(t) & urban(t) \end{pmatrix}_{(1\times 25)} \begin{pmatrix} \beta_{i1} \\ \beta_{i2} \\ \vdots \\ \beta_{i25} \end{pmatrix}_{(25\times 1)} \\
&\quad +\delta_i \;\phi\left(\begin{pmatrix} 1 & p_1(t) & \ldots & p_{18}(t) & m(t) & NE(t) & NW(t) & CW(t) & C(t) & urban(t) \end{pmatrix}_{(1\times 25)} \begin{pmatrix} \alpha_{i1} \\ \alpha_{i2} \\ \vdots \\ \alpha_{i25} \end{pmatrix}_{(25\times 1)}\right) \\
&\quad + \underset{(1\times 1)}{\xi_i}, \\
&= \Phi[\alpha_{i1} + \alpha_{i2}p_1(t) + \ldots + \alpha_{i19}p_{18}(t) + \alpha_{i20}m(t) + \alpha_{i21}NE(t) + \alpha_{i22}NW(t) + \alpha_{i23}CW(t) + \alpha_{i24}C(t) + \alpha_{i25}urban(t)] \\
&\quad \times[\beta_{i1} + \beta_{i2}p_1(t) + \ldots + \beta_{i19}p_{18}(t) + \beta_{i20}m(t) + \beta_{i21}NE(t) + \beta_{i22}NW(t) + \beta_{i23}CW(t) + \beta_{i24}C(t) + \beta_{i25}urban(t)] \\
&\quad +\delta_i \;\phi[\alpha_{i1} + \alpha_{i2}p_1(t) + \ldots + \alpha_{i19}p_{18}(t) + \alpha_{i20}m(t) + \alpha_{i21}NE(t) + \alpha_{i22}NW(t) + \alpha_{i23}CW(t) + \alpha_{i24}C(t) + \alpha_{i25}urban(t)] \\
&\quad +\xi_i(t), \quad i = 1, \ldots, 18.
\end{aligned} \tag{4.2}
$$

Equation (4.2) is estimated in two steps. First, maximum-likelihood probit estimates $\hat{\boldsymbol{\alpha}}_i$ of $\boldsymbol{\alpha}_i$ for $i = 1, 2, \ldots, 18$ are obtained by using the binary dependent variable $d_i(t) = 1$ if $q_i(t) > 0$ and $d_i(t) = 0$ otherwise. That is, estimate the following probit models (Equation (3.7)) by maximum likelihood

$$
\begin{aligned}
(4.3)\quad & P[d_i(t) = 1|\mathbf{z}_i(t)] \\
& = \Phi\left[\alpha_{i1} + \alpha_{i2}p_1(t) + \ldots + \alpha_{i19}p_{18}(t) + \alpha_{i20}m(t) + \alpha_{i21}NE(t)\right. \\
& \quad \left. + \alpha_{i22}NW(t) + \alpha_{i23}CW(t) + \alpha_{i24}C(t) + \alpha_{i25}urban(t)\right] \\
& = \Phi[\mathbf{z}_i'(t)\boldsymbol{\alpha}_i], \quad i = 1, \ldots, 18.
\end{aligned}
$$

However, to incorporate the stratification variable *wgt* into the analysis, the estimation procedure multiplies "the contribution of each observation to the likelihood function... by the value of the weight variable" (see SAS Institute Inc., 2004, p. 3754).

Second, calculate $\Phi[\mathbf{z}_i'(t)\hat{\boldsymbol{\alpha}}_i]$ and $\phi[\mathbf{z}_i'(t)\hat{\boldsymbol{\alpha}}_i]$ and estimate $\boldsymbol{\beta}_1$, $\boldsymbol{\beta}_2$, ... , $\boldsymbol{\beta}_M$, δ_1, δ_2, ... , δ_M in the system,

$$
\begin{aligned}
(4.4)\quad q_i(t) &= \Phi\left[\hat{\alpha}_{i1} + \hat{\alpha}_{i2}p_1(t) + \ldots + \hat{\alpha}_{i19}p_{18}(t) + \hat{\alpha}_{i20}m(t) + \hat{\alpha}_{i21}NE(t)\right. \\
& \quad \left. + \hat{\alpha}_{i22}NW(t) + \hat{\alpha}_{i23}CW(t) + \hat{\alpha}_{i24}C(t) + \hat{\alpha}_{i25}urban(t)\right] \\
& \times \left[\beta_{i1} + \beta_{i2}p_1(t) + \ldots + \beta_{i19}p_{18}(t) + \beta_{i20}m(t) + \beta_{i21}NE(t)\right. \\
& \quad \left. + \beta_{i22}NW(t) + \beta_{i23}CW(t) + \beta_{i24}C(t) + \beta_{i25}urban(t)\right] \\
& + \delta_i \ \phi\left[\hat{\alpha}_{i1} + \hat{\alpha}_{i2}p_1(t) + \ldots + \hat{\alpha}_{i19}p_{18}(t) + \hat{\alpha}_{i20}m(t) + \hat{\alpha}_{i21}NE(t)\right. \\
& \quad \left. + \hat{\alpha}_{i22}NW(t) + \hat{\alpha}_{i23}CW(t) + \hat{\alpha}_{i24}C(t) + \hat{\alpha}_{i25}urban(t)\right] + \xi_i(t) \\
&= \Phi[\mathbf{z}_i'(t)\hat{\boldsymbol{\alpha}}_i]\mathbf{x}_i'(t)\boldsymbol{\beta}_i + \delta_i\phi[\mathbf{z}_i'(t)\hat{\boldsymbol{\alpha}}_i] + \xi_i(t), \quad i = 1, \ldots, 18,
\end{aligned}
$$

by seemingly unrelated regression (SUR) procedure.[10] Because in stratified samples the weighted estimator is consistent (Wooldridge, 2001, p. 464), all observations are weighted by the weight variable prior to estimation. "[If we] use weights w_i in the weighted least squares estimation, [we] will obtain the same point estimates...; however, in complex surveys, the standard errors and hypothesis tests the software

[10]For an applied review on seemingly unrelated regressions see López (2008).

provides will be incorrect and should be ignored" (Lohr, 1999, p. 355). Consequently, parameter estimates in this study need to be estimated by one of the procedures discussed in Section 2.6.4.4. This study applies the bootstrap procedure by using SAS software. As explained in Section 2.7, the bootstrap is a resampling method that can be used to estimate standard errors of parameter estimates when other estimation methods are inappropriate or not feasible. Finally, in the second step, the estimation of the system of censored demand equations needs to be based on the full system of $M = 18$ equations because the parametric restriction of adding-up is not imposed in the model (see also Yen, Kan, and Su, 2002, p. 1801).

To illustrate how Equation (4.4) can be estimated by SUR, the following additional vectors and matrices are defined:

$$\underset{(T\times 1)}{\mathbf{q}_i} = \begin{bmatrix} q_i(1) \\ q_i(2) \\ \vdots \\ q_i(T) \end{bmatrix}, \quad \underset{(T\times T)}{\mathbf{g}_i} = \begin{bmatrix} \Phi[\mathbf{z}_i'(1)\hat{\boldsymbol{\alpha}}_i] & 0 & \dots & 0 \\ 0 & \Phi[\mathbf{z}_i'(2)\hat{\boldsymbol{\alpha}}_i] & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \Phi[\mathbf{z}_i'(T)\hat{\boldsymbol{\alpha}}_i] \end{bmatrix},$$

$$\underset{(T\times K_2)}{\mathbf{X}_i} = \begin{bmatrix} \mathbf{x}_i'(1) \\ \mathbf{x}_i'(2) \\ \vdots \\ \mathbf{x}_i'(T) \end{bmatrix}, \quad \underset{(T\times 1)}{\mathbf{f}_i} = \begin{bmatrix} \phi[\mathbf{z}_i'(1)\hat{\boldsymbol{\alpha}}_i] \\ \phi[\mathbf{z}_i'(2)\hat{\boldsymbol{\alpha}}_i] \\ \vdots \\ \phi[\mathbf{z}_i'(T)\hat{\boldsymbol{\alpha}}_i] \end{bmatrix}, \quad \underset{(T\times 1)}{\boldsymbol{\xi}_i} = \begin{bmatrix} \xi_i(1) \\ \xi_i(2) \\ \vdots \\ \xi_i(T) \end{bmatrix}.$$

Therefore, Equation (4.1) is equivalent to

$$\text{(4.5)} \quad \mathbf{q}_i = \mathbf{g}_i\mathbf{X}_i\boldsymbol{\beta}_i + \delta_i\mathbf{f}_i + \boldsymbol{\xi}_i$$

or

$$\begin{bmatrix} q_i(1) \\ q_i(2) \\ \vdots \\ q_i(T) \end{bmatrix} = \begin{bmatrix} \Phi[\mathbf{z}_i'(1)\hat{\boldsymbol{\alpha}}_i] & 0 & \dots & 0 \\ 0 & \Phi[\mathbf{z}_i'(2)\hat{\boldsymbol{\alpha}}_i] & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \Phi[\mathbf{z}_i'(T)\hat{\boldsymbol{\alpha}}_i] \end{bmatrix} \begin{bmatrix} \mathbf{x}_i'(1) \\ \mathbf{x}_i'(2) \\ \vdots \\ \mathbf{x}_i'(T) \end{bmatrix} \begin{bmatrix} \beta_{i1} \\ \beta_{i2} \\ \vdots \\ \beta_{iK_2} \end{bmatrix}$$

$$+\delta_i \begin{bmatrix} \phi[\mathbf{z}_i'(1)\hat{\boldsymbol{\alpha}}_i] \\ \phi[\mathbf{z}_i'(2)\hat{\boldsymbol{\alpha}}_i] \\ \vdots \\ \phi[\mathbf{z}_i'(T)\hat{\boldsymbol{\alpha}}_i] \end{bmatrix} + \begin{bmatrix} \xi_i(1) \\ \xi_i(2) \\ \vdots \\ \xi_i(T) \end{bmatrix}$$

$$= \begin{bmatrix} \Phi[\mathbf{z}_i'(1)\hat{\boldsymbol{\alpha}}_i] & 0 & \dots & 0 \\ 0 & \Phi[\mathbf{z}_i'(2)\hat{\boldsymbol{\alpha}}_i] & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \Phi[\mathbf{z}_i'(T)\hat{\boldsymbol{\alpha}}_i] \end{bmatrix} \begin{bmatrix} \mathbf{x}_i'(1)\boldsymbol{\beta}_i \\ \mathbf{x}_i'(2)\boldsymbol{\beta}_i \\ \vdots \\ \mathbf{x}_i'(T)\boldsymbol{\beta}_i \end{bmatrix}$$

$$+\delta_i \begin{bmatrix} \phi[\mathbf{z}_i'(1)\hat{\boldsymbol{\alpha}}_i] \\ \phi[\mathbf{z}_i'(2)\hat{\boldsymbol{\alpha}}_i] \\ \vdots \\ \phi[\mathbf{z}_i'(T)\hat{\boldsymbol{\alpha}}_i] \end{bmatrix} + \begin{bmatrix} \xi_i(1) \\ \xi_i(2) \\ \vdots \\ \xi_i(T) \end{bmatrix}$$

$$= \begin{bmatrix} \Phi[\mathbf{z}_i'(1)\hat{\boldsymbol{\alpha}}_i]\mathbf{x}_i'(1)\boldsymbol{\beta}_i \\ \Phi[\mathbf{z}_i'(2)\hat{\boldsymbol{\alpha}}_i]\mathbf{x}_i'(2)\boldsymbol{\beta}_i \\ \vdots \\ \Phi[\mathbf{z}_i'(T)\hat{\boldsymbol{\alpha}}_i]\mathbf{x}_i'(T)\boldsymbol{\beta}_i \end{bmatrix} + \delta_i \begin{bmatrix} \phi[\mathbf{z}_i'(1)\hat{\boldsymbol{\alpha}}_i] \\ \phi[\mathbf{z}_i'(2)\hat{\boldsymbol{\alpha}}_i] \\ \vdots \\ \phi[\mathbf{z}_i'(T)\hat{\boldsymbol{\alpha}}_i] \end{bmatrix} + \begin{bmatrix} \xi_i(1) \\ \xi_i(2) \\ \vdots \\ \xi_i(T) \end{bmatrix}.$$

In addition, Equation (4.5) can be written as

$$\text{(4.6)} \qquad \underset{(T\times1)}{\mathbf{q}_i} = \begin{bmatrix} \underset{(T\times K_2)}{\mathbf{g}_i'\mathbf{X}_i} & \underset{(T\times1)}{\mathbf{f}_i} \end{bmatrix}_{(T\times(K_2+1))} \begin{bmatrix} \boldsymbol{\beta}_{i(K_2\times1)} \\ \delta_{i(1\times1)} \end{bmatrix}_{((K_2+1)\times1)} + \underset{(T\times1)}{\boldsymbol{\xi}_i}$$

$$= \underset{(T\times(K_2+1))}{\mathbb{X}_i} \; \underset{((K_2+1)\times1)}{\mathbb{B}_i} + \underset{(T\times1)}{\boldsymbol{\xi}_i}, \quad i = 1, \dots, M.$$

Therefore, using Equation (4.6), the system of $M = 18$ equations in Equation

(4.4) can be written into one model as

$$(4.7)\quad \begin{bmatrix} \mathbf{q}_1 \\ \mathbf{q}_2 \\ \vdots \\ \mathbf{q}_M \end{bmatrix} = \begin{bmatrix} \mathbb{X}_1 & 0 & \dots & 0 \\ 0 & \mathbb{X}_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \mathbb{X}_M \end{bmatrix} \begin{bmatrix} \mathbb{B}_1 \\ \mathbb{B}_2 \\ \vdots \\ \mathbb{B}_M \end{bmatrix} + \begin{bmatrix} \boldsymbol{\xi}_1 \\ \boldsymbol{\xi}_2 \\ \vdots \\ \boldsymbol{\xi}_M \end{bmatrix}$$

or

$$(4.8)\quad \underset{(MT\times 1)}{\mathbf{q}} = \underset{(MT\times \bar{M}(K_2+1))}{\mathbf{X}} \underset{(M(K_2+1)\times 1)}{\boldsymbol{\beta}} + \underset{(MT\times 1)}{\mathbf{u}}.$$

Then, applying the procedure explained by Zellner (1962) gives SUR estimates $\hat{\boldsymbol{\beta}}_i$ and $\hat{\delta}_i$ of $\boldsymbol{\beta}_i$ and δ_i respectively for $i = 1, 2, \dots, 18$.

Subsequently, the unconditional means of $q_i(t)$ (Equation (3.23)), $i = 1, 2, \dots, 18$, are estimated by

$$(4.9)\quad \hat{q}_i(t) = \Phi[\mathbf{z}_i'(t)\hat{\boldsymbol{\alpha}}_i]\mathbf{x}_i'(t)\hat{\boldsymbol{\beta}}_i + \hat{\delta}_i\phi[\mathbf{z}_i'(t)\hat{\boldsymbol{\alpha}}_i], \quad i = 1, \dots, 18.$$

Then, uncompensated or Marshallian price elasticities, meat expenditure elasticities, and artificial elasticities for binary variables are approximated by

$$(4.10)\quad \hat{e}_{i(j-1)}(t) = \Big[\Phi(\mathbf{z}_i'(t)\hat{\boldsymbol{\alpha}}_i)\hat{\beta}_{ij} + \mathbf{x}_i'(t)\hat{\boldsymbol{\beta}}_i\phi(\mathbf{z}_i'(t)\hat{\boldsymbol{\alpha}}_i)\hat{\alpha}_{ij} - \hat{\delta}_i(\mathbf{z}_i'(t)\hat{\boldsymbol{\alpha}}_i)\phi(\mathbf{z}_i'(t)\hat{\boldsymbol{\alpha}}_i)\hat{\alpha}_{ij}\Big] \times \frac{x_{ij}(t)}{\hat{q}_i(t)}, \quad i = 1, \dots, 18, \quad j = 2, \dots, 19,$$

$$(4.11)\quad \hat{e}_i(t) = \Big[\Phi(\mathbf{z}_i'(t)\hat{\boldsymbol{\alpha}}_i)\hat{\beta}_{ij} + \mathbf{x}_i'(t)\hat{\boldsymbol{\beta}}_i\phi(\mathbf{z}_i'(t)\hat{\boldsymbol{\alpha}}_i)\hat{\alpha}_{ij} - \hat{\delta}_i(\mathbf{z}_i'(t)\hat{\boldsymbol{\alpha}}_i)\phi(\mathbf{z}_i'(t)\hat{\boldsymbol{\alpha}}_i)\hat{\alpha}_{ij}\Big] \times \frac{x_{ij}(t)}{\hat{q}_i(t)}, \quad i = 1, \dots, 18, \quad j = 20,$$

$$(4.12)\quad \hat{e}_{ij}(t) = \Big[\Phi(\mathbf{z}_i'(t)\hat{\boldsymbol{\alpha}}_i)\hat{\beta}_{ij} + \mathbf{x}_i'(t)\hat{\boldsymbol{\beta}}_i\phi(\mathbf{z}_i'(t)\hat{\boldsymbol{\alpha}}_i)\hat{\alpha}_{ij} - \hat{\delta}_i(\mathbf{z}_i'(t)\hat{\boldsymbol{\alpha}}_i)\phi(\mathbf{z}_i'(t)\hat{\boldsymbol{\alpha}}_i)\hat{\alpha}_{ij}\Big] \times \frac{x_{ij}(t)}{\hat{q}_i(t)}, \quad i = 1, \dots, 18, \quad j = 21, \dots, 25.$$

Finally, the compensated or Hicksian price elasticities are computed from

$$(4.13)\quad \hat{e}^c_{i(j-1)}(t) = \hat{e}_{ij}(t) + \hat{e}_i(t)\left(\frac{p_j(t)\,\hat{q}_j(t)}{m(t)}\right), \quad i = 1, \dots, 18, \quad j = 2, \dots, 19.$$

Of course, these elasticities need to be evaluated using sample means of explanatory variables.[11] However, the elasticity of commodity i with respect to a demographic variable is "not strictly defined... [but] allow convenient assessment of the significance of corresponding variables in a complex functional relationship" (Su and Yen, 2000, p. 736).

The use of binary variables for the major Mexican regions and urbanization levels as well as the evaluation of sample means of explanatory variables in these corresponding regions and urbanization levels, allow this study to compute price and expenditure elasticities by region and urbanization level. In general, when demand parameters by region and urbanization level are estimated in this way, it is assumed that regional and urbanization factors shift the demand of the i^{th} meat cut in a parallel fashion. That is, it is assumed regional and urbanization-level differences in consumption of the i^{th} meat cut can be appropriately modeled by parallel shifts of the demand equations.

Elasticities by region and urbanization level may also be obtained by estimating the model within each region and urbanization level or by creating new variables from interactions of continuous and binary explanatory variables. However, the latter procedure will significantly increase the number of parameters to be estimated because this study considers nineteen continuous explanatory variables and five binary explanatory variables (seven if including the omitted regional and urbanization-level variables). The large number of interaction variables may also decrease the number of parameters per equation that are statistically different from zero. Therefore, the latter procedure is not adopted, but the model could be modified if such estimates are desired. More importantly, the study presents an efficient way for identifying current and future trends in regional meat consumption at the table cut level of disaggregation, and it is an excellent reference for future comparisons.

[11] Since the data sample used in this study (ENIGH) is a stratified sample, means of explanatory variables are computed incorporating the variables strata and weight (see SAS Institute Inc., 2004, pp. 4313–4362).

4.2.3 Stratified Sampling

It is important to analyze ENIGH as a stratified sample, which is different from a random sample. In stratified sampling the population is divided into subgroups (strata), which are often of interest to the investigator, and a simple random sample is taken from each stratum (Lohr, 1999, p. 24). ENIGH is a survey of household incomes and expenditures. If ENIGH applies a stratified sampling technique is probably because they think households in the same stratum tend to be more similar than randomly selected elements from the whole population. Consequently, precision could be increased by a using a stratified sample to analyze household expenditures (e.g., meat consumption). Furthermore, ENIGH recommends incorporating stratification variables when using its data (INEGI, personal communication).

Table 4.5 reports the number of observations, the sum of weights, and the average household size per each stratum in ENIGH 2006. Note that multiplying the sum of weights by the average household size will approximate the total population of Mexico that consumed meat during the week of interview. This number is less than the population of Mexico, which in 2006 was about 105 million (International Monetary Fund, 2008, IFS Online Database), because not all households reported consumption of at least one meat cut during the week of interview.

Table 4.5: Observation Numbers, Sum of Weights and Household Sizes Per Stratum.

Strata	No. of Obs.	Sum of Weights	Avg. hhsize
Str1	7,285	11,473,327	3.99
Str2	3,942	3,241,161	4.13
Str3	1,574	2,837,679	4.52
Str4	4,108	4,554,086	4.28
Total	16,909	22,106,253	4.14

Source: ENIGH 2006 Database, computed by author.

Previous studies on Mexican meat demand (Malaga, Pan, and Duch, 2007; 2006; Dong, Gould, and Kaiser, 2004; Gould and Villarreal, 2002; Gould et al., 2002; Golan, Perloff, and Shen, 2001; Sabates, Gould, and Villarreal, 2001; García Vega and García, 2000; Heien, Jarvis, and Perali, 1989), which have used the same data source (ENIGH), have neither taken into account the fact that the sample is stratified nor provided an explanation about excluding stratification variables. Ignoring stratification variables (e.g., weight and strata) results in parameter estimates that may not be representative of the population or that may not capture potential differences among the subpopulations (Lohr, 1999, pp. 221–254). For example, not incorporating from ENIGH 2006 the variable weight into the analysis is equivalent to assigning a constant weight of 1,307.37 (i.e., 22,106,253/16,909) to each observation (see Table 4.5); therefore, assuming each household member represents the same number of households nationally. Figure 4.1, which depicts a histogram of the weight variable for each stratum from ENIGH 2006, shows this is clearly not the case. Additionally, taking a random sample of 1,000 households from the 16,909 households and not incorporating the weight variable (e.g., see Golan, Perloff, and Shen, 2001) will only produce a sample that is representative of the 16,909 households assuming a constant weight, which is incorrect.

There are also studies (Malaga, Pan, and Duch, 2007; 2006; Dong, Gould, and Kaiser, 2004) who have restricted their analysis to only strata 1 and 2 (i.e., households that live in cities or towns with a population of 15,000 or more), which in ENIGH 2006 is equivalent to excluding 7,391,765 households of the target population (Table 4.5). They claimed they had to ignore strata 3 and 4 (i.e., households that live in cities or towns with a population of 14,999 or less) because of the problem of assigning a dollar value (i.e., a price) to the meat produced at home. In other words, to avoid the problem of "valuation of home-produced goods" (Dong, Gould, and Kaiser, 2004, p. 1099). However, ENIGH does not record consumption transactions of home-produced goods when the households do not make a living by selling home-produced goods (INEGI, personal communication). In addition, Malaga, Pan, and Duch (2007; 2006) and Dong, Gould, and Kaiser (2004) did not have an indicator in the data to demonstrate how many rural households who produced meat at home were not included in data. That is, they excluded a segment of the population based on their belief that many people from strata 3 and 4 consume meat produced at home. However, the urban sector has, as well, a chance of consuming home-produced goods. The fact that a household lives in an urban or rural location does not eliminate the possibility of consuming home-produced goods. To avoid complications of this matter, this study will not exclude any segment of the population.

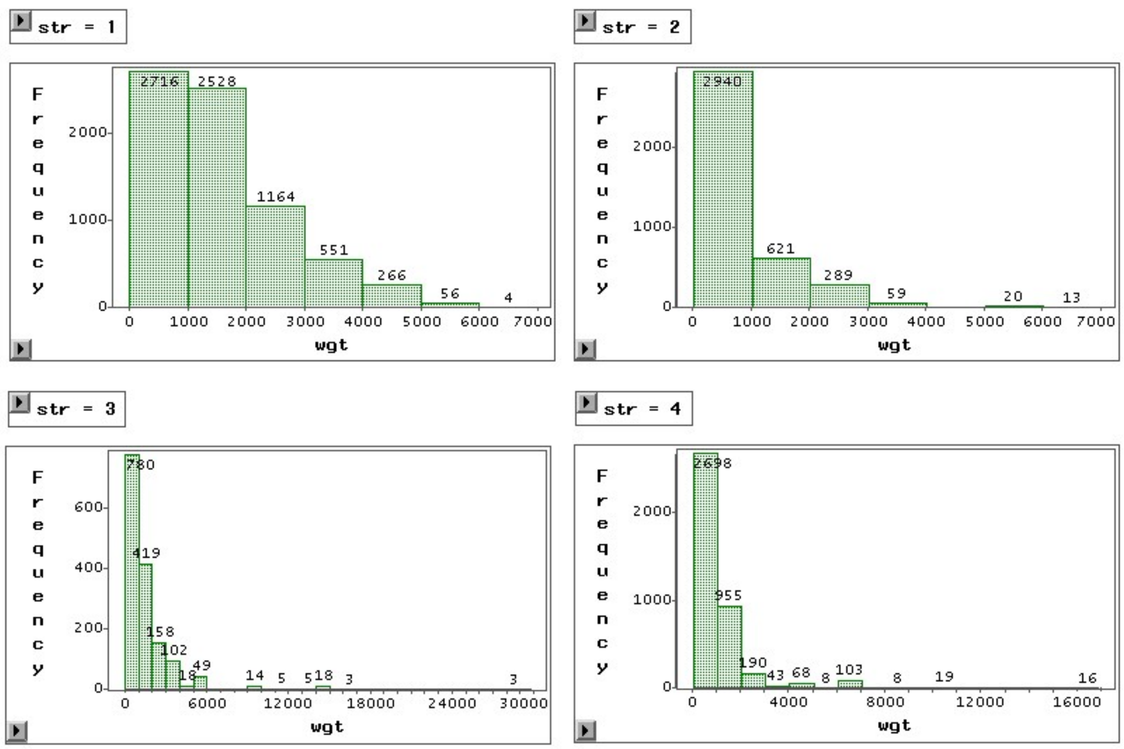

Figure 4.1: Histogram of the Survey Weight Variable Per Stratum.
Source: ENIGH 2006 Database, computed by author.

To investigate further about the importance of incorporating stratification variables into the analysis, DuMouchel and Duncan's (1983) test, which was explained in Section 2.6.4.1, was applied to each of the eighteen cuts considered in this study (after price imputation). That is, eighteen tests were performed (one test at a time) using as dependent variables q_i, and as independent variables a constant, p_1, p_2, ... , p_{18}, m, *NE*, *NW*, *CW*, *C*, and *urban*. Table 4.6 shows the F test statistic and corresponding p-value for each of the eighteen tests. The critical F values at the 0.01 and

0.05 significance levels are also presented. At the 0.05 significance level, sixteen out of eighteen tests reject the null hypothesis of using the simple linear homoscedastic model. Similarly, at the 0.10 significance level, seventeen out of eighteen tests reject the null hypothesis in favor of the alternative hypothesis of using the weighted least squares estimator. The stratification variable wgt is said to be informative, and it is critical to treat ENIGH as a stratified sample (instead of a simple random sample).

Consequently, one of the advantages of this study is that, besides using a consistent two-step estimation procedure of a censored demand system, the study incorporates estimation techniques from stratified sampling theory into the analysis. For instance, it incorporates stratification variables (strata and weight) in data preparation, in each of the two-step estimation procedure, and in computing standard errors.

Table 4.6: DuMouchel and Duncan's (1983) Test Results.

Equation	F	p-value
q_1	1.7907	0.0090
q_2	2.0893	0.0011
q_3	1.7377	0.0126
q_4	1.9422	0.0032
q_5	1.3806	0.0976
q_6	4.3003	<0.0001
q_7	3.0603	<0.0001
q_8	1.7962	0.0086
q_9	1.7718	0.0101
q_{10}	4.4449	<0.0001
q_{11}	1.6708	0.0191
q_{12}	8.3251	<0.0001
q_{13}	2.4402	0.0001
q_{14}	9.2035	<0.0001
q_{15}	7.3924	<0.0001
q_{16}	1.9762	0.0026
q_{17}	1.1127	0.3166
q_{18}	3.7224	<0.0001
Critical Values		
$F^*_{25;16,884}(0.01) = 1.77$		
$F^*_{25;16,884}(0.05) = 1.52$		

4.3 Forecast and Simulation Analysis

Once elasticities are evaluated using sample means of explanatory variables, as explained in Section 4.2.2, they can be used to perform forecasts and a simulation analysis. However, to provide a better estimate of the effect of real per household income on Mexican meat consumption and imports, expenditure elasticities are transformed into income elasticities as follows

$$\hat{\eta}_i(t) = \hat{e}_i(t)\frac{\partial m(t)}{\partial inc(t)}\frac{inc(t)}{m(t)}. \tag{4.14}$$

To estimate $\frac{\partial m(t)}{\partial inc(t)}$, this study regressed total per capita expenditure per week on a constant and total household income per week. This regression incorporated stratification variables (weight and strata) into the estimation procedure (see SAS Institute Inc., 2004, pp. 4363–4418).

The income elasticities combined with the Mexican per household real gross domestic product (GDP) growth projection allows to forecast the Mexican per capita consumption by meat cut. Then, the per capita consumption of meat cut i, combined with the Mexican population projection allow to forecast the total Mexican consumption by meat cut. Per household real GDP growth projection is the percentage change in per household real GDP from the previous year, $\frac{\nabla GDP(t)}{GDP(t-1)}$. Per household real GDP was obtained by multiplying household size by per capita real GDP. Per capita real GDP is real GDP divided by population. Real GDP and population are projected using FAPRI real GDP growth projection and FAPRI population growth projection. That is, Mexican per capita consumption of meat cut i is projected by

$$q_i(t+1) = q_i(t) + \eta_i\frac{\nabla GDP(t)}{GDP(t-1)}q_i(t) = q_i(t)\left(1 + \eta_i\frac{\nabla GDP(t)}{GDP(t-1)}\right), \tag{4.15}$$

where $q_i(t)$ is the per capita consumption of meat cut i, $GDP(t)$ is per household real GDP, t represents the year, and ∇ is the lag-1 difference operator (i.e., $\nabla GDP(t) = GDP(t) - GDP(t-1)$). To forecast beef, pork, and chicken, the projection of the corresponding meat cuts is aggregated.

Similarly, the income and the Marshallian own-price elasticities combined with the Mexican per household real GDP growth projection and the real exchange rate growth projection allow to forecast total Mexican imports by meat cut. The real exchange rate growth projection is the percentage change in the real exchange rate (RER) from the previous year. The RER (pesos/dollar) equals the nominal exchange rate (NER), in pesos/dollar, divided by the ratio of the GDP deflator in Mexico ($GDPD^{MEX}$) and the GDP deflator in the United States ($GDPD^{US}$), $RER = \frac{NER}{\frac{GDPD^{MEX}}{GDPD^{US}}}$. The GDPD in Mexico and in the United States are projected by using FAPRI GDPD growth projections. Finally, the NER is also projected by using FAPRI NER growth projection. That is, Mexican imports of meat cut i are projected by

$$
\begin{aligned}
(4.16)\quad q_i(t+1) &= q_i(t) + \eta_i \frac{\nabla GDP(t)}{GDP(t-1)} q_i(t) + e_{ij} \frac{\nabla RER(t)}{RER(t-1)} q_i(t) \\
&= q_i(t) \left(1 + \eta_i \frac{\nabla GDP(t)}{GDP(t-1)} + e_{ij} \frac{\nabla RER(t)}{RER(t-1)} \right), \quad i = j,
\end{aligned}
$$

where $RER(t)$ is the real exchange rate (pesos/dollar). Similar to consumption aggregates, beef, pork, and chicken imports are obtained by adding the corresponding meat cuts in each category.

However, Mexican imports of beef and pork are currently not reported by meat cut.[12] Therefore, this study assumes the structure of the Mexican beef and pork consumption by meat cut is the same as the structure of the Mexican beef and pork imports by meat cut (i.e., assuming the import structure is the same as the consumption structure that is obtained from column six of Table 4.3). That is, of the total volume of Mexican beef imports in 2006, the study assumes that approximately 49.92% were beefsteak, 17.09% were ground beef, 26.01% were other beef, and 6.99% were beef offal. Similarly, of the total volume of Mexican pork imports in 2006, the study assumes that approximately 4.28% were pork steak, 78.95% were pork leg and shoulder, 1.49% were ground pork, and 15.28% were other pork. Even though this is a strong assumption that may not represent the current situation, this information is known by U.S. meat exporters. Consequently, the analysis of beef and pork im-

[12]The closest analysis that can be done using the harmonized system is presented in the Appendix, Table A.8 and Table A.9.

ports by meat cuts could be easily modified with the real structure to obtain an even more realistic scenario. In the case of chicken, however, it is possible to recover the import structure of three meat cuts used in this study. That is, of the total volume of Mexican chicken imports in 2006, approximately 82.41% are chicken legs, thighs and breast; 8.11% is whole chicken; and 9.48% is chicken offal (see Appendix, Table A.10).

Finally provided that these Mexican consumption and imports are computed from demand elasticities and FAPRI assumptions, it is implied that same Mexican meat production trend will continue. That is, any future unexpected Mexican increase in production is not incorporated in the analysis. If Mexican meat production drastically increases, Mexican meat trade may significantly decrease. Likewise, any future unanticipated trade barrier or incentive could similarly change trade and consumption.

CHAPTER V
RESULTS AND DISCUSSION

This chapter presents the demand parameter and elasticity estimates from the censored system of equations. Given that the censored demand system is estimated in two steps, Section 5.1.1 reports parameter estimates from the first step while Section 5.1.2 reports the estimates from the second step. More specifically, Section 5.1.1 provides maximum-likelihood parameter estimates from univariate probit models as well as their corresponding standard errors. It also contains the marginal effect of independent variables on the probability of consuming meat cut i. Section 5.1.2 presents the parameter estimates from the seemingly unrelated equations of the censored demand system. Parameter estimates and their corresponding standard errors are reported. The marginal effects of independent variables on the typical consumption of meat cut i are also approximated and presented. Section 5.1.3 uses the parameter estimates from Section 5.1.2 to compute elasticity estimates and contrast them with previous studies. Section 5.3 provides a comparison of the elasticity estimates of the major Mexican regions, which were obtained from the use of regional dummy variables and the evaluation of explanatory variables at their corresponding regional sample means. Selective empirical elasticity distributions are also presented. Finally, with the purpose of highlighting the importance and usefulness of demand elasticities, Section 5.2 projects and forecasts Mexican consumption and imports of table cuts of meats, and compares aggregate estimates with the predictions of another study.

5.1 Two-Step Censored Demand System Estimates

The results from the censored demand system are presented after the estimation of each step. First, maximum-likelihood probit estimates are presented. Then, the parameter estimates from the system of seemingly unrelated equations are reported.

5.1.1 Step 1 - Maximum-Likelihood Probit Parameter Estimates

Since ENIGH 2006 is a stratified sample, the survey *wgt* variable needs to be incorporated into the model (as explained in Section 3.4). Therefore, in the first step, when estimating univariate maximum-likelihood probit parameter estimates of $\boldsymbol{\alpha}_i$, $i = 1, 2, \ldots, M =$ beefsteak, ground beef, ... , shellfish, the contribution of each observation to the likelihood function is multiplied by the value of the weight variable.[1] Table 5.1 reports these univariate maximum-likelihood probit parameter estimates with their corresponding bootstrap standard errors. A description of each variable was provided in Table 4.4. Note that the excluded dummy variables from each equation are the Southeast region (*SE*) and the rural sector (*rural*).

From a total of 450 parameters estimated in the first step (25 parameters estimated at a time for 18 equations), 204, 157, and 137 parameters were statistically different from zero at the 0.20, 0.10, and 0.05 significance levels respectively. Considering only parameter estimates corresponding to binary variables, from a total of 90 parameters, 68, 59, and 51 were statistically different from zero at the 0.20, 0.10, and 0.05 significance levels respectively. These significant determinants of the probability of consuming meat cut i are stated in Table 5.1. For example, at the 20% significance level, the significant determinant of the probability of consuming beefsteak are the prices of pork steak; pork leg and shoulder; other pork; chicken ham and similar products; and shellfish; as well as total meat expenditure; Northeast region; Northwest region; Central-West region; Central region and urban sector. Similarly, the significant determinants of the probability of consuming pork steak are the prices of beef offal; ham, bacon and similar products from beef and pork; other processed beef and pork; chicken legs, thighs and breasts; chicken ham and similar products; and shellfish; as well as total meat expenditure; Northeast region; Northwest region; Central-West region; Central region; and urban sector. This information is used in identifying meat cut prices, regions and urbanization sectors that affect (positively or negatively) the probability of buying a meat cut.

[1]See SAS Institute Inc., 2004, p. 3754.

When the significant determinants are binary variables, it means that there are differences by region or urbanization level in the probability of consuming a particular meat cut. For example, households from the rural sector in the Southeast region typically have a higher probability of consuming beefsteak than households from the rural sector in the Northeast region (refer to Table 5.1 and Equation (3.7)). However, households from the rural sector in the Southeast region typically have a lower probability of consuming beefsteak than households from the rural sector in the Central-West region or the rural sector in the Central region.

In general, the urban sector has a higher probability of consuming any meat cut (except for chicken offal and fish) than the rural sector, but the probability of consuming a particular meat cut varies by geographical region. For example, the typical household from the urban sector in the Central-West region statistically has the highest probability of consuming beefsteak. Similarly, the urban sector of the Northwest region statistically has the highest probability of consuming ground beef, other beef, chorizo, and chicken legs, thighs and breast. The urban sector of the Southeast region statistically has the highest probability of consuming pork steak. The urban sector in the Northeast region statistically has the highest probability of consuming chicken ham and similar products. The urban sector in the Central region statistically has the highest probability of consuming other pork; ham, bacon and similar products; other processed products from beef and pork; and chicken legs, thighs and breast. The urban sector of the Northwest, Central and Southeast regions have the highest probability of consuming beef offal. The urban sector of Northwest, Central-West and Southeast regions have the highest probability of consuming pork leg and shoulder. The urban sector in the Central-West, Central and Southeast regions have the highest probability of consuming ground pork. The urban sector in the Central-West and Southeast regions have the highest probability of consuming whole chicken. The Central and Southeast regions have the highest probability of consuming chicken offal. On the other hand, fish consumption is not statistically different in each region (except for the Northwest region, which statistically has a lower probability of consuming fish than the Southeast region). Finally, the Northeast region typically has the highest probability of consuming of shellfish. Notice that the parameter estimates corresponding to the *urban* variable resulted most of the times statistically significant (13 occasions statistically different from zero at the 0.05 level, and 15 occasions statistically different from zero at the 0.20 level), except for chicken offal, fish, and shellfish. In general, all this information is very important for U.S. meat exporters who want to decide where in Mexico a particular meat cut will sell better.

Moreover, the partial effect of a continuous variable, z_{ik} (e.g., $p_1, \ldots, p_{18}$ or m), on the probability of buying meat cut i, which is given by Equation (3.14), can be estimated from Table 4.2 and Table 5.1.[2] Similarly, the partial effect of a binary variable, z_{ik} (e.g., *NE*, *NW*, *CW*, *C*, *urban*), changing from 0 to 1 on the probability of buying meat cut i is given by Equation (3.15). Table 5.2 reports estimates of the marginal effect of independent variables on the probability of consuming meat cut i. These marginal effects estimate how changes in the independent variables affect the probability of consuming a particular meat cut, holding all other variables constant. This information is relevant and useful to meat producers and Mexican policy makers in quantifying how changes in prices, total meat expenditure, regional location, or urbanization level affect the probability of consuming a particular meat cut. For example, an increase of one peso/kg in the price of pork leg and shoulder decreases the probability of consuming beefsteak by 0.0035, other things held constant. Likewise, an increase of one peso in total meat expenditures increases the probability of consuming ground beef by 0.0020, other things held constant. Furthermore, the probability of consuming other beef in the Northwest region is about 0.1615 higher than the probability of consuming other beef in the Southeast region. Similarly, the urban sector has a probability of consuming chicken legs, thighs and breasts that is about 0.1254 higher than the rural sector.

[2]Average total meat expenditure is 33.0374 pesos per capita per week. The standard error of average total meat expenditure is 0.3450.

Table 5.1: ML Parameter Estimates from Univariate Probit Regressions (Step 1).

Var.	Beefsteak Param. Est.	Beefsteak Bootstr. Std. Err.	Ground Beef Param. Est.	Ground Beef Bootstr. Std. Err.	Other Beef Param. Est.	Other Beef Bootstr. Std. Err.	Beef Offal Param. Est.	Beef Offal Bootstr. Std. Err.	Pork Steak Param. Est.	Pork Steak Bootstr. Std. Err.
const.	-0.6046	0.5169	-0.7441†	0.4906	-0.2887	0.5569	-0.6048	0.6586	0.4161	0.7201
p_1	-0.0011	0.0016	0.0047*	0.0017	-0.0047*	0.0018	-0.0005	0.0026	-0.0016	0.0020
p_2	0.0012	0.0023	-0.0012	0.0033	-0.0063*	0.0025	-0.0019	0.0033	-0.0038	0.0032
p_3	-0.0010	0.0019	-0.0000	0.0018	-0.0005	0.0022	-0.0008	0.0032	0.0017	0.0025
p_4	-0.0028	0.0029	-0.0036	0.0035	0.0064‡	0.0036	0.0007	0.0060	-0.0067†	0.0043
p_5	0.0101‡	0.0058	-0.0007	0.0040	0.0057†	0.0039	-0.0079†	0.0062	0.0026	0.0073
p_6	-0.0091*	0.0031	-0.0032	0.0034	-0.0069*	0.0034	0.0016	0.0037	-0.0060	0.0050
p_7	0.0084	0.0066	0.0082	0.0062	0.0003	0.0083	0.0028	0.0083	-0.0046	0.0100
p_8	0.0030†	0.0021	-0.0019	0.0021	-0.0055*	0.0028	-0.0001	0.0045	-0.0007	0.0029
p_9	0.0011	0.0010	0.0002	0.0010	-0.0014†	0.0009	-0.0065*	0.0029	0.0003	0.0013
p_{10}	0.0012	0.0013	0.0015	0.0013	0.0011	0.0012	-0.0007	0.0023	-0.0067*	0.0023
p_{11}	0.0007	0.0025	0.0007	0.0027	-0.0070*	0.0026	-0.0020	0.0037	0.0031	0.0040
p_{12}	-0.0008	0.0009	-0.0021†	0.0014	0.0003	0.0008	-0.0030†	0.0020	-0.0024†	0.0017
p_{13}	-0.0011	0.0019	-0.0024	0.0019	-0.0007	0.0020	0.0005	0.0026	-0.0046†	0.0033
p_{14}	-0.0002	0.0021	0.0001	0.0029	0.0015	0.0022	-0.0018	0.0041	-0.0048	0.0037
p_{15}	0.0029	0.0034	0.0057	0.0039	0.0064	0.0045	0.0012	0.0048	0.0047	0.0043
p_{16}	-0.0057*	0.0019	-0.0057*	0.0021	-0.0016	0.0018	0.0005	0.0028	-0.0037†	0.0027
p_{17}	0.0000	0.0011	0.0009	0.0011	0.0006	0.0012	-0.0040‡	0.0021	0.0007	0.0011
p_{18}	-0.0092*	0.0020	-0.0128*	0.0020	-0.0062*	0.0018	-0.0016	0.0024	-0.0061*	0.0028
m	0.0112*	0.0027	0.0085*	0.0006	0.0097*	0.0006	0.0037*	0.0009	0.0045*	0.0007
NE	-0.2030‡	0.0998	-0.1764†	0.1256	0.2429*	0.1046	-0.0361	0.1626	-1.1071*	0.1617
NW	0.0207	0.1259	1.1140*	0.1447	0.6158*	0.1393	0.0177	0.2380	-1.3065*	0.2121
CW	0.3399*	0.1007	0.1291	0.1031	0.2278*	0.0925	-0.3667*	0.1408	-0.4446*	0.1182
C	0.1808‡	0.0967	0.2106‡	0.1051	0.2959*	0.1058	0.0590	0.1413	-0.1934†	0.1313
urban	0.4952*	0.0590	0.5259*	0.0601	0.1378*	0.0589	0.1952*	0.0902	0.3051*	0.0826

Note: Number of bootstrap resamples = 1,000. Bootstrap significance levels of 0.05, 0.10 and 0.20 are indicated by asterisks (*), double daggers (‡), and daggers (†) respectively.

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Table 5.1: *Continued*

Var.	Pork Leg & Shoulder		Ground Pork		Other Pork		Chorizo		Ham, Bacon & Sim.	
	Param. Est.	Bootstr. Std. Err.	Param. Est.	Bootstr. Std. Err.	Param. Est.	Bootstr. Std. Err.	Param. Est.	Bootstr. Std. Err.	Param. Est.	Bootstr. Std. Err.
const.	-0.4357	0.6013	-0.6155	0.9587	-0.6625	0.5918	0.0611	0.4888	-1.7267*	0.4797
p_1	-0.0045*	0.0020	-0.0116*	0.0037	-0.0015	0.0028	0.0011	0.0015	0.0002	0.0015
p_2	-0.0024	0.0030	-0.0026	0.0040	-0.0010	0.0028	-0.0009	0.0026	-0.0035†	0.0023
p_3	0.0003	0.0016	0.0014	0.0025	0.0002	0.0020	-0.0000	0.0016	0.0040	0.0025
p_4	0.0048†	0.0032	0.0078†	0.0066	0.0078*	0.0038	0.0065*	0.0031	0.0037	0.0032
p_5	-0.0099*	0.0050	-0.0023	0.0078	0.0074†	0.0046	-0.0026	0.0042	0.0099*	0.0041
p_6	-0.0019	0.0049	-0.0053	0.0067	-0.0008	0.0036	-0.0075*	0.0038	-0.0019	0.0031
p_7	0.0108†	0.0084	0.0008	0.0131	0.0025	0.0079	0.0057	0.0065	0.0029	0.0066
p_8	-0.0073*	0.0037	-0.0044	0.0044	-0.0015	0.0032	-0.0023	0.0029	-0.0003	0.0024
p_9	-0.0007	0.0010	-0.0025	0.0030	-0.0025†	0.0018	-0.0002	0.0013	0.0011	0.0010
p_{10}	-0.0019	0.0019	0.0026	0.0023	-0.0038*	0.0017	-0.0047*	0.0018	0.0008	0.0014
p_{11}	0.0021	0.0051	0.0096*	0.0043	-0.0003	0.0037	-0.0013	0.0037	0.0014	0.0028
p_{12}	0.0003	0.0009	-0.0036	0.0032	-0.0017†	0.0012	-0.0016	0.0013	-0.0012†	0.0009
p_{13}	0.0014	0.0020	-0.0028	0.0034	-0.0052*	0.0024	-0.0019	0.0020	0.0010	0.0018
p_{14}	-0.0068‡	0.0034	-0.0021	0.0045	-0.0064‡	0.0035	-0.0013	0.0028	0.0002	0.0020
p_{15}	0.0022	0.0036	0.0000	0.0051	0.0043	0.0036	-0.0003	0.0033	-0.0042†	0.0032
p_{16}	-0.0014	0.0021	-0.0089*	0.0044	-0.0063*	0.0027	-0.0082*	0.0022	-0.0017	0.0017
p_{17}	0.0022†	0.0013	-0.0022	0.0023	-0.0017	0.0015	0.0002	0.0011	0.0018†	0.0011
p_{18}	-0.0055*	0.0021	-0.0001	0.0031	-0.0049*	0.0021	-0.0049*	0.0022	-0.0037*	0.0016
m	0.0056*	0.0008	0.0020*	0.0008	0.0070*	0.0009	0.0026*	0.0006	0.0025*	0.0050
NE	-0.7101*	0.1277	-0.4137†	0.2435	-0.4823*	0.1307	0.2086‡	0.1122	0.2219*	0.0992
NW	-0.1058	0.1406	-0.4367†	0.2523	-0.1597	0.1601	0.4600*	0.1302	0.2592*	0.1229
CW	-0.0075	0.0965	-0.0658	0.1655	0.1657†	0.0991	0.3260*	0.0896	0.3855*	0.0845
C	-0.2069*	0.1084	0.1218	0.2087	0.4077*	0.1112	0.3163*	0.1017	0.6755*	0.0887
urban	0.1591*	0.0639	0.2755†	0.1653	0.2128*	0.0679	0.1083†	0.0673	0.3802*	0.0598

Note: Number of bootstrap resamples = 1,000. Bootstrap significance levels of 0.05, 0.10 and 0.20 are indicated by asterisks (*), double daggers (‡) and daggers (†) respectively.

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Table 5.1: *Continued*

Var.	Beef & Pork Sausages		Other Process B&P		Chicken LT&B		Whole Chicken		Chicken Offal	
	Param. Est.	Bootstr. Std. Err.	Param. Est.	Bootstr. Std. Err.	Param. Est.	Bootstr. Std. Err.	Param. Est.	Bootstr. Std. Err.	Param. Est.	Bootstr. Std. Err.
const.	-0.9235*	0.4886	-0.0969	0.5262	-1.0725*	0.4966	1.9760*	0.4652	-0.3209	0.7091
p_1	-0.0005	0.0015	0.0009	0.0015	-0.0029‡	0.0016	-0.0001	0.0015	-0.0006	0.0021
p_2	-0.0018	0.0026	-0.0038†	0.0028	-0.0054*	0.0025	0.0021	0.0024	0.0044†	0.0033
p_3	0.0008	0.0016	-0.0014	0.0021	0.0009	0.0015	-0.0064*	0.0019	0.0008	0.0020
p_4	-0.0044	0.0035	-0.0040	0.0039	-0.0036†	0.0029	0.0060‡	0.0034	-0.0048	0.0045
p_5	0.0015	0.0049	-0.0050	0.0043	0.0033	0.0039	-0.0095*	0.0043	0.0023	0.0062
p_6	-0.0063‡	0.0038	-0.0045	0.0037	-0.0028	0.0031	-0.0070*	0.0031	-0.0103†	0.0065
p_7	0.0127*	0.0066	0.0136‡	0.0075	0.0177*	0.0071	-0.0019	0.0063	-0.0074	0.0090
p_8	0.0029	0.0028	-0.0026	0.0029	0.0031†	0.0021	-0.0053*	0.0025	0.0004	0.0044
p_9	0.0007	0.0011	0.0005	0.0010	0.0005	0.0009	-0.0010	0.0009	-0.0015	0.0022
p_{10}	-0.0013	0.0017	-0.0035†	0.0020	0.0030*	0.0013	-0.0046*	0.0015	-0.0080*	0.0031
p_{11}	-0.0005	0.0033	-0.0082*	0.0031	-0.0009	0.0024	-0.0001	0.0033	-0.0121*	0.0058
p_{12}	-0.0030*	0.0010	-0.0006	0.0014	-0.0003	0.0010	-0.0012†	0.0008	0.0010	0.0010
p_{13}	-0.0004	0.0022	-0.0009	0.0020	-0.0009	0.0019	-0.0017	0.0016	-0.0019	0.0036
p_{14}	-0.0047‡	0.0025	0.0013	0.0020	-0.0024	0.0021	-0.0016	0.0025	0.0004	0.0031
p_{15}	-0.0012	0.0034	0.0087*	0.0035	0.0024	0.0029	0.0046	0.0034	-0.0006	0.0059
p_{16}	-0.0024	0.0022	-0.0062*	0.0027	0.0012	0.0018	-0.0058*	0.0018	0.0012	0.0026
p_{17}	0.0019†	0.0013	-0.0002	0.0012	0.0011	0.0010	-0.0040*	0.0013	-0.0020	0.0019
p_{18}	-0.0059*	0.0018	-0.0038*	0.0017	-0.0070*	0.0017	-0.0061*	0.0018	0.0049*	0.0019
m	0.0021*	0.0006	0.0045*	0.0007	0.0091*	0.0007	0.0053*	0.0007	-0.0001	0.0008
NE	0.1987‡	0.1154	-0.3549*	0.1199	-0.1915‡	0.1017	-0.8905*	0.1038	-0.8270*	0.1679
NW	0.7742*	0.1305	-0.3784*	0.1500	-0.0158	0.1239	-0.5827*	0.1350	-0.7101*	0.1743
CW	0.2487*	0.0996	-0.1436†	0.0980	-0.4299*	0.0809	-0.0635	0.0866	-0.5012*	0.1331
C	0.3111*	0.1036	0.2957*	0.0990	0.5860*	0.0890	-0.2947*	0.0927	0.0037	0.1316
urban	0.3026*	0.0608	0.1344*	0.0632	0.3516*	0.0557	0.1297*	0.0574	-0.0261	0.0896

Note: Number of bootstrap resamples = 1,000. Bootstrap significance levels of 0.05, 0.10 and 0.20 are indicated by asterisks (*), double daggers (‡) and daggers (†) respectively.

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Table 5.1: *Continued*

Var.	Chicken Ham & Similar		Fish		Shellfish	
	Param. Est.	Bootstr. Std. Err.	Param. Est.	Bootstr. Std. Err.	Param. Est.	Bootstr. Std. Err.
const.	-2.1980*	0.4765	-0.6609†	0.4931	-3.2053*	0.7133
p_1	0.0004	0.0014	-0.0004	0.0016	-0.0015	0.0033
p_2	-0.0008	0.0024	-0.0026	0.0024	0.0021	0.0037
p_3	0.0033*	0.0015	0.0017	0.0016	0.0010	0.0020
p_4	-0.0059†	0.0035	-0.0061‡	0.0031	0.0113*	0.0039
p_5	0.0153*	0.0046	0.0074†	0.0053	0.0094	0.0082
p_6	0.0006	0.0034	-0.0023	0.0034	-0.0024	0.0045
p_7	-0.0049	0.0067	-0.0070	0.0063	0.0152†	0.0094
p_8	0.0005	0.0019	0.0003	0.0022	-0.0022	0.0037
p_9	0.0010	0.0010	-0.0018†	0.0011	0.0006	0.0016
p_{10}	0.0029*	0.0013	0.0013	0.0013	0.0026†	0.0020
p_{11}	0.0014	0.0023	0.0019	0.0025	0.0029	0.0028
p_{12}	0.0004	0.0007	0.0005	0.0010	-0.0039*	0.0018
p_{13}	0.0025†	0.0017	-0.0008	0.0017	-0.0001	0.0024
p_{14}	0.0012	0.0021	0.0024	0.0025	-0.0004	0.0028
p_{15}	0.0077*	0.0031	0.0056‡	0.0031	0.0054	0.0046
p_{16}	0.0020	0.0025	0.0029†	0.0018	-0.0043	0.0033
p_{17}	0.0009	0.0011	-0.0004	0.0013	0.0015	0.0016
p_{18}	-0.0065*	0.0017	-0.0019	0.0019	-0.0020	0.0032
m	0.0036*	0.0005	0.0069*	0.0014	0.0060*	0.0016
NE	0.4273*	0.0984	-0.0565	0.1029	0.2383‡	0.1460
NW	0.2169†	0.1387	-0.3530*	0.1247	-0.3684‡	0.2000
CW	-0.0007	0.0899	-0.0971	0.0913	-0.0217	0.1284
C	-0.1225	0.0957	-0.0574	0.0923	-0.3706*	0.1517
urban	0.4125*	0.0587	-0.0312	0.0567	0.0722	0.0934

Note: Number of bootstrap resamples = 1,000. Bootstrap significance levels of 0.05, 0.10 and 0.20 are indicated by asterisks (*), double daggers (‡) and daggers (†) respectively.

Table 5.2: Marginal Effect Estimates of Independent Variables on the Probability of Consuming Meat Cut i.

Table entries estimate $\frac{\partial P(d_i=1|\mathbf{z}_i)}{\partial z_{ik}}$.

	p_1	p_2	p_3	p_4	p_5	p_6	p_7	p_8	p_9	p_{10}	p_{11}	p_{12}
$P(d_1 = 1\|\mathbf{z}_1)$	-0.0004	0.0005	-0.0004	-0.0011	0.0039	-0.0035	0.0032	0.0012	0.0004	0.0005	0.0003	-0.0003
$P(d_2 = 1\|\mathbf{z}_2)$	0.0011	-0.0003	0.0000	-0.0009	-0.0002	-0.0008	0.0020	-0.0005	0.0000	0.0004	0.0002	-0.0005
$P(d_3 = 1\|\mathbf{z}_3)$	-0.0012	-0.0016	-0.0001	0.0016	0.0014	-0.0017	0.0001	-0.0014	-0.0004	0.0003	-0.0017	0.0001
$P(d_4 = 1\|\mathbf{z}_4)$	0.0000	-0.0002	-0.0001	0.0001	-0.0007	0.0001	0.0003	0.0000	-0.0006	-0.0001	-0.0002	-0.0003
$P(d_5 = 1\|\mathbf{z}_5)$	-0.0001	-0.0003	0.0001	-0.0006	0.0002	-0.0005	-0.0004	-0.0001	0.0000	-0.0006	0.0003	-0.0002
$P(d_6 = 1\|\mathbf{z}_6)$	-0.0006	-0.0003	0.0000	0.0006	-0.0013	-0.0002	0.0014	-0.0010	-0.0001	-0.0003	0.0003	0.0000
$P(d_7 = 1\|\mathbf{z}_7)$	-0.0005	-0.0001	0.0001	0.0003	-0.0001	-0.0002	0.0000	-0.0002	-0.0001	0.0001	0.0004	-0.0002
$P(d_8 = 1\|\mathbf{z}_8)$	-0.0003	-0.0002	0.0000	0.0016	0.0015	-0.0002	0.0005	-0.0003	-0.0005	-0.0008	-0.0001	-0.0003
$P(d_9 = 1\|\mathbf{z}_9)$	0.0003	-0.0002	0.0000	0.0017	-0.0007	-0.0020	0.0015	-0.0006	0.0000	-0.0013	-0.0003	-0.0004
$P(d_{10} = 1\|\mathbf{z}_{10})$	0.0001	-0.0011	0.0013	0.0012	0.0031	-0.0006	0.0009	-0.0001	0.0004	0.0002	0.0005	-0.0004
$P(d_{11} = 1\|\mathbf{z}_{11})$	-0.0001	-0.0004	0.0002	-0.0010	0.0003	-0.0014	0.0028	0.0006	0.0001	-0.0003	-0.0001	-0.0007
$P(d_{12} = 1\|\mathbf{z}_{12})$	0.0002	-0.0009	-0.0003	-0.0010	-0.0012	-0.0011	0.0032	-0.0006	0.0001	-0.0008	-0.0019	-0.0001
$P(d_{13} = 1\|\mathbf{z}_{13})$	-0.0011	-0.0020	0.0003	-0.0013	0.0012	-0.0010	0.0065	0.0011	0.0002	0.0011	-0.0003	-0.0001
$P(d_{14} = 1\|\mathbf{z}_{14})$	0.0000	0.0007	-0.0022	0.0021	-0.0033	-0.0024	-0.0007	-0.0018	-0.0004	-0.0016	0.0000	-0.0004
$P(d_{15} = 1\|\mathbf{z}_{15})$	-0.0001	0.0004	0.0001	-0.0005	0.0002	-0.0010	-0.0007	0.0000	-0.0001	-0.0008	-0.0011	0.0001
$P(d_{16} = 1\|\mathbf{z}_{16})$	0.0001	-0.0002	0.0007	-0.0013	0.0033	0.0001	-0.0011	0.0001	0.0002	0.0006	0.0003	0.0001
$P(d_{17} = 1\|\mathbf{z}_{17})$	-0.0001	-0.0008	0.0005	-0.0019	0.0023	-0.0007	-0.0022	0.0001	-0.0006	0.0004	0.0006	0.0001
$P(d_{18} = 1\|\mathbf{z}_{18})$	-0.0001	0.0001	0.0001	0.0008	0.0007	-0.0002	0.0010	-0.0001	0.0000	0.0002	0.0002	-0.0003

Note: $i = 1, 2, \ldots, 18$, where 1 = Beefsteak, 2 = Ground Beef, 3 = Other Beef, 4 = Beef Offal, 5 = Pork Steak, 6 = Pork Leg & Shoulder, 7 = Ground Pork, 8 = Other Pork, 9 = Chorizo, 10 = Ham, Bacon & Similar Products from Beef & Pork, 11 = Beef & Pork Sausages, 12 = Other Processed Beef & Pork, 13 = Chicken Legs, Thighs & Breasts, 14 = Whole Chicken, 15 = Chicken Offal, 16 = Chicken Ham & Similar Products, 17 = Fish, 18 = Shellfish.

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Table 5.2: *Continued*

Table entries estimate $\frac{\partial P(d_i=1|\mathbf{z}_i)}{\partial z_{ik}}$.

	p_{13}	p_{14}	p_{15}	p_{16}	p_{17}	p_{18}	m	NE	NW	CW	C	$urban$
$P(d_1 = 1\|\mathbf{z}_1)$	-0.0004	-0.0001	0.0011	-0.0022	0.0000	-0.0035	0.0043	-0.0716	0.0077	0.1317	0.0688	0.1842
$P(d_2 = 1\|\mathbf{z}_2)$	-0.0006	0.0000	0.0014	-0.0014	0.0002	-0.0031	0.0020	-0.0291	0.3419	0.0257	0.0440	0.1155
$P(d_3 = 1\|\mathbf{z}_3)$	-0.0002	0.0004	0.0016	-0.0004	0.0001	-0.0016	0.0024	0.0530	0.1615	0.0493	0.0664	0.0336
$P(d_4 = 1\|\mathbf{z}_4)$	0.0000	-0.0002	0.0001	0.0000	-0.0004	-0.0001	0.0003	-0.0035	0.0018	-0.0271	0.0062	0.0167
$P(d_5 = 1\|\mathbf{z}_5)$	-0.0004	-0.0004	0.0004	-0.0003	0.0001	-0.0005	0.0004	-0.0822	-0.0853	-0.0526	-0.0273	0.0235
$P(d_6 = 1\|\mathbf{z}_6)$	0.0002	-0.0009	0.0003	-0.0002	0.0003	-0.0007	0.0008	-0.0700	-0.0160	-0.0012	-0.0292	0.0204
$P(d_7 = 1\|\mathbf{z}_7)$	-0.0001	-0.0001	0.0000	-0.0004	-0.0001	0.0000	0.0001	-0.0135	-0.0140	-0.0030	0.0068	0.0110
$P(d_8 = 1\|\mathbf{z}_8)$	-0.0011	-0.0013	0.0009	-0.0013	-0.0003	-0.0010	0.0014	-0.0623	-0.0257	0.0327	0.0923	0.0610
$P(d_9 = 1\|\mathbf{z}_9)$	-0.0005	-0.0004	-0.0001	-0.0022	0.0001	-0.0013	0.0007	0.0479	0.1195	0.0795	0.0768	0.0284
$P(d_{10} = 1\|\mathbf{z}_{10})$	0.0003	0.0000	-0.0013	-0.0006	0.0006	-0.0012	0.0008	0.0572	0.0680	0.1068	0.2079	0.1151
$P(d_{11} = 1\|\mathbf{z}_{11})$	-0.0001	-0.0010	-0.0003	-0.0005	0.0004	-0.0013	0.0005	-0.0243	0.1916	0.0461	0.0600	0.0636
$P(d_{12} = 1\|\mathbf{z}_{12})$	-0.0002	0.0003	0.0020	-0.0015	0.0000	-0.0009	0.0011	-0.0697	-0.0733	-0.0317	0.0809	0.0311
$P(d_{13} = 1\|\mathbf{z}_{13})$	-0.0003	-0.0009	0.0009	0.0004	0.0004	-0.0026	0.0033	-0.0641	-0.0055	-0.1329	0.2260	0.1254
$P(d_{14} = 1\|\mathbf{z}_{14})$	-0.0006	-0.0006	0.0016	-0.0020	-0.0014	-0.0021	0.0018	-0.2718	-0.1973	-0.0242	-0.1077	0.0446
$P(d_{15} = 1\|\mathbf{z}_{15})$	-0.0002	0.0000	-0.0001	0.0001	-0.0002	0.0005	0.0000	-0.0639	-0.0598	-0.0493	0.0005	-0.0025
$P(d_{16} = 1\|\mathbf{z}_{16})$	0.0005	0.0003	0.0017	0.0004	0.0002	-0.0014	0.0008	0.1123	0.0516	-0.0002	-0.0242	0.0828
$P(d_{17} = 1\|\mathbf{z}_{17})$	-0.0002	0.0007	0.0017	0.0009	-0.0001	-0.0006	0.0021	-0.0183	-0.1026	-0.0310	-0.0186	-0.0097
$P(d_{18} = 1\|\mathbf{z}_{18})$	0.0000	0.0000	0.0004	-0.0003	0.0001	-0.0001	0.0004	0.0269	-0.0248	-0.0020	-0.0249	0.0049

Note: $i = 1, 2, \ldots, 18$, where 1 = Beefsteak, 2 = Ground Beef, 3 = Other Beef, 4 = Beef Offal, 5 = Pork Steak, 6 = Pork Leg & Shoulder, 7 = Ground Pork, 8 = Other Pork, 9 = Chorizo, 10 = Ham, Bacon & Similar Products from Beef & Pork, 11 = Beef & Pork Sausages, 12 = Other Processed Beef & Pork, 13 = Chicken Legs, Thighs & Breasts, 14 = Whole Chicken, 15 = Chicken Offal, 16 = Chicken Ham & Similar Products, 17 = Fish, 18 = Shellfish.

5.1.2 Step 2 - SUR Parameter Estimates from the System of Equations

In the second step, the estimation of the system of censored demand equations is based on the full system of $M = 18$ equations because the parametric restriction of adding-up was not imposed in the model (see also Yen, Kan, and Su, 2002, p. 1801). Given that in stratified samples the weighted estimator is consistent (Wooldridge, 2001, p. 464), all observations are weighted by the weight variable prior to estimation. However, "[if we] use weights w_i in the weighted least squares estimation, [we] will obtain the same point estimates...; however, in complex surveys, the standard errors and hypothesis tests the software provides will be incorrect and should be ignored" (Lohr, 1999, p. 355). Consequently, parameters in this study are estimated using the bootstrap procedure. Table 5.3 presents the SUR parameter estimates as well as their corresponding bootstrap standard errors from the censored system of eighteen equations. From a total of 468 parameter estimated in the second step; 200, 128, and 67 parameters were statistically different from zero at the 0.20, 0.10, and 0.05 levels respectively. In other words, about 11.11, 7.11, and 3.72 parameters per equation are statistically different from zero at the 0.20, 0.10, and 0.05 levels respectively, where there are 26 parameters in each equation.

Moreover, the partial effect of a common continuous variable in $\mathbf{x}_i$ and $\mathbf{z}_i$ (e.g., p_1, p_2, ... , p_{18} or m) on the unconditional mean of the per capita consumption per week of meat cut i, which is given by Equation (3.28), can be obtained from Table 4.2 and Table 5.3.[3] Similarly, the partial effect of a common binary variable (e.g., *NE*, *NW*, *CW*, *C* or *urban*) changing from 0 to 1 on the unconditional mean of the per capita consumption per week of meat cut i is given by Equation (3.29). Table 5.4 reports estimates of the marginal effect of independent variables on the unconditional mean of the per capita consumption per week of meat cut i. The marginal effects are used to estimate how changes in the independent variables affect the unconditional mean of the per capita consumption per week of meat cut i, holding all other variables

[3] Average total meat expenditure is 33.0374 pesos per capita per week. The standard error of average total meat expenditure is 0.3450.

constant. This information is relevant and useful to meat producers and Mexican policy makers in quantifying how changes in prices, total meat expenditure, regional location, or urbanization level affect the per capita consumption of a particular meat cut per week. For example, an increase of one peso/kg in the price of pork leg and shoulder decreases per capita consumption of beefsteak by 0.0007 kg per week, other things held constant.[4] Likewise, an increase of one peso in total meat expenditures increases per capita consumption of ground beef by 0.0006 kg per week, other things held constant. Furthermore, the typical per capita consumption of other beef in the Northwest region is about 0.0611 kg per week higher than the typical per capita consumption per week of other beef in the Southeast region.[5] Similarly, the urban sector has a typical per capita consumption of chicken legs, thighs and breasts that is about 0.0554 kg per week higher than typical per capita consumption per week of chicken legs, thighs and breasts in the rural sector.

Following Equation (4.10), the marginal effects of independent variables on the unconditional mean of the per capita consumption per week of meat cut i (Table 5.4) can be used with the estimates of the unconditional mean of q_i (Table 5.5) and the average prices (Table 4.2) to compute the Marshallian price elasticities (Table 5.6). For example, $\hat{e}_{0101} = \frac{\partial \mathrm{E}(q_1|\mathbf{x}_1,\mathbf{z}_1)}{\partial p_1} \frac{p_1}{\hat{q}_1} = -0.001837 \frac{60.878543}{0.108897} \approx -1.0270$. Similarly, $\hat{e}_{0113} = \frac{\partial \mathrm{E}(q_1|\mathbf{x}_1,\mathbf{z}_1)}{\partial p_{13}} \frac{p_{13}}{\hat{q}_1} = -0.000872 \frac{34.685852}{0.108897} \approx -0.2778$. Similarly, expenditure and Hicksian elasticities can be estimated by following Equation (4.11) and Equation (4.12) respectively. The following section compares and contrast these estimates with findings from other studies.

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[4] An increase of 5 pesos/kg in the price of pork leg and shoulder decreases consumption of beefsteak by approximately 0.1231 lbs per household per month, which is $5 \times 0.0007 \frac{\text{kg}}{\text{adult equivalent}} \times \frac{1}{\text{week}} \times 3.9876 \frac{\text{adult equivalent}}{\text{household}} \times 2.2046 \frac{\text{lbs}}{\text{kg}} \times 4 \frac{\text{week}}{\text{month}}$.

[5] Equivalently, the typical consumption of other beef in the Northwest region is about 2.1485 lbs per household per month higher than the typical consumption per household per month of other beef in the Southeast region. Where $2.1485 = 0.0611 \frac{\text{kg}}{\text{adult equivalent}} \times \frac{1}{\text{week}} \times 3.9876 \frac{\text{adult equivalent}}{\text{household}} \times 2.2046 \frac{\text{lbs}}{\text{kg}} \times 4 \frac{\text{week}}{\text{month}}$.

Table 5.3: SUR Parameter Estimates from System of Equations (Step 2).

Variable	Beefsteak ($i=1$)		Ground Beef ($i=2$)		Other Beef ($i=3$)		Beef Offal ($i=4$)		Pork Steak ($i=5$)	
	Param. Est.	Bootstr. Std. Err.	Param. Est.	Bootstr. Std. Err.	Param. Est.	Bootstr. Std. Err.	Param. Est.	Bootstr. Std. Err.	Param. Est.	Bootstr. Std. Err.
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)$	1.6951*	0.3939	0.6607	0.4387	2.0916*	0.7051	13.0161	16.0844	1.5472†	0.8903
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\,p_1$	-0.0038*	0.0015	-0.0002	0.0007	-0.0038*	0.0022	-0.0057	0.0080	0.0051†	0.0040
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\,p_2$	0.0000	0.0008	-0.0130*	0.0046	0.0053‡	0.0031	0.0176	0.0230	0.0022	0.0069
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\,p_3$	-0.0016*	0.0007	-0.0005	0.0006	-0.0109*	0.0040	0.0035	0.0090	-0.0019	0.0028
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\,p_4$	0.0008	0.0013	0.0006	0.0016	-0.0019	0.0026	-0.0497*	0.0168	0.0075	0.0115
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\,p_5$	-0.0067*	0.0024	0.0022†	0.0023	0.0044†	0.0050	0.0504	0.0884	-0.0235*	0.0105
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\,p_6$	0.0050*	0.0021	0.0030‡	0.0016	0.0009	0.0044	-0.0061	0.0183	0.0027	0.0108
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\,p_7$	-0.0072*	0.0021	-0.0011	0.0027	-0.0236	0.0080	-0.0320	0.0333	-0.0017	0.0090
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\,p_8$	-0.0020*	0.0007	0.0014	0.0011	-0.0036	0.0034	-0.0006	0.0036	0.0045†	0.0025
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\,p_9$	-0.0007*	0.0003	-0.0002	0.0002	0.0021	0.0022	0.0528	0.0738	-0.0024‡	0.0014
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\,p_{10}$	-0.0009‡	0.0004	-0.0003	0.0004	-0.0003	0.0009	0.0035	0.0077	0.0062	0.0115
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\,p_{11}$	-0.0007	0.0007	-0.0009	0.0007	0.0070*	0.0030	0.0208	0.0238	-0.0035	0.0055
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\,p_{12}$	0.0005	0.0004	0.0007	0.0006	-0.0008†	0.0007	0.0192	0.0345	0.0028	0.0043
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\,p_{13}$	-0.0014*	0.0008	0.0009	0.0011	-0.0025‡	0.0017	-0.0097	0.0069	0.0052	0.0080
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\,p_{14}$	-0.0002	0.0005	0.0017	0.0022	-0.0008	0.0011	0.0085	0.0202	0.0021	0.0087
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\,p_{15}$	-0.0018†	0.0010	-0.0011	0.0009	-0.0006	0.0027	-0.0026	0.0171	-0.0043	0.0071
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\,p_{16}$	0.0032*	0.0011	0.0014	0.0011	0.0019†	0.0014	-0.0053	0.0066	0.0090	0.0069
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\,p_{17}$	-0.0002	0.0007	-0.0007‡	0.0004	-0.0016†	0.0010	0.0206	0.0455	-0.0009	0.0013
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\,p_{18}$	0.0049*	0.0016	0.0021	0.0017	0.0014	0.0021	0.0162	0.0179	0.0058	0.0103
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\,m$	-0.0003	0.0018	0.0005	0.0009	0.0010	0.0020	-0.0215	0.0410	-0.0033	0.0072
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\,NE$	0.1933*	0.0552	0.1172*	0.0624	0.1733‡	0.1201	-0.2618	0.4762	0.9236	1.9232
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\,NW$	0.0432	0.0487	-0.0280	0.1539	-0.0402	0.1721	-1.1865*	0.4623	1.4056	2.2352
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\,CW$	-0.0888	0.0734	-0.0384	0.0437	-0.0149	0.0911	2.0145	4.2729	0.5291	0.7748
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\,C$	-0.0698	0.0504	0.0683†	0.0541	0.1229	0.1251	-0.9158	0.7403	0.1874	0.3540
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\,urban$	-0.2890*	0.0938	-0.1448†	0.0895	-0.0609	0.0614	-1.4360	2.2463	-0.2713	0.5124
$\phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)$	-0.8134*	0.2837	-0.1105	0.1768	-0.3410	0.3433	-8.2907	13.4497	-1.1200	1.9879

Note: Number of bootstrap resamples = 1,000. Bootstrap significance levels of 0.05, 0.10 and 0.20 are indicated by asterisks (*), double daggers (‡) and daggers (†) respectively.

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Table 5.3: *Continued*

Variable	Pork Leg & Shoulder ($i=6$)		Ground Pork ($i=7$)		Other Pork ($i=8$)		Chorizo ($i=9$)		Ham, Bacon & Sim. ($i=10$)	
	Param. Est.	Bootstr. Std. Err.	Param. Est.	Bootstr. Std. Err.	Param. Est.	Bootstr. Std. Err.	Param. Est.	Bootstr. Std. Err.	Param. Est.	Bootstr. Std. Err.
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)$	1.8362	1.6606	-4.4229†	7.7401	2.8979	2.3180	3.5369†	3.1361	1.4720	1.7561
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ p_1$	-0.0008	0.0058	-0.0679‡	0.0671	0.0009	0.0038	-0.0038†	0.0037	0.0004†	0.0004
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ p_2$	-0.0001	0.0038	-0.0155‡	0.0163	0.0036	0.0029	0.0032†	0.0031	0.0001	0.0023
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ p_3$	-0.0003	0.0015	0.0083‡	0.0083	0.0016	0.0022	0.0004	0.0004	-0.0011	0.0020
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ p_4$	-0.0013	0.0059	0.0414‡	0.0452	-0.0048	0.0089	-0.0247†	0.0224	-0.0030	0.0024
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ p_5$	0.0062	0.0139	-0.0190‡	0.0141	0.0008	0.0087	0.0123†	0.0094	-0.0051	0.0058
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ p_6$	-0.0272†	0.0165	-0.0306‡	0.0315	0.0116†	0.0072	0.0274†	0.0259	0.0016	0.0014
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ p_7$	-0.0062	0.0133	-0.0568‡	0.0306	-0.0148†	0.0099	-0.0215†	0.0200	-0.0053*	0.0025
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ p_8$	0.0097	0.0102	-0.0240‡	0.0253	-0.0513‡	0.0315	0.0085†	0.0081	0.0005	0.0005
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ p_9$	-0.0002	0.0028	-0.0123†	0.0147	0.0062	0.0084	-0.0023†	0.0013	-0.0005	0.0007
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ p_{10}$	0.0002	0.0029	0.0131†	0.0141	0.0044	0.0053	0.0164†	0.0166	-0.0026*	0.0009
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ p_{11}$	-0.0018	0.0034	0.0537‡	0.0545	0.0055	0.0065	0.0046†	0.0045	0.0004	0.0012
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ p_{12}$	0.0019‡	0.0013	-0.0225‡	0.0210	0.0001	0.0030	0.0055†	0.0056	0.0011†	0.0007
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ p_{13}$	-0.0006	0.0030	-0.0157‡	0.0161	0.0035	0.0068	0.0066†	0.0067	-0.0002	0.0007
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ p_{14}$	0.0027	0.0083	-0.0144‡	0.0118	0.0029	0.0080	0.0041	0.0047	0.0005†	0.0003
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ p_{15}$	-0.0022	0.0027	-0.0022	0.0023	-0.0038	0.0067	-0.0006	0.0011	-0.0002	0.0027
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ p_{16}$	0.0027	0.0021	-0.0490‡	0.0515	0.0009	0.0071	0.0300†	0.0284	0.0016	0.0012
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ p_{17}$	-0.0015	0.0026	-0.0132‡	0.0125	0.0004	0.0028	-0.0010†	0.0008	-0.0007	0.0010
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ p_{18}$	0.0071	0.0082	-0.0017	0.0018	0.0067	0.0075	0.0187†	0.0168	0.0028	0.0023
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ m$	-0.0016	0.0063	0.0114‡	0.0114	-0.0020	0.0073	-0.0075	0.0089	0.0005	0.0017
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ NE$	0.4270	0.9449	-2.2970‡	2.4447	-0.0817	0.5549	-0.7745†	0.7287	-0.0832	0.1475
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ NW$	-0.0316	0.1780	-3.0687‡	2.6346	-0.2631†	0.2457	-1.7314†	1.5986	-0.1742	0.1693
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ CW$	0.2325†	0.1559	-0.2732†	0.4092	-0.1842	0.2729	-1.2578†	1.1374	-0.1778	0.2625
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ C$	0.0771	0.2778	0.9720*	0.7454	-0.4199	0.5297	-1.2158†	1.1016	-0.3205	0.4376
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ urban$	-0.0593	0.2274	1.7303‡	1.6117	-0.2038	0.3108	-0.4061†	0.3732	-0.1869	0.2490
$\phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)$	-0.7357	1.5018	6.7876‡	6.6536	-0.7913	1.5155	-4.6992†	4.4765	-0.5728	0.8679

Note: Number of bootstrap resamples = 1,000. Bootstrap significance levels of 0.05, 0.10 and 0.20 are indicated by asterisks (*), double daggers (‡) and daggers (†) respectively.

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Table 5.3: *Continued*

Variable	Beef & Pork Sausages ($i=11$) Param. Est.	Beef & Pork Sausages ($i=11$) Bootstr. Std. Err.	Other Process B&P ($i=12$) Param. Est.	Other Process B&P ($i=12$) Bootstr. Std. Err.	Chicken LT&B ($i=13$) Param. Est.	Chicken LT&B ($i=13$) Bootstr. Std. Err.	Whole Chicken ($i=14$) Param. Est.	Whole Chicken ($i=14$) Bootstr. Std. Err.	Chicken Offal ($i=15$) Param. Est.	Chicken Offal ($i=15$) Bootstr. Std. Err.
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)$	7.5961‡	4.4091	-0.6625	0.9770	1.4179*	0.3422	-0.8733†	0.8707	-10.6252	24.2149
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\, p_1$	0.0011	0.0015	0.0014†	0.0012	0.0004	0.0013	0.0030‡	0.0022	-0.0075	0.0136
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\, p_2$	0.0067‡	0.0043	-0.0066‡	0.0052	0.0042*	0.0014	-0.0072*	0.0033	0.0559	0.0959
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\, p_3$	-0.0026†	0.0017	-0.0015†	0.0015	-0.0005	0.0007	0.0121‡	0.0074	0.0098	0.0189
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\, p_4$	0.0155†	0.0111	-0.0097*	0.0058	-0.0019†	0.0015	-0.0150*	0.0062	-0.0553	0.1075
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\, p_5$	-0.0023	0.0032	-0.0123*	0.0085	-0.0002	0.0026	0.0206*	0.0097	0.0345	0.0628
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\, p_6$	0.0229‡	0.0154	-0.0055‡	0.0049	0.0050‡	0.0021	0.0162*	0.0074	-0.1225	0.2309
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\, p_7$	-0.0505‡	0.0305	0.0183‡	0.0144	-0.0078‡	0.0029	0.0022	0.0038	-0.1079	0.1589
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\, p_8$	-0.0095‡	0.0065	-0.0043‡	0.0033	-0.0029‡	0.0009	0.0120	0.0055	0.0058	0.0104
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\, p_9$	-0.0025‡	0.0015	0.0009‡	0.0007	0.0001	0.0005	0.0015	0.0015	-0.0367	0.0399
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\, p_{10}$	0.0052‡	0.0032	-0.0061*	0.0043	-0.0008	0.0006	0.0080‡	0.0046	-0.1242	0.1911
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\, p_{11}$	-0.0082	0.0054	-0.0097†	0.0092	0.0006	0.0012	-0.0012	0.0014	-0.1337	0.2522
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\, p_{12}$	0.0120‡	0.0069	-0.0066*	0.0010	0.0008†	0.0006	0.0029*	0.0015	0.0139	0.0225
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\, p_{13}$	0.0017†	0.0012	0.0012†	0.0013	-0.0144*	0.0017	0.0042*	0.0023	-0.0255	0.0404
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\, p_{14}$	0.0188‡	0.0114	0.0015	0.0016	-0.0004	0.0009	-0.0161*	0.0032	0.0012	0.0107
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\, p_{15}$	0.0028	0.0038	0.0073†	0.0071	-0.0024	0.0019	-0.0070†	0.0046	-0.1786*	0.0643
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\, p_{16}$	0.0109*	0.0058	-0.0068†	0.0067	0.0008	0.0009	0.0126*	0.0061	0.0255	0.0282
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\, p_{17}$	-0.0069‡	0.0043	-0.0001	0.0005	-0.0004	0.0004	0.0024	0.0043	-0.0287	0.0438
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\, p_{18}$	0.0257*	0.0141	-0.0041†	0.0041	0.0056*	0.0012	0.0134*	0.0060	0.0597	0.1027
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\, m$	-0.0070‡	0.0050	0.0071*	0.0048	0.0006	0.0012	-0.0027	0.0051	0.0072‡	0.0039
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\, NE$	-0.7873‡	0.4928	-0.5485‡	0.4591	0.0608	0.0606	1.4454‡	0.8976	-11.0706	18.7969
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\, NW$	-3.1321‡	1.8659	-0.5801‡	0.4681	-0.1150†	0.0823	0.7856†	0.6318	-8.2967	15.6189
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\, CW$	-1.1088*	0.6343	-0.3506*	0.1787	0.0550	0.0703	-0.0849	0.0817	-7.7540	11.4372
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\, C$	-1.3896*	0.7763	0.2860†	0.2955	-0.3188*	0.0663	0.2450	0.3209	-1.1132*	0.4957
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\, urban$	-1.2522‡	0.7336	0.1987‡	0.1548	-0.1449*	0.1391	-0.2925*	0.1341	-0.4994	0.5909
$\phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)$	-4.9890‡	3.0252	1.8683‡	1.4337	-0.6688*	0.0489	-2.6202*	1.4761	16.2106	26.0488

Note: Number of bootstrap resamples = 1,000. Bootstrap significance levels of 0.05, 0.10 and 0.20 are indicated by asterisks (*), double daggers (‡) and daggers (†) respectively.

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Table 5.3: *Continued*

Variable	Chicken, Ham & Similar ($i = 16$) Param. Est.	Chicken, Ham & Similar ($i = 16$) Bootstr. Std. Err.	Fish ($i = 17$) Param. Est.	Fish ($i = 17$) Bootstr. Std. Err.	Shellfish ($i = 18$) Param. Est.	Shellfish ($i = 18$) Bootstr. Std. Err.
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)$	-2.0427	3.0995	1.4410	1.3302	6.0505‡	2.8943
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ p_1$	-0.0001	0.0005	0.0002	0.0012	-0.0036	0.0037
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ p_2$	0.0006	0.0012	0.0018	0.0024	0.0005	0.0035
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ p_3$	0.0014	0.0026	-0.0012	0.0013	-0.0054*	0.0021
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ p_4$	-0.0013	0.0046	0.0045	0.0044	-0.0140†	0.0083
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ p_5$	0.0140†	0.0161	-0.0016	0.0067	-0.0071	0.0081
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ p_6$	0.0012	0.0017	-0.0016	0.0030	0.0052	0.0052
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ p_7$	-0.0092*	0.0057	-0.0031	0.0068	-0.0191†	0.0101
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ p_8$	0.0032†	0.0022	0.0007	0.0013	-0.0008	0.0033
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ p_9$	0.0006	0.0009	0.0013	0.0021	-0.0007	0.0018
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ p_{10}$	0.0016	0.0024	0.0002	0.0013	-0.0021	0.0025
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ p_{11}$	0.0022†	0.0020	-0.0008	0.0020	0.0007	0.0035
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ p_{12}$	0.0003	0.0005	-0.0003	0.0006	0.0056	0.0040
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ p_{13}$	0.0021†	0.0022	0.0003	0.0014	-0.0013	0.0021
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ p_{14}$	0.0007	0.0014	-0.0008	0.0024	0.0003	0.0028
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ p_{15}$	0.0037	0.0061	-0.0025	0.0036	-0.0049	0.0045
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ p_{16}$	-0.0050†	0.0027	-0.0018	0.0023	0.0137*	0.0053
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ p_{17}$	0.0005	0.0010	-0.0055*	0.0019	-0.0020	0.0013
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ p_{18}$	-0.0019	0.0061	0.0039*	0.0017	-0.0253*	0.0067
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ m$	0.0034†	0.0032	-0.0003	0.0045	-0.0038	0.0037
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ NE$	0.4715†	0.4508	0.1592‡	0.0940	-0.1832	0.2384
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ NW$	0.1186	0.2605	0.0448	0.2585	0.5742†	0.3359
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ CW$	0.0285	0.0396	0.0886	0.0990	0.1159	0.1169
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ C$	-0.0255	0.1120	0.0301	0.0824	0.6246†	0.3099
$\Phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)\ urban$	0.2323	0.4023	-0.0701‡	0.0435	0.3100‡	0.1607
$\phi(\mathbf{z}_i'\hat{\boldsymbol{\alpha}}_i)$	0.8600	1.2388	-0.8191	0.9959	-1.1673	0.8448

Note: Number of bootstrap resamples = 1,000. Bootstrap significance levels of 0.05, 0.10 and 0.20 are indicated by asterisks (*), double daggers (‡) and daggers (†) respectively.

Table 5.4: Marginal Effect Estimates of Independent Variables on the Unconditional Mean of q_i.

Table entries estimate $\frac{\partial \mathrm{E}(q_i|\mathbf{x}_i,\mathbf{z}_i)}{\partial x_{ij}}$.

	p_1	p_2	p_3	p_4	p_5	p_6	p_7	p_8	p_9	p_{10}	p_{11}	p_{12}
$\mathrm{E}(q_1\|\mathbf{x}_1,\mathbf{z}_1)$	-0.0018	0.0004	-0.0009	-0.0005	0.0003	-0.0007	-0.0004	0.0001	0.0000	0.0000	-0.0001	-0.0001
$\mathrm{E}(q_2\|\mathbf{x}_2,\mathbf{z}_2)$	0.0002	-0.0024	-0.0001	-0.0001	0.0003	0.0003	0.0003	0.0001	0.0000	0.0000	-0.0001	0.0000
$\mathrm{E}(q_3\|\mathbf{x}_3,\mathbf{z}_3)$	-0.0012	0.0002	-0.0020	0.0004	0.0014	-0.0006	-0.0041	-0.0013	0.0002	0.0001	0.0004	-0.0001
$\mathrm{E}(q_4\|\mathbf{x}_4,\mathbf{z}_4)$	-0.0005	0.0001	-0.0001	-0.0021	-0.0004	0.0003	-0.0005	-0.0001	0.0002	-0.0001	0.0002	-0.0002
$\mathrm{E}(q_5\|\mathbf{x}_5,\mathbf{z}_5)$	0.0001	-0.0001	0.0000	-0.0001	-0.0010	-0.0003	-0.0004	0.0002	-0.0001	-0.0001	0.0000	0.0000
$\mathrm{E}(q_6\|\mathbf{x}_6,\mathbf{z}_6)$	-0.0004	-0.0002	0.0000	0.0003	-0.0003	-0.0022	0.0004	0.0001	-0.0001	-0.0001	0.0000	0.0002
$\mathrm{E}(q_7\|\mathbf{x}_7,\mathbf{z}_7)$	-0.0002	0.0000	0.0000	0.0000	-0.0001	-0.0001	-0.0013	0.0000	0.0000	0.0000	0.0001	-0.0001
$\mathrm{E}(q_8\|\mathbf{x}_8,\mathbf{z}_8)$	-0.0001	0.0004	0.0003	0.0004	0.0011	0.0015	-0.0017	-0.0072	0.0005	0.0001	0.0007	-0.0002
$\mathrm{E}(q_9\|\mathbf{x}_9,\mathbf{z}_9)$	0.0001	0.0000	0.0001	0.0000	0.0005	-0.0002	0.0000	-0.0001	-0.0006	-0.0003	-0.0001	-0.0001
$\mathrm{E}(q_{10}\|\mathbf{x}_{10},\mathbf{z}_{10})$	0.0001	-0.0005	0.0003	-0.0003	0.0001	0.0001	-0.0010	0.0001	0.0000	-0.0006	0.0003	0.0001
$\mathrm{E}(q_{11}\|\mathbf{x}_{11},\mathbf{z}_{11})$	-0.0002	-0.0001	0.0001	-0.0004	0.0005	-0.0005	0.0003	0.0004	0.0000	0.0000	-0.0015	0.0000
$\mathrm{E}(q_{12}\|\mathbf{x}_{12},\mathbf{z}_{12})$	0.0001	-0.0003	0.0000	-0.0008	-0.0010	0.0000	0.0003	-0.0002	0.0000	-0.0003	0.0001	-0.0009
$\mathrm{E}(q_{13}\|\mathbf{x}_{13},\mathbf{z}_{13})$	-0.0007	0.0000	0.0001	-0.0017	0.0008	0.0010	0.0020	-0.0002	0.0002	0.0005	0.0000	0.0002
$\mathrm{E}(q_{14}\|\mathbf{x}_{14},\mathbf{z}_{14})$	0.0009	-0.0008	-0.0006	-0.0006	-0.0001	0.0002	-0.0006	0.0001	-0.0002	-0.0006	-0.0004	0.0001
$\mathrm{E}(q_{15}\|\mathbf{x}_{15},\mathbf{z}_{15})$	0.0000	0.0001	0.0000	0.0002	0.0004	0.0002	-0.0009	0.0001	-0.0010	-0.0014	0.0008	0.0001
$\mathrm{E}(q_{16}\|\mathbf{x}_{16},\mathbf{z}_{16})$	0.0000	0.0001	0.0000	0.0001	0.0013	0.0001	-0.0011	0.0005	0.0000	0.0001	0.0003	0.0000
$\mathrm{E}(q_{17}\|\mathbf{x}_{17},\mathbf{z}_{17})$	0.0000	-0.0001	0.0001	-0.0003	0.0013	-0.0009	-0.0023	0.0002	-0.0001	0.0003	0.0002	0.0000
$\mathrm{E}(q_{18}\|\mathbf{x}_{18},\mathbf{z}_{18})$	-0.0002	0.0001	-0.0002	0.0000	0.0002	0.0001	0.0001	-0.0001	0.0000	0.0001	0.0002	0.0000

Note: $i = 1, 2, \ldots, 18$, where 1 = Beefsteak, 2 = Ground Beef, 3 = Other Beef, 4 = Beef Offal, 5 = Pork Steak, 6 = Pork Leg & Shoulder, 7 = Ground Pork, 8 = Other Pork, 9 = Chorizo, 10 = Ham, Bacon & Similar Products from Beef & Pork, 11 = Beef & Pork Sausages, 12 = Other Processed Beef & Pork, 13 = Chicken Legs, Thighs & Breasts, 14 = Whole Chicken, 15 = Chicken Offal, 16 = Chicken Ham & Similar Products, 17 = Fish, 18 = Shellfish.

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Table 5.4: *Continued*

Table entries estimate $\frac{\partial \mathrm{E}(q_i|\mathbf{x}_i,\mathbf{z}_i)}{\partial x_{ij}}$.

	p_{13}	p_{14}	p_{15}	p_{16}	p_{17}	p_{18}	m	*NE*	*NW*	*CW*	*C*	*urban*
$\mathrm{E}(q_1\|\mathbf{x}_1,\mathbf{z}_1)$	-0.0009	-0.0001	0.0001	-0.0004	-0.0001	-0.0008	0.0032	0.0054	0.0215	0.0746	0.0277	0.0440
$\mathrm{E}(q_2\|\mathbf{x}_2,\mathbf{z}_2)$	0.0000	0.0003	0.0002	-0.0001	-0.0001	-0.0004	0.0006	0.0031	0.0854	0.0007	0.0204	0.0114
$\mathrm{E}(q_3\|\mathbf{x}_3,\mathbf{z}_3)$	-0.0005	0.0000	0.0006	0.0001	-0.0002	-0.0005	0.0013	0.0483	0.0611	0.0159	0.0474	0.0059
$\mathrm{E}(q_4\|\mathbf{x}_4,\mathbf{z}_4)$	-0.0003	-0.0002	0.0003	-0.0001	-0.0004	0.0002	0.0003	-0.0262	-0.0517	-0.0357	-0.0220	0.0043
$\mathrm{E}(q_5\|\mathbf{x}_5,\mathbf{z}_5)$	0.0000	-0.0002	0.0001	0.0002	0.0000	-0.0001	0.0001	-0.0172	-0.0162	-0.0065	-0.0051	0.0063
$\mathrm{E}(q_6\|\mathbf{x}_6,\mathbf{z}_6)$	0.0001	-0.0004	0.0000	0.0001	0.0001	0.0001	0.0003	-0.0179	-0.0112	0.0200	-0.0104	0.0080
$\mathrm{E}(q_7\|\mathbf{x}_7,\mathbf{z}_7)$	0.0000	-0.0001	-0.0001	-0.0001	0.0000	0.0000	0.0000	-0.0002	-0.0045	0.0018	0.0075	0.0031
$\mathrm{E}(q_8\|\mathbf{x}_8,\mathbf{z}_8)$	-0.0003	-0.0005	0.0001	-0.0008	-0.0002	0.0002	0.0007	-0.0430	-0.0393	0.0038	0.0088	0.0045
$\mathrm{E}(q_9\|\mathbf{x}_9,\mathbf{z}_9)$	-0.0001	-0.0002	-0.0003	-0.0002	0.0000	0.0000	0.0004	0.0095	0.0115	0.0044	0.0054	0.0029
$\mathrm{E}(q_{10}\|\mathbf{x}_{10},\mathbf{z}_{10})$	0.0001	0.0002	-0.0007	0.0002	0.0001	0.0002	0.0005	0.0120	-0.0023	0.0144	0.0213	0.0109
$\mathrm{E}(q_{11}\|\mathbf{x}_{11},\mathbf{z}_{11})$	0.0000	-0.0001	-0.0003	0.0002	0.0001	0.0002	0.0002	0.0125	0.0282	-0.0005	-0.0026	0.0088
$\mathrm{E}(q_{12}\|\mathbf{x}_{12},\mathbf{z}_{12})$	0.0004	0.0000	-0.0006	0.0001	0.0000	0.0001	0.0002	-0.0154	-0.0157	-0.0233	-0.0173	0.0035
$\mathrm{E}(q_{13}\|\mathbf{x}_{13},\mathbf{z}_{13})$	-0.0054	-0.0008	-0.0002	0.0006	0.0002	0.0001	0.0027	-0.0372	-0.0399	-0.0886	0.0722	0.0554
$\mathrm{E}(q_{14}\|\mathbf{x}_{14},\mathbf{z}_{14})$	0.0001	-0.0061	0.0010	0.0000	-0.0020	0.0000	0.0028	-0.2143	-0.1940	-0.0901	-0.1576	0.0074
$\mathrm{E}(q_{15}\|\mathbf{x}_{15},\mathbf{z}_{15})$	-0.0001	-0.0002	-0.0091	0.0006	-0.0002	0.0000	0.0005	0.0867	0.1091	0.1396	-0.0033	-0.0162
$\mathrm{E}(q_{16}\|\mathbf{x}_{16},\mathbf{z}_{16})$	0.0002	0.0000	0.0002	-0.0008	0.0000	0.0001	0.0003	0.0511	0.0204	-0.0001	-0.0076	0.0072
$\mathrm{E}(q_{17}\|\mathbf{x}_{17},\mathbf{z}_{17})$	-0.0001	0.0003	0.0006	0.0002	-0.0014	0.0005	0.0015	0.0068	0.0707	0.0130	0.0069	0.0049
$\mathrm{E}(q_{18}\|\mathbf{x}_{18},\mathbf{z}_{18})$	-0.0001	0.0000	0.0001	0.0003	0.0000	-0.0011	0.0002	0.0359	-0.0161	-0.0020	-0.0162	0.0100

Note: $i = 1, 2, \ldots, 18$, where 1 = Beefsteak, 2 = Ground Beef, 3 = Other Beef, 4 = Beef Offal, 5 = Pork Steak, 6 = Pork Leg & Shoulder, 7 = Ground Pork, 8 = Other Pork, 9 = Chorizo, 10 = Ham, Bacon & Similar Products from Beef & Pork, 11 = Beef & Pork Sausages, 12 = Other Processed Beef & Pork, 13 = Chicken Legs, Thighs & Breasts, 14 = Whole Chicken, 15 = Chicken Offal, 16 = Chicken Ham & Similar Products, 17 = Fish, 18 = Shellfish.

Table 5.5: Unconditional Mean Estimates of q_i.

	Mean (Kg/Capita/Week)	**Std. Error of Mean**
$\hat{q}_1$	0.1089	0.0012
$\hat{q}_2$	0.0384	0.0005
$\hat{q}_3$	0.0578	0.0008
$\hat{q}_4$	0.0154	0.0002
$\hat{q}_5$	0.0109	0.0002
$\hat{q}_6$	0.0215	0.0002
$\hat{q}_7$	0.0040	0.0001
$\hat{q}_8$	0.0405	0.0007
$\hat{q}_9$	0.0234	0.0002
$\hat{q}_{10}$	0.0348	0.0003
$\hat{q}_{11}$	0.0260	0.0002
$\hat{q}_{12}$	0.0225	0.0005
$\hat{q}_{13}$	0.1454	0.0015
$\hat{q}_{14}$	0.1367	0.0014
$\hat{q}_{15}$	0.0246	0.0008
$\hat{q}_{16}$	0.0308	0.0004
$\hat{q}_{17}$	0.0698	0.0007
$\hat{q}_{18}$	0.0127	0.0003

Note: $\hat{q}_i$, $i = 1, 2, \ldots, 18$, where 1 = Beefsteak, 2 = Ground Beef, 3 = Other Beef, 4 = Beef Offal, 5 = Pork Steak, 6 = Pork Leg & Shoulder, 7 = Ground Pork, 8 = Other Pork, 9 = Chorizo, 10 = Ham, Bacon & Similar Products from Beef & Pork, 11 = Beef & Pork Sausages, 12 = Other Processed Beef & Pork, 13 = Chicken Legs, Thighs & Breasts, 14 = Whole Chicken, 15 = Chicken Offal, 16 = Chicken Ham & Similar Products, 17 = Fish, 18 = Shellfish.

5.1.3 Elasticity Estimates and Previous Studies

A demand function can be described in terms of its elasticity values. The *elasticities* measure the percentage response of the quantity consumed to a one percent change in price or total expenditure, holding all other variables constant. The *own-price elasticity* of demand of a commodity is defined as the percent decrease (increase) in the quantity demanded resulting from a 1% percent increase (decrease) in its own price. If the own price elasticity is *less than 1*, the demand of that commodity is *inelastic*, while if it is *greater than 1*, the demand of that commodity is *elastic*. The *cross-price elasticity of demand* is defined as the percent increase or decrease in the quantity demanded of a commodity resulting from a 1% percent increase or decrease in the price of another commodity. If the cross price elasticity of demand is *positive*, the commodities are *substitutes*, while if it is *negative* the commodities are *complements*. Similarly, the *expenditure elasticity of demand* of a commodity is defined as the percent increase or decrease in the quantity demanded of a commodity from a 1% percent increase or decrease in total expenditure. If the expenditure elasticity is *positive*, the commodity is *normal*; however, if it is *negative* the commodity is *inferior*. In addition, luxury commodities and necesary commodities can be defined in terms of the expenditure elasticity of demand. *Luxuries* are commodities with high expenditure elasticities of demand (usually greater than 1). *Necessities* are goods with low expenditure elasticities of demand (usually less than 1). The *uncompensated (or Marshallian) demand elasticity does not compensate* the consumer when the price of a commodity changes so that the same utility level cannot be maintained. *Compensated (or Hicksian) demand elasticities compensate* the consumer when the price of a commodity changes so that the same utility level can be maintained.

Table 5.6 and Table 5.7 report the Marshallian and Hicksian price elasticities respectively. Observe that the expected negative sign was obtained for all Marshallian and Hicksian own-price elasticities. In addition, there are slightly more positive cross-price elasticities (160 Marshallians and 178 Hicksians) than negative cross-price elasticities (146 Marshallians and 128 Hicksians). A positive cross-price elasticity suggests a case of substitutes meat cuts while a negative cross-price elasticity suggest a case of complement meat cuts. In Table 5.6 and Table 5.7, the sign of the Marshallian and Hicksian price elasticities was the same in all but 18 cases ($\hat{e}_{0110}$, $\hat{e}_{0111}$, $\hat{e}_{0112}$, $\hat{e}_{0114}$, $\hat{e}_{0117}$, $\hat{e}_{0212}$, $\hat{e}_{0917}$, $\hat{e}_{1110}$, $\hat{e}_{1113}$, $\hat{e}_{1214}$, $\hat{e}_{1311}$, $\hat{e}_{1416}$, $\hat{e}_{1418}$, $\hat{e}_{1601}$, $\hat{e}_{1701}$, $\hat{e}_{1713}$, $\hat{e}_{1814}$, and $\hat{e}_{1817}$). In addition, examples of (gross and net) substitutes include beefsteak and pork steak, and vice versa (i.e., $\hat{e}_{0105}$ and $\hat{e}^c_{0105}$, $\hat{e}_{0501}$ and $\hat{e}^c_{0501}$); beef offal and chicken offal, and vice versa (i.e., $\hat{e}_{0415}$ and $\hat{e}^c_{0415}$, $\hat{e}_{1504}$ and $\hat{e}^c_{1504}$); and ham, bacon and similar beef and pork products and chicken ham and similar products, and vice versa (i.e., $\hat{e}_{1016}$ and $\hat{e}^c_{1016}$, $\hat{e}_{1610}$ and $\hat{e}^c_{1610}$). Similarly, examples of (gross and net) complementarity include beefsteak and other beef, and vice versa (i.e., $\hat{e}_{0103}$ and $\hat{e}^c_{0103}$, $\hat{e}_{0301}$ and $\hat{e}^c_{0301}$); pork steak and pork leg and shoulder, and vice versa (i.e., $\hat{e}_{0506}$ and $\hat{e}^c_{0506}$, $\hat{e}_{0605}$ and $\hat{e}^c_{0605}$); and whole chicken is a (gross and net) substitute of chicken legs, thighs and breasts, but not vice versa (i.e., $\hat{e}_{1314}$ and $\hat{e}^c_{1314}$, but neither $\hat{e}_{1413}$ nor $\hat{e}^c_{1413}$). The expenditure elasticities are reported in Table 5.8. They will be discussed in more detail and compared with previous findings in Section 5.1.3.7.

In general, the own-price elasticities had the lowest values among the price elasticities (except for $\hat{e}_{0303}$, $\hat{e}_{1010}$, $\hat{e}_{1616}$, $\hat{e}_{1717}$, $\hat{e}^c_{0303}$, $\hat{e}^c_{1010}$, $\hat{e}^c_{1616}$, and $\hat{e}^c_{1717}$).[6] This suggests that Mexican consumers are very price sensitive with respect to the consumptions and changes in the own prices of these commodities. There might be two reasons why this study found low own-price elasticity values. First, it may be due to the fact that in the model Mexican consumers can substitute a beef cut with another beef cut, a pork cut with another pork cut, a processed meat cut with another processed meat cut, and so on, hence, making them more price sensitive. In other words, the own-price elasticities of aggregated meat categories (i.e., beef, pork, and chicken) tend to be more inelastic because consumers are given less potential substitutes, not only across meat categories but most importantly within a meat category. Consequently, consumers might be more reluctant to substitute an aggregated meat category. On the other hand, when disaggregated commodities are considered, there are more potential

[6]That is, high absolute values.

substitutes. In this study, there are more potential substitutes across and within categories. Consequently, consumers have more choices (specially within a meat category); and therefore, own-price elasticities tend to be more elastic. Second, it may be due to the high number of censored observations. On one hand, an imputation approach tends to reduce price variability (as explained in Section 2.5), and on the other hand, there are several censored quantities (which implies that there are several occasions in the data sample in which consumption goes from zero (censored) to non-negative and positive (non-censored)). In fact, a comparison of the number of censored observations from Table 4.2 and Table 4.3 with the extreme elastic cases reveals that these cases are likely to occur when the number of censored observations is very high. Therefore, even when using a consistent censored demand system, the combination of a price imputation approach with censored quantities may still influence the own-price elasticities to be very small (i.e., big absolute values). For instance, in four of eighteen occasions, the Marshallian own-price elasticities resulted in values lower than -5 ($\hat{e}_{0707} = -15.9428$, $\hat{e}_{0808} = -8.3019$, $\hat{e}_{1515} = -9.1730$, and $\hat{e}_{1818} = -7.5997$) and similarly for the Hicksian own-price elasticities ($\hat{e}^c_{0707} = -15.9417$, $\hat{e}^c_{0808} = -8.2689$, $\hat{e}^c_{1515} = -9.1617$, and $\hat{e}^c_{1818} = -7.5851$). For illustration purposes, Figure 5.1 and Figure 5.2 show the Marshallian and Hicksian price elasticities after removing these low values. The expenditure elasticities are depicted in Figure 5.3.

These estimates of elasticities at the table-cut level of disaggregation are currently not available for Mexico. Therefore, a direct comparison of elasticities is not possible. When comparing elasticities, it critical to remember that model functional forms, sample sizes, time periods, and assumptions influence elasticities to differ from one study to another. An indirect comparison of this study's findings with previous estimates is presented in the following sub-subsections. The main purpose is to get a general idea on how this study's findings compare to previous ones.

5.1.3.1 Marshallian Beef-Price Elasticities

The Marshallian beef-beef elasticity in previous studies ranges from -1.4300 in Malaga, Pan, and Duch (2006) to -0.3450 in González Sánchez (2001) (i.e., refer to the beef-beef column of Table B.1 in Appendix). In this study, there are sixteen Marshallian beef-beef elasticities ($\hat{e}_{ij},\ i,j = 1,2,3,4$) and most of their values range from $\hat{e}_{0401} = -1.8100$ (excluding $\hat{e}_{0404} = -4.8186$ and $\hat{e}_{0202} = -3.4594$ whose values are much lower than all the others) to $\hat{e}_{0402} = 0.4889$ (Table 5.6). However, all beef-beef elasticities in previous studies are own-price elasticities of beef. Clearly, in this study beef-beef elasticities consist of own-price elasticities ($\hat{e}_{ij},\ i,j = 1,2,3,4,$ $i = j$) and cross-price elasticities ($\hat{e}_{ij},\ i,j = 1,2,3,4,\ i \neq j$). Therefore, different from previous studies, disaggregating elasticities allowed this study to identify gross substitutes among beef cuts. For example, ground beef is a gross substitute for beefsteak ($\hat{e}_{0102}$), ground beef is a gross substitute for other beef ($\hat{e}_{0302}$), beef offal is a gross substitute for other beef ($\hat{e}_{0304}$), beefsteak is a gross substitute for ground beef ($\hat{e}_{0201}$), and ground beef is a gross substitute for beef offal ($\hat{e}_{0402}$). Similar to beef-beef elasticities, in this study there are Marshallian price elasticities among beef and processed beef and pork. These elasticities ($\hat{e}_{ij},\ i = 1,2,3,4,\ j = 9,10,11,12$) range from $\hat{e}_{0412} = -0.7262$ to $\hat{e}_{0409} = 0.6108$. In this case, the minimum value from the price elasticities among beef and processed beef and pork is closer to most of the previous beef-beef elasticity values (i.e., refer to beef-beef column of Table B.1 in Appendix).

The Marshallian beef-pork elasticity in previous studies range from -0.2610 in García Vega (1995) to 0.0300 in Malaga, Pan, and Duch (2006) (i.e., refer to the beef-pork column of Table B.1 in Appendix). In contrast, Marshallian beef-pork elasticities in Table 5.6 ($\hat{e}_{ij},\ i = 1,2,3,4,\ j = 5,6,7,8$) range from $\hat{e}_{0407} = -1.5508$ (excluding $\hat{e}_{0307} = -3.3987$ whose value is much lower than all the others) to $\hat{e}_{0406} = 0.8117$ (excluding $\hat{e}_{0305} = 1.2346$ whose value is much higher than all the others). Hence, the range of beef-pork elasticity values is wider when disaggregating elasticities into table cuts.

The Marshallian beef-chicken elasticity in previous studies ranges from -0.2324 in Clark (2006) to 0.2700 in Malaga, Pan, and Duch (2006) (i.e., refer to the beef-chicken column of Table B.1 in Appendix). In this study, the sixteen beef-chicken elasticities ($\hat{e}_{ij}$, $i = 1, 2, 3, 4$, $j = 13, 14, 15, 16$) have a slightly wider range of values. The minimum beef-chicken elasticity value is $\hat{e}_{0413} = -0.6557$ and the maximum beef-chicken elasticity value is $\hat{e}_{0415} = 0.4998$ (Table 5.6). In some studies, chicken was found to be a gross substitute for beef (López, 2008; Fernández, 2007; Malaga, Pan, and Duch, 2006; Dong, Gould, and Kaiser, 2004; González Sánchez, 2001) while in others it was found to be a gross complement (Malaga, Pan, and Duch, 2007; Clark, 2006; García Vega, 1995). Even though these findings are influenced by different functional forms, sample sizes, time periods, and assumptions, it may also suggest that for particular meat cuts, chicken is a gross complement for beef ($\hat{e}_{0413}$, $\hat{e}_{0414}$, $\hat{e}_{0313}$, $\hat{e}_{0113}$, $\hat{e}_{0416}$, $\hat{e}_{0116}$, $\hat{e}_{0216}$, and $\hat{e}_{0114}$) while for others it is a gross substitute ($\hat{e}_{0213}$, $\hat{e}_{0314}$, $\hat{e}_{0115}$, $\hat{e}_{0215}$, $\hat{e}_{0316}$, $\hat{e}_{0214}$, $\hat{e}_{0315}$, and $\hat{e}_{0415}$). Consequently, it is more insightful to analyze price elasticities at the table-cut level of disaggregation.

Finally, only one previous study reports a Marshallian beef-fish elasticity (i.e., refer to the beef-fish column of Table B.1 in Appendix). Dong, Gould, and Kaiser (2004) found a Marshallian fish-beef elasticity of -0.0452, which is closest in value to $\hat{e}_{0217} = -0.0950$ and $\hat{e}_{0117} = -0.0394$ in Table 5.6. In this study, Marshallian beef-fish elasticities ($\hat{e}_{ij}$, $i = 1, 2, 3, 4$, $j = 17$) range from $\hat{e}_{0417} = -1.3958$ to $\hat{e}_{0117} = -0.0394$. Similarly, Marshallian beef-shellfish elasticities ($\hat{e}_{ij}$, $i = 1, 2, 3, 4$, $j = 18$) in Table 5.6 range from $\hat{e}_{0218} = -0.9724$ to $\hat{e}_{0418} = 1.1782$.

5.1.3.2 Marshallian Pork-Price Elasticities

The Marshallian pork-beef elasticity in previous studies ranges from -0.5790 in García Vega (1995) to 0.1462 in Clark (2006) (i.e., refer to the pork-beef column of Table B.2 in Appendix). In addition, there are as many negative pork-beef elasticities (Fernández, 2007; Dong, Gould, and Kaiser, 2004; González Sánchez, 2001; García Vega, 1995) as there are positives (López, 2008; Malaga, Pan, and Duch, 2007; Clark, 2006; Malaga, Pan, and Duch, 2006). In other words, some studies have found beef to be a gross substitute for pork (i.e., positive Marshallian cross-price elasticities) while others have found it to be a gross complement (i.e., negative Marshallian cross-price elasticities). However, previous studies compare the same pork-beef elasticity, while this study considers sixteen different pork-beef elasticities ($\hat{e}_{ij}$, $i = 5, 6, 7, 8$, $j = 1, 2, 3, 4$), which result from different table cuts of pork and beef.

There are almost as many negative pork-beef elasticities ($\hat{e}_{0701}$, $\hat{e}_{0601}$, $\hat{e}_{0502}$, $\hat{e}_{0702}$, $\hat{e}_{0602}$, $\hat{e}_{0504}$, and $\hat{e}_{0801}$) in Table 5.6 as there are positives ($\hat{e}_{0603}$, $\hat{e}_{0503}$, $\hat{e}_{0704}$, $\hat{e}_{0703}$, $\hat{e}_{0803}$, $\hat{e}_{0804}$, $\hat{e}_{0604}$, $\hat{e}_{0802}$, $\hat{e}_{0501}$). In addition, their values range from $\hat{e}_{0601} = -1.2086$ (excluding $\hat{e}_{0701} = -2.4904$ whose value is much lower than all others) to $\hat{e}_{0501} = 0.7866$. There are also sixteen Marshallian price elasticities among pork and processed beef and pork ($\hat{e}_{ij}$, $i = 5, 6, 7, 8$, $j = 9, 10, 11, 12$). Similarly, there are as many negative price elasticities among pork and processed beef and pork ($\hat{e}_{0712}$, $\hat{e}_{0510}$, $\hat{e}_{0509}$, $\hat{e}_{0812}$, $\hat{e}_{0610}$, $\hat{e}_{0609}$, $\hat{e}_{0512}$, and $\hat{e}_{0710}$) as there are positives ($\hat{e}_{0611}$, $\hat{e}_{0810}$, $\hat{e}_{0511}$, $\hat{e}_{0709}$, $\hat{e}_{0811}$, $\hat{e}_{0612}$, $\hat{e}_{0809}$, and $\hat{e}_{0711}$).

The Marshallian pork-pork elasticity in previous studies ranges from -1.5100 in Malaga, Pan, and Duch (2006) to 0.0270 in Dong and Gould (2000) (i.e., refer to the pork-pork column of Table B.2 in Appendix). In this study, the own-price elasticities from pork meat cuts resulted in values lower than usual (i.e., high absolute values). For example, the own-price elasticity of ground pork has a value of $\hat{e}_{0707} = -15.9428$. This means that a 1% increase in the price of ground pork will decrease the consumption of ground pork by 15.9428%, all other things held constant. This means that ground pork consumers are very price sensitive. Similarly, the own-price elasticities of other pork, pork leg and shoulder, and pork steak are $\hat{e}_{0808} = -8.3019$, $\hat{e}_{0606} = -4.8375$, and $\hat{e}_{0505} = -4.4711$ respectively. Given that Mexican consumers are well known for their high preference for pork, it is surprising these elasticity estimates are very elastic. However, they might be very elastic because in the model Mexican consumers can substitute a pork cut with another pork cut, which makes them more price sensitive. When excluding these four own-price elasticities, the pork-

pork elasticities in Table 5.6 ($\hat{e}_{ij}$, $i, j = 5, 6, 7, 8$, $i \neq j$) range from $\hat{e}_{0807} = -1.9708$ to $\hat{e}_{0806} = 1.6971$. Consequently, this study identifies gross substitutes and complements among pork cuts.

The Marshallian pork-chicken elasticity in previous studies ranges from -0.4295 in Fernández (2007) to 0.2600 in Malaga, Pan, and Duch (2006) (i.e., refer to the pork-chicken column of Table B.2 in Appendix). However, in most of the studies it has a negative sign (López, 2008; Fernández, 2007; Malaga, Pan, and Duch, 2007; Dong, Gould, and Kaiser, 2004; González Sánchez, 2001), which means that chicken is a gross complement for pork. When several pork and chicken cuts are considered, there are cases where chicken is a gross complement for pork ($\hat{e}_{0816}$, $\hat{e}_{0716}$, $\hat{e}_{0714}$, $\hat{e}_{0514}$, $\hat{e}_{0614}$, $\hat{e}_{0814}$, $\hat{e}_{0715}$, $\hat{e}_{0713}$, $\hat{e}_{0813}$, and $\hat{e}_{0513}$) and cases where it is a gross substitute ($\hat{e}_{0615}$, $\hat{e}_{0815}$, $\hat{e}_{0613}$, $\hat{e}_{0616}$, $\hat{e}_{0515}$, and $\hat{e}_{0516}$). They ($\hat{e}_{ij}$, $i = 5, 6, 7, 8$, $j = 13, 14, 15, 16$) range from $\hat{e}_{0816} = -0.8650$ to $\hat{e}_{0516} = 0.8314$ (Table 5.6). Similarly, the Marshallian price elasticities among pork and processed beef and pork range from $\hat{e}_{0712} = -1.4896$ to $\hat{e}_{0711} = 0.6991$.

Finally, only Dong, Gould, and Kaiser (2004) report a Marshallian pork-fish elasticity (i.e., refer to the pork-fish column of Table B.2 in Appendix). This elasticity (-0.0507) is between the values of the pork-fish elasticities of $\hat{e}_{0817} = -0.2177$ and $\hat{e}_{0517} = 0.0147$ in Table 5.6. In general, Marshallian pork-fish elasticities ($\hat{e}_{ij}$, $i = 5, 6, 7, 8$, $j = 17$) in Table 5.6 range from $\hat{e}_{0717} = -0.4851$ to $\hat{e}_{0617} = 0.1516$. Likewise, Marshallian pork-shellfish elasticities ($\hat{e}_{ij}$, $i = 5, 6, 7, 8$, $j = 18$) in Table 5.6 range from $\hat{e}_{0518} = -0.9145$ to $\hat{e}_{0818} = 0.4907$.

5.1.3.3 Marshallian Chicken-Price Elasticities

The Marshallian chicken-beef elasticity in previous studies ranges from -0.9942 in Clark (2006) to 0.5300 in Malaga, Pan, and Duch (2006) (i.e., refer to the chicken-beef column of Table B.3 in Appendix). Additionally, most studies have found beef to be a gross complement for chicken (Fernández, 2007; Malaga, Pan, and Duch, 2007; Clark, 2006; González Sánchez, 2001; García Vega, 1995), but there are studies where it is a gross substitute (López, 2008; Malaga, Pan, and Duch, 2006; Dong, Gould, and Kaiser, 2004). In Table 5.6, most chicken-beef elasticities ($\hat{e}_{ij}$, $i = 13, 14, 15, 16$, $j = 1, 2, 3, 4$) are positive ($\hat{e}_{1302}$, $\hat{e}_{1501}$, $\hat{e}_{1303}$, $\hat{e}_{1503}$, $\hat{e}_{1603}$, $\hat{e}_{1604}$, $\hat{e}_{1502}$, $\hat{e}_{1602}$, $\hat{e}_{1504}$, and $\hat{e}_{1401}$). The same tendency is also observed for the Marshallian chicken-pork elasticities ($\hat{e}_{ij}$, $i = 13, 14, 15, 16$, $j = 5, 6, 7, 8$) and the Marshallian price elasticities among chicken and processed beef and pork ($\hat{e}_{ij}$, $i = 13, 14, 15, 16$, $j = 9, 10, 11, 12$), but not for the Marshallian chicken-chicken elasticities ($\hat{e}_{ij}$, $i, j = 13, 14, 15, 16$), where there are about as many positive elasticities as there are negatives. Finally, the chicken-beef elasticities in Table 5.6 fall within the range of Clark (2006) and Malaga, Pan, and Duch (2006), which is $[-0.9942, 0.5300]$. They range from $\hat{e}_{1304} = -0.4099$ to $\hat{e}_{1401} = 0.3895$.

The Marshallian chicken-pork elasticity in previous studies ranges from -0.6400 in Malaga, Pan, and Duch (2007) to 1.0030 in García Vega (1995) (i.e., refer to the chicken-pork column of Table B.3 in Appendix). All the Marshallian chicken-pork elasticities ($\hat{e}_{ij}$, $i = 13, 14, 15, 16$, $j = 5, 6, 7, 8$) in Table 5.6 fall within the range provided by previous studies (except for $\hat{e}_{1607} = -1.7323$, $\hat{e}_{1507} = -1.7283$, and $\hat{e}_{1605} = 2.1079$). Excluding $\hat{e}_{1607}$, $\hat{e}_{1507}$, and $\hat{e}_{1605}$; they range from $\hat{e}_{1407} = -0.2241$ to $\hat{e}_{1505} = 0.7168$. Similarly, the Marshallian price elasticities among chicken and processed beef and pork ($\hat{e}_{ij}$, $i = 13, 14, 15, 16$, $j = 9, 10, 11, 12$) in Table 5.6 almost fall between -0.6400 and 1.0030 (except for $\hat{e}_{1510} = -2.6776$ and $\hat{e}_{1509} = -2.0678$). Excluding $\hat{e}_{1510}$ and $\hat{e}_{1509}$, they fall within the interval $[-0.2281, 1.0031]$.

The Marshallian chicken-chicken elasticity in previous studies ranges from -1.4300 in Malaga, Pan, and Duch (2006) to -0.1300 in Dong and Gould (2000) (i.e., refer to the chicken-chicken column of Table B.3 in Appendix). While the chicken-chicken elasticities from previous studies only refer to one own-price elasticity, the chicken-chicken elasticities in Table 5.6 consist of four own price elasticities ($\hat{e}_{ij}$, $i, j = 13, 14, 15, 16$, $i = j$) and twelve cross-price elasticities ($\hat{e}_{ij}$, $i, j = 13, 14, 15, 16$, $i \neq j$). Consequently, this analysis has the advantage of considering not only one chicken-chicken elasticity but sixteen. That is, this study further analyzes cases of gross complementarity (i.e., cases of negative cross-price elasticities) and gross substitutability (i.e., cases of positive cross-price elasticities) among chicken cuts. On the other hand, the own-price elasticity of chicken offal has a low unusual value, $\hat{e}_{1515} = -9.1730$. This means that a 1% increase in the price of chicken offal will decrease the consumption of chicken offall by 9.1730%, all other things held constant. A low value is unusual because Mexican consumers are popular for their preference for meat offal and becasue chicken offal is the cheapest meat cut (average price equals 24.8824 pesos/kg, Table 4.2). Similar to the pork own-price elasticities, a very elastic own-price elasticity might be related to the fact that in the model Mexican consumers can substitute a chicken cut with another chicken cut (which makes consumers more price sensitive).

Finally, only one Marshallian chicken-fish elasticity has been reported in previous studies (i.e., refer to the chicken-fish column of Table B.3 in Appendix). Dong, Gould, and Kaiser (2004) reported this elasticity to be -0.0818, which is between $\hat{e}_{1517} = -0.4770$ and $\hat{e}_{1617} = 0.0404$ in Table 5.6. In general, Marshallian chicken-fish elasticities ($\hat{e}_{ij}$, $i = 13, 14, 15, 16$, $j = 17$) range from $\hat{e}_{1417} = -0.7013$ to $\hat{e}_{1317} = 0.0551$ (Table 5.6). Similarly, Marshallian chicken-shellfish elasticities ($\hat{e}_{ij}$, $i = 13, 14, 15, 16$, $j = 18$) range from $\hat{e}_{1518} = -0.0833$ to $\hat{e}_{1618} = 0.1742$ (Table 5.6).

5.1.3.4 Hicksian Beef-Price Elasticities

The Hicksian beef-beef elasticity in previous studies ranges from -0.8700 in Malaga, Pan, and Duch (2006) to -0.0494 in González Sánchez (2001) (i.e., refer to the beef-beef column of Table B.4 in Appendix). As explained before, there are sixteen Hicksian beef-beef elasticities ($\hat{e}^c_{ij}$, $i, j = 1, 2, 3, 4$) in this study. Most of their values range from $\hat{e}^c_{0401} = -1.6814$ (excluding $\hat{e}^c_{0404} = -4.8079$ and $\hat{e}^c_{0202} = -3.4253$ whose values are much lower than all the others) to $\hat{e}^c_{0402} = 0.5308$ (Table 5.7). Therefore, different from previous studies, disaggregating elasticities allowed this study to identify net substitutes among beef cuts. For example, ground beef is a net substitute for beefsteak ($\hat{e}^c_{0102}$), ground beef is a net substitute for other beef ($\hat{e}^c_{0302}$), beef offal is a net substitute for other beef ($\hat{e}^c_{0304}$), beefsteak is a net substitute for ground beef ($\hat{e}^c_{0201}$), and ground beef is a net substitute for beef offal ($\hat{e}^c_{0402}$). In this study, there are also price elasticities among beef and processed beef and pork, which are currently not available in previous studies. These elasticities ($\hat{e}^c_{ij}$, $i = 1, 2, 3, 4$, $j = 9, 10, 11, 12$) range from $\hat{e}^c_{0412} = -0.6940$ to $\hat{e}^c_{0409} = 0.6341$. In this case, the minimum value is closer to most previous beef-beef elasticity estimates (i.e., refer to the beef-beef column of Table B.4 in Appendix). However, all beef-beef elasticities in previous studies refer to the own-price elasticities of beef; while the beef-beef elasticities in this study refer to four own-price elasticities ($\hat{e}^c_{ij}$, $i, j = 1, 2, 3, 4$, $i = j$) and twelve cross-price elasticities ($\hat{e}^c_{ij}$, $i, j = 1, 2, 3, 4$, $i \neq j$).

The Hicksian beef-pork elasticity in previous studies range from -0.0419 in González Sánchez (2001) to 0.6500 in Malaga, Pan, and Duch (2007) (i.e., refer to the beef-pork column of Table B.4 in Appendix). In contrast, Marshallian beef-pork price elasticities ($\hat{e}^c_{ij}$, $i = 1, 2, 3, 4$, $j = 5, 6, 7, 8$) in Table 5.7 range from $\hat{e}^c_{0407} = -1.5471$ (excluding $\hat{e}^c_{0307} = -3.3945$ whose value is much lower than all the others) to $\hat{e}^c_{0406} = 0.8313$ (excluding $\hat{e}^c_{0305} = 1.2467$ whose value is much higher than all the others). Hence, the range of beef-pork elasticity values is wider when disaggregating elasticities.

The Hicksian beef-chicken elasticity in previous studies ranges from -0.1609 in Clark (2006) to 0.7100 in Malaga, Pan, and Duch (2006) (i.e., refer to the beef-chicken column of Table B.4 in Appendix). The sixteen beef-chicken elasticities ($\hat{e}^c_{ij}$, $i = 1, 2, 3, 4$, $j = 13, 14, 15, 16$) in Table 5.7 have lower minimum and maximum values ($\hat{e}^c_{0413} = -0.5577$ and $\hat{e}^c_{0415} = 0.5117$). In some studies, chicken is a net substitute for beef (López, 2008; Fernández, 2007; Malaga, Pan, and Duch, 2007; 2006; Golan, Perloff, and Shen, 2001; González Sánchez, 2001) while in others it is a net complement (Clark, 2006; García Vega, 1995). In Table 5.7, there are some meat cuts for which chicken is a net complement of beef ($\hat{e}^c_{0413}$, $\hat{e}^c_{0414}$, $\hat{e}^c_{0313}$, $\hat{e}^c_{0416}$, $\hat{e}^c_{0113}$, $\hat{e}^c_{0116}$, and $\hat{e}^c_{0216}$) and some for which it is a net substitute for beef ($\hat{e}^c_{0115}$, $\hat{e}^c_{0114}$, $\hat{e}^c_{0213}$, $\hat{e}^c_{0314}$, $\hat{e}^c_{0215}$, $\hat{e}^c_{0316}$, $\hat{e}^c_{0315}$, $\hat{e}^c_{0214}$, and $\hat{e}^c_{0415}$). This may indicate that it is important to analyze price elasticities at the table-cut level of disaggregation.

Finally, there is only one previous study that reports a Hicksian beef-fish elasticity (i.e., refer to the beef-fish column of Table B.4 in Appendix), which is Golan, Perloff, and Shen's (2001) elasticity of 0.1660. This is closest in value to $\hat{e}^c_{0117} = 0.0591$ in Table 5.7. However, Hicksian beef-fish elasticities ($\hat{e}^c_{ij}$, $i = 1, 2, 3, 4$, $j = 17$) range from $\hat{e}^c_{0417} = -1.3309$ to $\hat{e}^c_{0117} = 0.0591$ and Hicksian beef-shellfish elasticities ($\hat{e}^c_{ij}$, $i = 1, 2, 3, 4$, $j = 18$) range from $\hat{e}^c_{0218} = -0.9549$ to $\hat{e}^c_{0418} = 1.1997$ (Table 5.7).

5.1.3.5 Hicksian Pork-Price Elasticities

The Hicksian pork-beef elasticity in previous studies ranges from -0.0412 in González Sánchez (2001) to 0.6700 in Malaga, Pan, and Duch (2006) (i.e., refer to the pork-beef column of Table B.5 in Appendix). Different from the Marshallian pork-beef elasticities, Hicksian pork-beef elasticities in most of the studies has been positive (López, 2008; Fernández, 2007; Malaga, Pan, and Duch, 2007; Clark, 2006; Malaga, Pan, and Duch, 2006; Golan, Perloff, and Shen, 2001; García Vega, 1995), but there is one study where it is negative (González Sánchez, 2001). However, previous studies refer one elasticity, while this study analyzes sixteen ($\hat{e}_{ij}$, $i = 5, 6, 7, 8$, $j = 1, 2, 3, 4$), which are combinations of different table cuts of pork and beef. As a result, some beef cuts are net complements of other beef cuts (i.e., negative Hicksian cross-price elasticity) while others are net substitutes (i.e., positive Hicksian cross-price elasticity).

Similar to the Marshallian pork-beef elasticities (Table 5.6), there are almost as many negative Hicksian pork-beef elasticities ($\hat{e}^c_{0701}$, $\hat{e}^c_{0601}$, $\hat{e}^c_{0502}$, $\hat{e}^c_{0702}$, $\hat{e}^c_{0602}$, $\hat{e}^c_{0504}$, and $\hat{e}^c_{0801}$) in Table 5.7 as there are positives ($\hat{e}^c_{0603}$, $\hat{e}^c_{0503}$, $\hat{e}^c_{0704}$, $\hat{e}^c_{0703}$, $\hat{e}^c_{0803}$, $\hat{e}^c_{0804}$, $\hat{e}^c_{0604}$, $\hat{e}^c_{0802}$, $\hat{e}^c_{0501}$). In addition, their values range from $\hat{e}^c_{0601} = -1.1054$ (excluding $\hat{e}^c_{0701} = -2.4533$ whose value is much lower than all others) to $\hat{e}^c_{0501} = 0.8650$. There are also sixteen Hicksian price elasticities among pork and processed beef and pork ($\hat{e}^c_{ij}$, $i = 5, 6, 7, 8$, $j = 9, 10, 11, 12$). Similarly, there are as many negative price elasticities among pork and processed beef and pork ($\hat{e}^c_{0712}$, $\hat{e}^c_{0510}$, $\hat{e}^c_{0509}$, $\hat{e}^c_{0812}$, $\hat{e}^c_{0610}$, $\hat{e}^c_{0609}$, $\hat{e}^c_{0512}$, and $\hat{e}^c_{0710}$) as there are positives ($\hat{e}^c_{0611}$, $\hat{e}^c_{0511}$, $\hat{e}^c_{0810}$, $\hat{e}^c_{0709}$, $\hat{e}^c_{0811}$, $\hat{e}^c_{0612}$, $\hat{e}^c_{0809}$, and $\hat{e}^c_{0711}$). These elasticities range from $\hat{e}^c_{0712} = -1.4803$ to $\hat{e}^c_{0711} = 0.7037$.

The Marshallian pork-pork elasticity in previous studies ranges from -1.3800 in Malaga, Pan, and Duch (2006) to -0.0312 in Fernández (2007) (i.e., refer to the pork-pork column of Table B.5 in Appendix). Similar to the Marshallian pork-pork own-price elasticities (Table 5.6), the Hicksian pork-pork own-price elasticities (Table 5.7) have unusual low values. For instance, the Hicksian own-price elasticity of ground pork is $\hat{e}^c_{0707} = -15.9417$, and it is then followed by the own-price elasticities of other pork ($\hat{e}^c_{0808} = -8.2689$), pork leg and shoulder ($\hat{e}^c_{0606} = -4.8218$), and pork steak ($\hat{e}^c_{0505} = -4.4646$). As explained before, these pork-pork own-price elasticities may be low because in the model Mexican consumers can substitute a pork cut with another pork cut, which makes them more price sensitive. When these four own-price elasticities are excluded, the remaining pork-pork elasticities in Table 5.7 ($\hat{e}^c_{ij}$, $i, j = 5, 6, 7, 8,\ i \neq j$) range from $\hat{e}^c_{0807} = -1.9675$ to $\hat{e}^c_{0806} = 1.7147$.

The Hicksian pork-chicken elasticity in previous studies ranges from -0.2700 in Malaga, Pan, and Duch (2007) to 0.7000 in Malaga, Pan, and Duch (2006) (i.e., refer to the pork-chicken column of Table B.5 in Appendix). Contrary to Marshallian pork-chicken elasticity (Appendix, Table B.2), which is most frequently reported having a negative sign, the Hicksian pork-chicken elasticity (Appendix, Table B.5) is most frequently reported having a positive sign (López, 2008; Clark, 2006; Malaga, Pan, and Duch, 2006; Golan, Perloff, and Shen, 2001; González Sánchez, 2001; García Vega, 1995). That is, most previous studies have concluded that chicken is a net substitute for pork. When several pork and chicken cuts are considered (Table 5.7), there are examples where chicken is a net complement for pork ($\hat{e}^c_{0816}$, $\hat{e}^c_{0716}$, $\hat{e}^c_{0714}$, $\hat{e}^c_{0514}$, $\hat{e}^c_{0614}$, $\hat{e}^c_{0715}$, $\hat{e}^c_{0814}$, $\hat{e}^c_{0713}$, $\hat{e}^c_{0813}$, and $\hat{e}^c_{0513}$) and examples where it is a net substitute ($\hat{e}^c_{0615}$, $\hat{e}^c_{0815}$, $\hat{e}^c_{0613}$, $\hat{e}^c_{0616}$, $\hat{e}^c_{0515}$, and $\hat{e}^c_{0516}$). In addition, the pork-chicken elasticities ($\hat{e}^c_{ij}$, $i = 5, 6, 7, 8,\ j = 13, 14, 15, 16$) in Table 5.7 range from $\hat{e}^c_{0816} = -0.8402$ to $\hat{e}^c_{0516} = 0.8482$.

Finally, only Golan, Perloff, and Shen (2001) report a Hicksian pork-fish elasticity (i.e., refer to the pork-fish of Table B.5 in Appendix), which is -0.1530. This elasticity falls between the pork-fish elasticities of $\hat{e}^c_{0817} = -0.1592$ and $\hat{e}^c_{0517} = 0.0542$ in Table

5.7. In general, Hicksian pork-fish elasticities ($\hat{e}^c_{ij}$, $i = 5, 6, 7, 8$, $j = 17$) in Table 5.7 range from $\hat{e}^c_{0717} = -0.4664$ to $\hat{e}_{0617} = 0.2036$. Similarly, Hicksian pork-shellfish elasticities ($\hat{e}^c_{ij}$, $i = 5, 6, 7, 8$, $j = 18$) in Table 5.7 range from $\hat{e}_{0518} = -0.9014$ to $\hat{e}^c_{0818} = 0.5101$.

5.1.3.6 Hicksian Chicken-Price Elasticities

The Hicksian chicken-beef elasticity in previous studies range from -0.3552 in Clark (2006) to 0.9200 in Malaga, Pan, and Duch (2006) (i.e., refer to the chicken-beef column of Table B.6 in the Appendix). Different from the Marshallian chicken-beef elasticities, Hicksian chicken-beef elasticities in most of the studies has been positive (López, 2008; Fernández, 2007; Malaga, Pan, and Duch, 2007; 2006; Golan, Perloff, and Shen, 2001; González Sánchez, 2001), but it has also been negative (Clark, 2006; García Vega, 1995). In Table 5.7, most of the Hicksian chicken-beef elasticities ($\hat{e}^c_{ij}$, $i = 13, 14, 15, 16$, $j = 1, 2, 3, 4$) are positive ($\hat{e}^c_{1601}$, $\hat{e}^c_{1302}$, $\hat{e}^c_{1603}$, $\hat{e}^c_{1303}$, $\hat{e}^c_{1503}$, $\hat{e}^c_{1501}$, $\hat{e}^c_{1604}$, $\hat{e}^c_{1602}$, $\hat{e}^c_{1502}$, $\hat{e}^c_{1504}$, and $\hat{e}^c_{1401}$). The same tendency is also observed for the Hicksian chicken-pork elasticities ($\hat{e}^c_{ij}$, $i = 13, 14, 15, 16$, $j = 5, 6, 7, 8$) and the Hicksian price elasticities among chicken processed beef and pork ($\hat{e}^c_{ij}$, $i = 13, 14, 15, 16$, $j = 9, 10, 11, 12$), but not for the Hicksian chicken-chicken elasticities ($\hat{e}^c_{ij}$, $i, j = 13, 14, 15, 16$), where there are about as many positive elasticities as there are negatives. In addition, similar to the Marshallian chicken-beef elasticities, all but one Hicksian chicken-beef elasticities in Table 5.7 fall within the range provided in previous studies. That is, Hicksian chicken-beef elasticities in Table 5.7 (excluding $\hat{e}^c_{1304} = -0.3996$ which falls outside) range from $\hat{e}^c_{1402} = -0.2978$ to $\hat{e}^c_{1401} = 0.5252$; therefore, they fall within the interval $[-0.3552, 0.9200]$.

The Hicksian chicken-pork elasticity in previous studies range from -0.3800 in Malaga, Pan, and Duch (2007) to 0.9210 in García Vega (1995) (i.e., refer to the chicken-pork column of Table B.6 in Appendix). Except for three Hicksian chicken-pork elasticities ($\hat{e}^c_{1607} = -1.7304$, $\hat{e}^c_{1507} = -1.7247$, and $\hat{e}^c_{1605} = 2.1135$) in Table 5.7, all the Hicksian chicken-pork elasticities in Table 5.7 fall within the interval provided in previous studies. More precisely, excluding $\hat{e}^c_{1607}$, $\hat{e}^c_{1507}$, and $\hat{e}^c_{1605}$, the chicken-pork elasticities ($\hat{e}^c_{ij}$, $i = 13, 14, 15, 16$, $j = 5, 6, 7, 8$) in Table 5.7 range from $\hat{e}^c_{1407} = -0.2202$ to $\hat{e}^c_{1505} = 0.7270$. Similarly, except for three Hicksian price elasticities among chicken and processed beef and pork elasticities ($\hat{e}^c_{1510} = -2.6461$, $\hat{e}^c_{1509} = -2.0457$, and $\hat{e}^c_{1511} = 1.0182$), these elasticities ($\hat{e}^c_{ij}$, $i = 13, 14, 15, 16$, $j = 9, 10, 11, 12$) in Table 5.7 fall within the interval $[-0.3800, 0.9210]$ from previous studies. More precisely, excluding $\hat{e}^c_{1510}$, $\hat{e}^c_{1509}$, and $\hat{e}^c_{1511}$, they range from -0.1933 to 0.2747.

The Hicksian chicken-chicken elasticity in previous studies range from -1.1300 in Malaga, Pan, and Duch (2006) to -0.1169 in Clark (2006) (i.e., refer to the chicken-chicken column of Table B.6 in Appendix). However, these elasticities refer only to the own-price elasticity of chicken while the chicken-chicken elasticities in Table 5.7 consist of four own price elasticities ($\hat{e}^c_{ij}$, $i, j = 13, 14, 15, 16$, $i = j$) and twelve cross-price elasticities ($\hat{e}^c_{ij}$, $i, j = 13, 14, 15, 16$, $i \neq j$). Consequently, by disaggregating meat into eighteen table cuts of meats, this study has the advantage of performing an analysis that is more in depth. That is, this study further analyzes possible cases of gross complementarity (i.e., cases of negative Hicksian cross-price elasticities) and substitutability (i.e., cases of positive Hicksian cross-price elasticities) among chicken cuts. Similar to the Marshallian own-price elasticity of chicken offal, the Hicksian own-price elasticity of chicken offal in Table 5.7 has a low unusual value, $\hat{e}^c_{1515} = -9.1617$. That is, a 1% increase in the price of chicken offal will decrease the consumption of chicken offall by 9.1617%, all other things held constant. As explained before, a low value is unsual because Mexican consumers are popular for their preference for meat offal and becasue chicken offal is the cheapest meat cut (average price equals 24.8824 pesos/kg, Table 4.2). However, a very elastic own-price elasticity for chicken offal may be related to the fact that in the model Mexican consumers can substitute a chicken cut with another chicken cut (which makes them more price sensitive).

Finally, only one Hicksian chicken-fish elasticity has been reported in previous studies (i.e., refer to the chicken-fish column of Table B.6 in the Appendix). Golan, Perloff, and Shen (2001) reported a Hicksian chicken-fish elasticity having a very small value of -0.0060. This Hicksian chicken-fish elasticity value is between the Hicksian chicken-fish elasticity values of $\hat{e}^c_{1517} = -0.4151$ and $\hat{e}^c_{1617} = 0.0743$ in Table 5.7. In general, Hicksian chicken-fish elasticities ($\hat{e}^c_{ij}$, $i = 13, 14, 15, 16$, $j = 17$) in Table 5.7 range from $\hat{e}^c_{1417} = -0.6328$ to $\hat{e}^c_{1317} = 0.1173$. Similarly, Hicksian chicken-shellfish elasticities ($\hat{e}^c_{ij}$, $i = 13, 14, 15, 16$, $j = 18$) in Table 5.7 range from $\hat{e}^c_{1518} = -0.0629$ to $\hat{e}^c_{1618} = 0.1854$.

5.1.3.7 Expenditure Elasticities

All expenditure elasticity estimates in Table 5.8 have the expected positive sign, which means all the meat cuts are normal goods and that consumption on all meat cuts is expected to increase as the economy grows. Additionally, since all the expenditure elasticities are less than one, none of the meat cuts is considered a "luxury" commodity. The expenditure elasticities ranges from 0.1846 for ground pork to 0.9733 for beefsteak. In addition, most pork cut elasticities have a lower value (therefore more necessary goods) than most beef and chicken cut elasticities, except for processed meat cuts (chorizo; ham, bacon and similar products from beef and pork; beef and pork sausages; other processed beef and pork; and chicken ham and similar products). This is clearly illustrated in Figure 5.3, which depicts the expenditure elasticities.

The expenditure elasticity of beef, pork, chicken and fish in previous studies fall within the intervals $[0.1020, 1.6710]$, $[0.1000, 1.5460]$, $[-0.1780.1.9800]$, and $[0.8800, 1.3040]$ respectively (i.e., Appendix, Table B.7). In this study, the expenditure elasticities of beef ($\hat{e}_i$, $i = 1, 2, 3, 4$), pork ($\hat{e}_i$, $i = 5, 6, 7, 8$), processed beef and pork ($\hat{e}_i$, $i = 9, 10, 11, 12$), and chicken ($\hat{e}_i$, $i = 13, 14, 15, 16$) fall within the intervals $[0.5228, 0.9733]$, $[0.1846, 0.5776]$, $[0.2728, 0.6190]$, and $[0.3354, 0.6761]$ respectively (Table 5.8). Finally, the expenditure elasticities of shellfish ($\hat{e}_{18}$) and fish ($\hat{e}_{17}$) are 0.4361 and 0.6970 respectively. Consequently, the expenditure elasticities reported in Table 5.8 are all within the ranges provided by previous studies (i.e., Appendix, Table B.7).

5.1.3.8 Artificial Elasticities for Binary Variables

An artificial elasticity is the elasticity obtained from a binary variable when this variable is treated as if it were a continuous variable. Table 5.9 reports the elasticity of meat cut i, $i = 1, 2, \ldots, 18$, with respect to geographical variables (*NE*, *NW*, *CW*, and C) and the urbanization variable (*urban*). These elasticities are not strictly defined, but when it is possible to test for their statistical significant, they are usually reported (see Su and Yen, 2000, p. 735). When elasticities are statistically significant, they allow a way to assess the statistical significance of the corresponding binary variable (Su and Yen, 2000, p. 736). However, when interested in the effect of a binary variable on the average consumption of meat cut i, it is better to use Table 5.4 instead of Table 5.9.

Table 5.6: Marshallian Price Elasticities.

Table entries estimate e_{ij}.

i\j	1	2	3	4	5	6	7	8	9	10	11
1	-1.0270*	0.1874†	-0.4383*	-0.1690	0.1565	-0.3042†	-0.1590	0.0375	0.0174	-0.0030	-0.0186
2	0.3941*	-3.4594*	-0.1164	-0.1068	0.4419	0.3923	0.3808	0.1548	-0.0236	0.0619	-0.0916
3	-1.2609*	0.2100	-1.7451*	0.2404	1.2346*	-0.5032	-3.3987*	-1.0235*	0.1885	0.0609	0.2369
4	-1.8100*	0.4889	-0.3440	-4.8186*	-1.3840	0.8117†	-1.5508	-0.2194	0.6108	-0.2380	0.5040
5	0.7866	-0.7295†	0.0720	-0.2287	-4.4711*	-1.1063	-1.6662†	0.7246†	-0.4432†	-0.5834‡	0.0896
6	-1.2086*	-0.5236	0.0135	0.4876†	-0.7959	-4.8375†	0.9168	0.3153	-0.1748	-0.3171	0.0492
7	-2.4904*	-0.5660	0.2482†	0.1254	-1.9010	-0.8229	-15.9428‡	-0.2945	0.1764	-0.0677	0.6991‡
8	-0.1314	0.4929	0.3194	0.3868†	1.4251‡	1.6971*	-1.9708†	-8.3019*	0.6219	0.0730	0.5472
9	0.1705	-0.0911	0.1114	-0.0318	0.9794‡	-0.3901	0.0174	-0.1277	-1.2275*	-0.6150	-0.0932
10	0.2400†	-0.7629*	0.4232*	-0.2591	0.1586	0.1704	-1.3375*	0.1069	0.0478†	-0.7832*	0.2719‡
11	-0.3879*	-0.1636	0.1905*	-0.5674‡	1.0437*	-0.8304‡	0.4634†	0.6703*	0.0787‡	-0.0091	-1.8406†
12	0.1538	-0.7593†	0.0713	-1.2194*	-2.2317*	0.0021	0.5628	-0.3655	0.1009	-0.6053*	0.0806
13	-0.2773‡	0.0030	0.0300	-0.4099*	0.2920	0.3180†	0.6752*	-0.0566	0.0603	0.1820*	-0.0051
14	0.3895†	-0.3419†	-0.2401	-0.1481‡	-0.0380	0.0698	-0.2241	0.0332	-0.0866	-0.2281†	-0.1014
15	0.0033	0.2217	0.0484	0.3276	0.7168	0.4577	-1.7283	0.1402	-2.0678	-2.6776	1.0031
16	-0.0592	0.2251	0.0547	0.1362	2.1079*	0.2196	-1.7323*	0.6956†	0.0533	0.1333	0.2558†
17	-0.0347	-0.1137	0.0638	-0.1373	0.9090*	-0.6018†	-1.6105‡	0.1549	-0.0718	0.2375†	0.1125
18	-1.0742‡	0.5885†	-0.6597*	0.1389	0.8832	0.3021	0.2106	-0.5493	0.0255	0.2046	0.4451†

Note: $i, j = 1, 2, \ldots, 18$, where 1 = Beefsteak, 2 = Ground Beef, 3 = Other Beef, 4 = Beef Offal, 5 = Pork Steak, 6 = Pork Leg & Shoulder, 7 = Ground Pork, 8 = Other Pork, 9 = Chorizo, 10 = Ham, Bacon & Similar Products from Beef & Pork, 11 = Beef & Pork Sausages, 12 = Other Processed Beef & Pork, 13 = Chicken Legs, Thighs & Breasts, 14 = Whole Chicken, 15 = Chicken Offal, 16 = Chicken Ham & Similar, 17 = Fish, 18 = Shellfish. Number of bootstrap resamples = 1,000. Bootstrap significance levels of 0.05, 0.10 and 0.20 are indicated by asterisks (*), double daggers (‡) and daggers (†) respectively.

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Table 5.6: *Continued*

Table entries estimate e_{ij}.

i\j	12	13	14	15	16	17	18
1	-0.0346	-0.2778*	-0.0361	0.0325	-0.1666†	-0.0394	-0.6354*
2	-0.0081	0.0032	0.2245	0.1064‡	-0.1294	-0.0950	-0.9724*
3	-0.1490	-0.3109*	0.0158	0.2704	0.1163	-0.1758	-0.6919*
4	-0.7262‡	-0.6557‡	-0.4232†	0.4998	-0.2088	-1.3958*	1.1782
5	-0.1335	-0.1423	-0.5410†	0.2138†	0.8314*	0.0147	-0.9145†
6	0.5835*	0.1087	-0.4584†	0.0094	0.1924	0.1516	0.3673
7	-1.4896*	-0.2333	-0.5569†	-0.3212	-0.6395	-0.4851†	-0.6696
8	-0.4080	-0.2200	-0.3565†	0.0529	-0.8650†	-0.2177	0.4907
9	-0.3774*	-0.1623	-0.2235†	-0.3070*	-0.3966†	-0.0510	0.0536
10	0.2156	0.0995	0.1305‡	-0.4764*	0.2149	0.0845‡	0.4884
11	-0.1287‡	-0.0014	-0.1101	-0.2771	0.3034	0.2344*	0.6494
12	-3.1156*	0.5946*	-0.0236	-0.6132*	0.2790‡	0.0330	0.3075
13	0.1125	-1.2841*	-0.1555*	-0.0368	0.1865‡	0.0551†	0.0615
14	0.0320	0.0290	-1.2640*	0.1768†	-0.0120	-0.7013*	-0.0068
15	0.2440	-0.1783	-0.2035	-9.1730*	1.1161†	-0.4770	-0.0833
16	0.0448	0.2076†	0.0365	0.1239	-1.2713*	0.0404	0.1742
17	0.0456	-0.0525	0.1371	0.2298‡	0.1382	-0.9825*	0.6658*
18	0.0774	-0.1591	-0.0278	0.1831	1.1353‡	-0.0001	-7.5997*

Note: $i, j = 1, 2, \ldots, 18$, where 1 = Beefsteak, 2 = Ground Beef, 3 = Other Beef, 4 = Beef Offal, 5 = Pork Steak, 6 = Pork Leg & Shoulder, 7 = Ground Pork, 8 = Other Pork, 9 = Chorizo, 10 = Ham, Bacon & Similar Products from Beef & Pork, 11 = Beef & Pork Sausages, 12 = Other Processed Beef & Pork, 13 = Chicken Legs, Thighs & Breasts, 14 = Whole Chicken, 15 = Chicken Offal, 16 = Chicken Ham & Similar, 17 = Fish, 18 = Shellfish. Number of bootstrap resamples = 1,000. Bootstrap significance levels of 0.05, 0.10 and 0.20 are indicated by asterisks (*), double daggers (‡) and daggers (†) respectively.

Table 5.7: Hicksian Price Elasticities.

Table entries estimate e^c_{ij}.

i\j	1	2	3	4	5	6	7	8	9	10	11
1	-0.8317*	0.2510‡	-0.3507*	-0.1528	0.1727	-0.2745	-0.1534	0.0933	0.0527†	0.0471	0.0054
2	0.4990*	-3.4253*	-0.0693	-0.0981	0.4506	0.4083	0.3838	0.1848	-0.0046	0.0888	-0.0787
3	-1.1152*	0.2574	-1.6797*	0.2525	1.2467*	-0.4810	-3.3945*	-0.9820*	0.2148	0.0983	0.2549†
4	-1.6814*	0.5308	-0.2862	-4.8079*	-1.3733	0.8313†	-1.5471	-0.1827	0.6341	-0.2050	0.5199
5	0.8650	-0.7040†	0.1072	-0.2222	-4.4646*	-1.0944	-1.6640†	0.7470†	-0.4291†	-0.5633‡	0.0993
6	-1.1054*	-0.4900	0.0598	0.4962†	-0.7873	-4.8218†	0.9197	0.3448	-0.1562	-0.2907	0.0619
7	-2.4533*	-0.5540	0.2649†	0.1284	-1.8980	-0.8173	-15.9417‡	-0.2839	0.1831	-0.0582	0.7037‡
8	-0.0155	0.5306†	0.3714	0.3964†	1.4347‡	1.7147*	-1.9675†	-8.2689*	0.6428	0.1027	0.5615
9	0.2947†	-0.0507	0.1672	-0.0215	0.9897‡	-0.3712	0.0210	-0.0922	-1.2050*	-0.5832	-0.0779
10	0.3313*	-0.7333*	0.4641*	-0.2516	0.1662	0.1843	-1.3349*	0.1329	0.0643‡	-0.7598*	0.2831*
11	-0.3331‡	-0.1458	0.2151*	-0.5628‡	1.0483*	-0.8221‡	0.4655†	0.6859*	0.0886*	0.0049	-1.8339†
12	0.2254	-0.7360†	0.1034	-1.2135*	-2.2258*	0.0130	0.5649	-0.3451	0.1138	-0.5869‡	0.0894
13	-0.1541	0.0431	0.0852	-0.3996*	0.3023	0.3368†	0.6788*	-0.0214	0.0825†	0.2136*	0.0101
14	0.5252*	-0.2978†	-0.1793	-0.1368†	-0.0267	0.0905	-0.2202	0.0720	-0.0621	-0.1933	-0.0847
15	0.1260	0.2615	0.1034	0.3378	0.7270	0.4764	-1.7247	0.1752	-2.0457	-2.6461	1.0182
16	0.0082	0.2470	0.0849	0.1417	2.1135*	0.2299	-1.7304*	0.7149†	0.0655	0.1506	0.2641†
17	0.1051	-0.0683	0.1265	-0.1257	0.9207*	-0.5805†	-1.6065‡	0.1949	-0.0465	0.2733‡	0.1298
18	-0.9867†	0.6169†	-0.6204*	0.1462	0.8904	0.3154	0.2131	-0.5244	0.0413	0.2271	0.4559†

Note: $i, j = 1, 2, \ldots, 18$, where 1 = Beefsteak, 2 = Ground Beef, 3 = Other Beef, 4 = Beef Offal, 5 = Pork Steak, 6 = Pork Leg & Shoulder, 7 = Ground Pork, 8 = Other Pork, 9 = Chorizo, 10 = Ham, Bacon & Similar Products from Beef & Pork, 11 = Beef & Pork Sausages, 12 = Other Processed Beef & Pork, 13 = Chicken Legs, Thighs & Breasts, 14 = Whole Chicken, 15 = Chicken Offal, 16 = Chicken Ham & Similar, 17 = Fish, 18 = Shellfish. Number of bootstrap resamples = 1,000. Bootstrap significance levels of 0.05, 0.10 and 0.20 are indicated by asterisks (*), double daggers (‡) and daggers (†) respectively.

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Table 5.7: *Continued*

Table entries estimate e^c_{ij}.

i\j	12	13	14	15	16	17	18
1	0.0143	-0.1292‡	0.0772	0.0506	-0.1248	0.0591	-0.6028*
2	0.0182	0.0830	0.2853†	0.1161‡	-0.1069	-0.0421	-0.9549*
3	-0.1125	-0.2001†	0.1003†	0.2839	0.1475	-0.1023	-0.6676‡
4	-0.6940‡	-0.5577†	-0.3486	0.5117	-0.1812	-1.3309*	1.1997
5	-0.1139	-0.0827	-0.4956†	0.2210†	0.8482*	0.0542	-0.9014
6	0.6093*	0.1872	-0.3985†	0.0190	0.2144	0.2036†	0.3845
7	-1.4803*	-0.2051	-0.5354†	-0.3177	-0.6316	-0.4664†	-0.6634
8	-0.3790	-0.1318	-0.2892	0.0636	-0.8402†	-0.1592	0.5101
9	-0.3463‡	-0.0678	-0.1515	-0.2955*	-0.3701†	0.0116	0.0743
10	0.2385	0.1688‡	0.1835*	-0.4679*	0.2344†	0.1305*	0.5036†
11	-0.1150‡	0.0403	-0.0783	-0.2720	0.3151	0.2621*	0.6585
12	-3.0977*	0.6491*	0.0179	-0.6066*	0.2944‡	0.0691	0.3194
13	0.1434	-1.1904*	-0.0840‡	-0.0254	0.2129*	0.1173*	0.0821
14	0.0659	0.1323†	-1.1853*	0.1894†	0.0170	-0.6328*	0.0158
15	0.2747	-0.0850	-0.1323	-9.1617*	1.1423†	-0.4151	-0.0629
16	0.0617	0.2588‡	0.0755	0.1301	-1.2569*	0.0743	0.1854
17	0.0806	0.0539	0.2182	0.2427*	0.1681	-0.9119*	0.6891*
18	0.0993	-0.0925	0.0230	0.1912	1.1540‡	0.0440	-7.5851*

Note: $i, j = 1, 2, \ldots, 18$, where 1 = Beefsteak, 2 = Ground Beef, 3 = Other Beef, 4 = Beef Offal, 5 = Pork Steak, 6 = Pork Leg & Shoulder, 7 = Ground Pork, 8 = Other Pork, 9 = Chorizo, 10 = Ham, Bacon & Similar Products from Beef & Pork, 11 = Beef & Pork Sausages, 12 = Other Processed Beef & Pork, 13 = Chicken Legs, Thighs & Breasts, 14 = Whole Chicken, 15 = Chicken Offal, 16 = Chicken Ham & Similar, 17 = Fish, 18 = Shellfish. Number of bootstrap resamples = 1,000. Bootstrap significance levels of 0.05, 0.10 and 0.20 are indicated by asterisks (*), double daggers (‡) and daggers (†) respectively.

Table 5.8: Expenditure Elasticities.

	i	e_i
1	Beefsteak	0.9733*
2	Ground Beef	0.5228*
3	Other Beef	0.7260*
4	Beef Offal	0.6413*
5	Pork Steak	0.3904*
6	Pork Leg & Shoulder	0.5141*
7	Ground Pork	0.1846
8	Other Pork	0.5776*
9	Chorizo	0.6190*
10	Ham, Bacon & Similar B&P	0.4547*
11	Beef & Pork Sausages	0.2728*
12	Other Processed Beef & Pork	0.3570*
13	Chicken Legs, Thighs & Breasts	0.6142*
14	Whole Chicken	0.6761*
15	Chicken Offal	0.6112*
16	Chicken Ham & Similar Products	0.3354*
17	Fish	0.6970*
18	Shellfish	0.4361*

Note: Number of bootstrap resamples = 1,000. Bootstrap significance levels of 0.05, 0.10 and 0.20 are indicated by asterisks (*), double daggers (‡) and daggers (†) respectively.

Table 5.9: Artificial Elasticities for Binary Variables.

Table entries estimate e_{il}.

i\l	*NE*	*NW*	*CW*	*C*	*urban*
Beefsteak	0.0116	0.0287†	0.1349*	0.0814*	0.1961*
Ground Beef	0.0194	0.2186*	0.0069	0.2223*	0.1197
Other Beef	0.0765*	0.1433*	0.0900†	0.3258*	0.0573
Beef Offal	-0.1230†	-0.4185*	-0.5104*	-0.4838†	0.0787
Pork Steak	-0.1868*	-0.1962†	-0.0627	-0.1067	0.3999‡
Pork Leg Shoulder	-0.0907*	-0.0676†	0.1770†	-0.1753*	0.2625†
Ground Pork	-0.0618	-0.5750*	0.0836	0.6323‡	1.0856*
Other Pork	-0.1485*	-0.1895*	-0.0100	0.0008	0.0351
Chorizo	0.0113	0.0176	-0.0343	-0.0385	0.0285
Ham, Bacon & Similar B&P	0.0231	-0.0297	0.0618	0.1423†	0.1232
Beef & Pork Sausages	0.0128	0.0376	-0.1106	-0.2160	-0.0314
Other Processed Beef & Pork	-0.0616†	-0.1089†	-0.2809*	-0.1921*	0.1598
Chicken Legs, Thighs & Breasts	-0.0501*	-0.0458‡	-0.3747*	0.5763*	0.7486*
Whole Chicken	-0.0901*	-0.1502*	-0.1151*	-0.3160*	-0.0102
Chicken Offal	-0.1482	0.1247	-0.7687	-0.8561*	-0.2558
Chicken Ham & Similar Products	0.1188*	0.0272†	0.0311	0.0286	0.2831*
Fish	0.0285†	-0.1296*	-0.0009	-0.0274	-0.2297*
Shellfish	0.0330	0.0315	0.0605	0.1321	0.8464*

Note: Number of bootstrap resamples = 1,000. Bootstrap significance levels of 0.05, 0.10 and 0.20 are indicated by asterisks (*), double daggers (‡) and daggers (†) respectively.

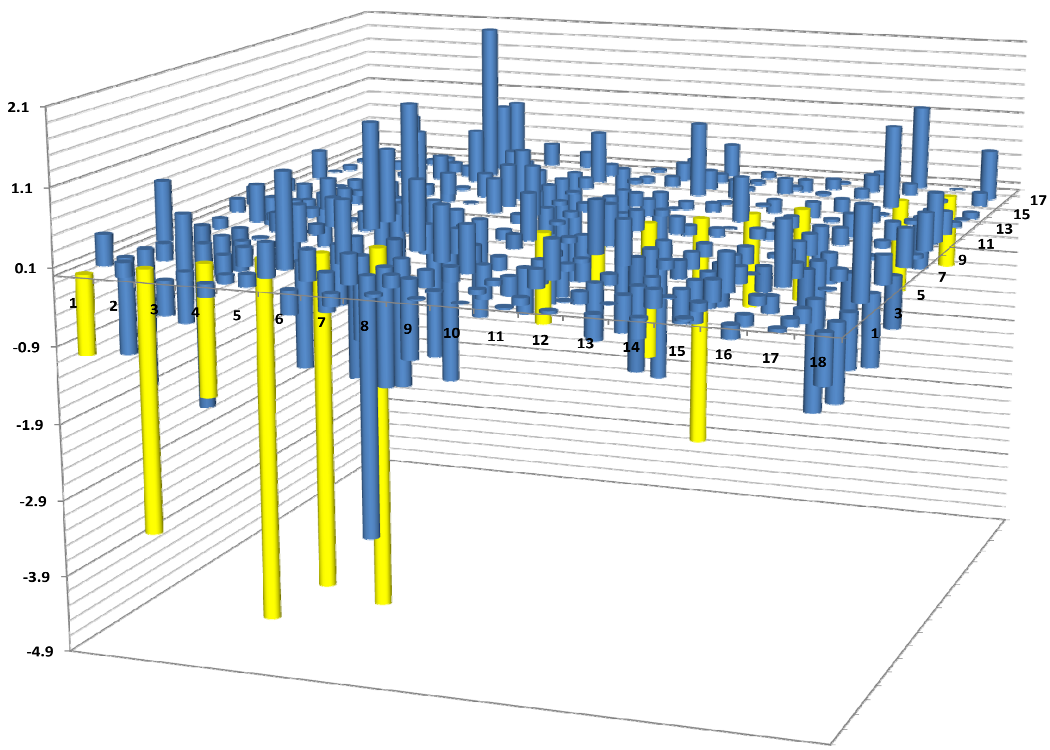

Figure 5.1: Marshallian Price Elasticities.

Note: Bars depict $\hat{e}_{ij}$, $i, j = 1, 2, \ldots, 18$, where 1 = Beefsteak, 2 = Ground Beef, 3 = Other Beef, 4 = Beef Offal, 5 = Pork Steak, 6 = Pork Leg & Shoulder, 7 = Ground Pork, 8 = Other Pork, 9 = Chorizo, 10 = Ham, Bacon & Similar Products from Beef & Pork, 11 = Beef & Pork Sausages, 12 = Other Processed Beef & Pork, 13 = Chicken Legs, Thighs & Breasts, 14 = Whole Chicken, 15 = Chicken Offal, 16 = Chicken Ham & Similar Products, 17 = Fish, 18 = Shellfish. Own-price elasticities are in yellow.

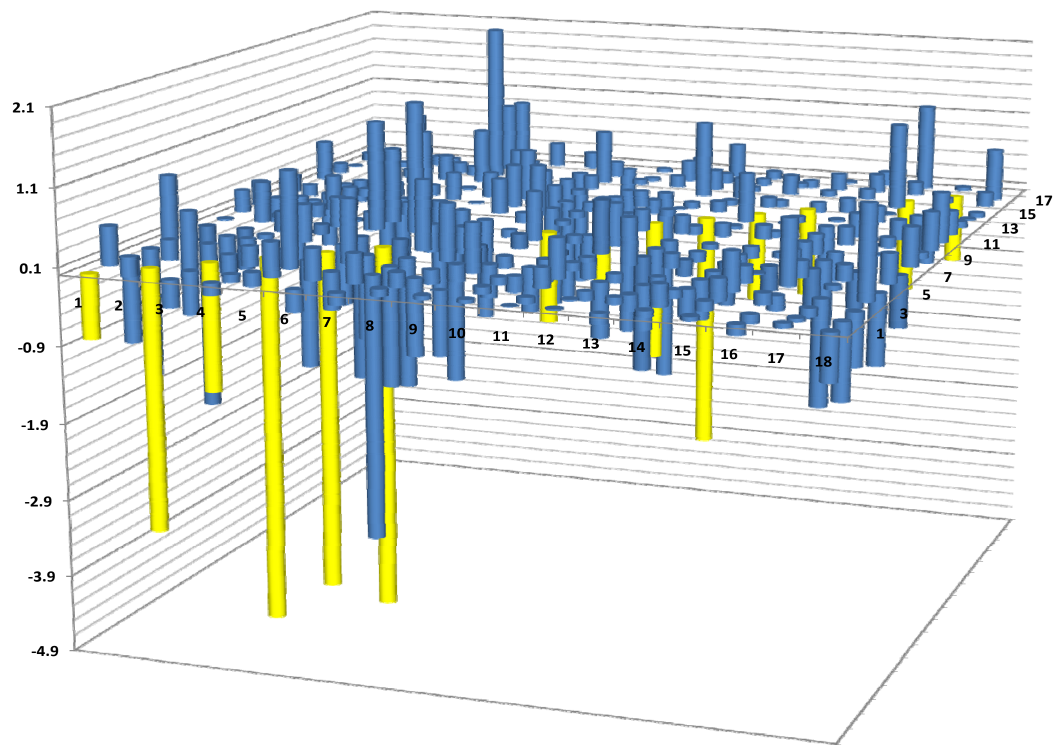

Figure 5.2: Hicksian Price Elasticities.

Note: Bars depict $\hat{e}^c_{ij}$, $i, j = 1, 2, \ldots, 18$, where 1 = Beefsteak, 2 = Ground Beef, 3 = Other Beef, 4 = Beef Offal, 5 = Pork Steak, 6 = Pork Leg & Shoulder, 7 = Ground Pork, 8 = Other Pork, 9 = Chorizo, 10 = Ham, Bacon & Similar Products from Beef & Pork, 11 = Beef & Pork Sausages, 12 = Other Processed Beef & Pork, 13 = Chicken Legs, Thighs & Breasts, 14 = Whole Chicken, 15 = Chicken Offal, 16 = Chicken Ham & Similar Products, 17 = Fish, 18 = Shellfish. Own-price elasticities are in yellow.

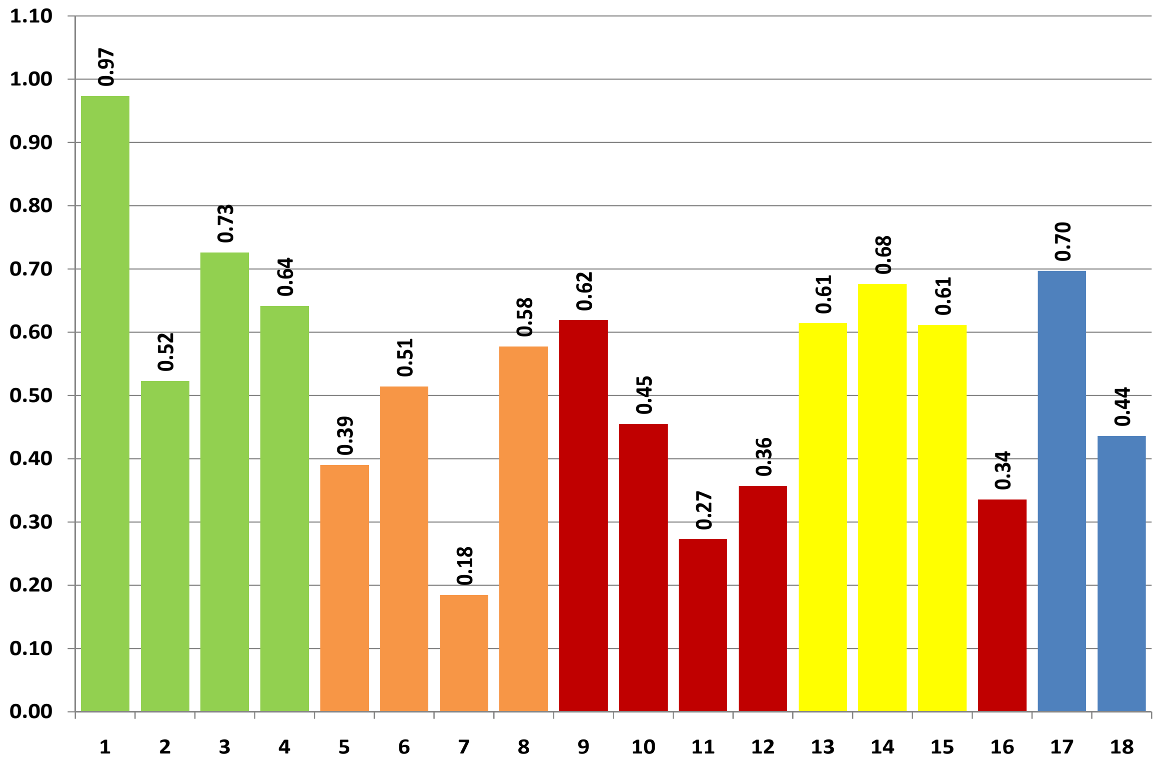

Figure 5.3: Expenditure Elasticities.

Note: Bars depict $\hat{e}_i$, $i = 1, 2, \ldots, 18$, where 1 = Beefsteak, 2 = Ground Beef, 3 = Other Beef, 4 = Beef Offal, 5 = Pork Steak, 6 = Pork Leg & Shoulder, 7 = Ground Pork, 8 = Other Pork, 9 = Chorizo, 10 = Ham, Bacon & Similar Products from Beef & Pork, 11 = Beef & Pork Sausages, 12 = Other Processed Beef & Pork, 13 = Chicken Legs, Thighs & Breasts, 14 = Whole Chicken, 15 = Chicken Offal, 16 = Chicken Ham & Similar Products, 17 = Fish, 18 = Shellfish.

5.2 Regional Differences

Most previous studies have characterized Mexico as having significant differences in food consumption patterns across regions and urbanization levels (see Section 2.1). This study also found significant differences in Mexican meat consumption across regions and urbanization levels, some of which were discussed in Section 5.1.1. These differences may be attributed to economic, cultural, and climatic variations across Mexico. For example, it is expected that households in the Northeast and Northwest regions of Mexico are influenced by U.S. preferences due to the high number of people crossing the border every year. In fact, the U.S.-Mexico border "is the most frequently crossed international border in the world, with about 250 million people crossing every year" (Wikipedia, 2009). In particular, according to Wikipedia (2009), there are 12 border crossings in the Northeast region (6 border crossings in Baja California and 6 border crossings in Sonora), and 20 border crossings in the Northwest region (6 in Chihuahua, 3 in Coahuila, 1 in Nuevo León, and 10 in Tamaulipas).[7] In addition, there are more than 15 million tourists visiting Mexico each year (Encyclopedia of the Nations, 2009; Dance with Shadows, 2009) and the two most popular destinations are Cancun in the state of Querétaro, Central-West region and Acapulco in the state of Guerrero, Southeast region (The Economist, 2004; 2005). Provided that about 80% or more of the tourists that go to Mexico come from the United States (Encyclopedia of the Nations, 2009), it is expected that these regions are also influeced by U.S. preferences. However, they may also be influenced by preferences from other countries. In general, it is expected that households living close to tourists attractions in Mexico are influenced by foreign preferences. On the other hand, it is also expected that households in the Central region are more traditional (i.e., more representative of the typical Mexican household).[8]

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[7]In the United States, that is 6 border crossings in California, 6 border crossings in Arizona, 3 border crossings in New Mexico, and 17 border crossings in Texas.

[8]It is also important to mention that there are small cities/towns in Mexico with extremely high poverty levels and that Mexico is also characterized by big differences in income levels among

Section 5.1.1 and Section 5.1.2 found differences in meat consumption between the urban and rural sector. Similarly, Section 5.1.3 found that Marshallian and Hicksian price elasticities and expenditure elasticities differ within and across meat categories (Figure 5.1, Figure 5.2, Figure 5.3). This section presents and compares elasticities across regions, which were obtained from the use of regional dummy variables and the evaluation of explanatory variables at their corresponding regional sample means. Detailed elasticity estimates by region are presented in Appendix D.

In Section 5.1.3, the own-price elasticities had the lowest values among the price elasticities (except for $\hat{e}_{0303}$, $\hat{e}_{1010}$, $\hat{e}_{1616}$, $\hat{e}_{1717}$, $\hat{e}^c_{0303}$, $\hat{e}^c_{1010}$, $\hat{e}^c_{1616}$, and $\hat{e}^c_{1717}$).[9] The same pattern is observed in the price elasticities by region (with the additional exceptions of $\hat{e}_{0101}$ and $\hat{e}^c_{0101}$, which did not have the lowest values in the beefsteak equations). As explained in Section 5.1.3, this suggests that Mexican consumers are very price sensitive with respect to the consumptions and changes in the own prices of these commodities.

There might be two reasons why this study found low own-price elasticity values. First, it may be due to the fact that in the model Mexican consumers can substitute a beef cut with another beef cut, a pork cut with another pork cut, a processed meat cut with another processed meat cut, and so on, hence, making them more price sensitive. In other words, the own-price elasticities of aggregated meat categories (i.e., beef, pork, and chicken) tend to be more inelastic because consumers are given less potential substitutes, not only across meat categories but most importantly within a meat category. Consequently, consumers might be more reluctant to substitute an aggregated meat category. On the other hand, when disaggregated commodities are considered, there are more potential substitutes. In this study, there are more potential substitutes across and within categories. Consequently, consumers have more choices (specially within a meat category); and therefore, own-price elasticities tend to be more elastic. Second, it may also be due to the high number of censored

households.

[9]That is, high absolute values.

observations. On one hand, an imputation approach tends to reduce price variability (as explained in Section 2.5), and on the other hand, there are several censored quantities (which implies that there are several occasions in the data sample in which consumption goes from zero (censored) to non-negative and positive (non-censored)). In fact, a comparison of the number of censored observations from Table 4.2 and Table 4.3 with the extreme elastic cases reveals that these cases are likely to occur when the number of censored observations is very high. Therefore, even when using a consistent censored demand system, the combination of a price imputation approach with censored quantities may still influence the own-price elasticities to be very low (i.e., very high absolute values).

For instance, there are own-price elasticities with unusual values that are lower than -10. In addition, the cases in which the Marshallian own-price elasticities had unusual values lower than -10 are the same cases in which the Hicksian own-price elasticities also have unusual values lower than -10. In the case of the Marshallian price elasticities, when elasticities are computed only for Mexico (Table 5.6), there is only one of these cases ($\hat{e}_{0707} = -15.9428$). However, when elasticities are computed by region (Appendix, Table D.1, Table D.3, Table D.5, Table D.7, Table D.9), the number of extreme elastic cases increases to thirteen (including one case of an own-price elasticity with a value greater than 10). For example, in the Northeast region, there are four cases ($\hat{e}_{0505} = -11.2313$, $\hat{e}_{0707} = -11.5638$, $\hat{e}_{1212} = -12.0059$, and $\hat{e}_{1515} = -17.5961$); however, none of the cases is statistically different from zero at the 0.20 significance level. In the Northwest region, there are two cases ($\hat{e}_{0808} = -18.3578$ and $\hat{e}_{1515} = -15.6209$), but the former is not statistically different from zero at the 0.20 significance level. There is also a case of a large and positive own-price elasticity ($\hat{e}_{1818} = 34.3129$), which is also not statistically different from zero at the 0.20 significance level. In the Central-West region, there are two cases ($\hat{e}_{0707} = -19.3798$ and $\hat{e}_{1515} = -10.3498$). Similarly, in the Central region, there are another two cases ($\hat{e}_{0707} = -18.0162$ and $\hat{e}_{1818} = -20.3552$), but the latter is not statistically different from zero at the 0.20 significance level. Finally, in the Southeast region, the last two cases are found ($\hat{e}_{0707} = -15.1776$ and $\hat{e}_{1515} = -20.9676$). Therefore, out of these fourteen extreme elastic cases, only half of them are statistically different from zero at at least 0.20 significance level ($\hat{e}_{0707}$ in Mexico and the Central-West, Central, and Southeast regions; and $\hat{e}_{1515}$ in the Northwest, Central-West and Southeast regions).

For illustration purposes, Figure 5.4 compares the Marshallian own-price elasticities across regions after removing these fourteen extreme elastic cases. The same Marshallian own-price elasticities, in different regions and in Mexico as a whole, have the same color. Figure 5.4 not only shows that there are differences in own-price elasticities across meat cuts (i.e., compare bars with different colors) but also across regions (i.e., compare bars with same colors). For example, the own-price elasticity of beefsteak ($\hat{e}_{0101}$) ranges from -1.1531 in the Central region to -0.8807 in the Northeast region. The own-price elasticity of pork steak ($\hat{e}_{0505}$) ranges from -5.3797 in the Central region to -2.4768 in the Northwest region. The own-price elasticity of chorizo ($\hat{e}_{0909}$) ranges from -2.0084 in the Northwest region to -0.9016 in the Northeast region. Similarly, the own-price elasticity of chicken legs, thighs and breasts ($\hat{e}_{1313}$) ranges from -2.2288 in the Central-West region to -0.8054 in the Northwest region. Finally, the own-price elasticity of fish ($\hat{e}_{1717}$) ranges from -1.2957 in the Central region to -0.6737 in the Southeast region. Additional comparisons can be made from Figure 5.4 (or Appendix, Table D.1, Table D.3, Table D.5, Table D.7, and Table D.9).

As in the Marshallian price elasticities, when the Hicksian price elasticities are computed only for Mexico (Table 5.7), there is only one case of a value lower than -10, $\hat{e}^c_{0707} = -15.9417$. Similarly, when elasticities are computed by region (Appendix, Table D.2, Table D.4, Table D.6, Table D.8, and Table D.10), the number of extreme elastic cases increases to thirteen (including one case of an own-price elasticity with a value greater than 10). For example, in the Northeast region, there are four cases ($\hat{e}^c_{0505} = -11.2301$, $\hat{e}^c_{0707} = -11.5632$, $\hat{e}^c_{1212} = -11.9977$, and $\hat{e}^c_{1515} = -17.5926$), but none of the cases is statistically different from zero at the 0.20 significance level. In the Northwest region, there are two cases ($\hat{e}^c_{0808} = -18.3444$ and $\hat{e}^c_{1515} = -15.6128$), but the former is not statistically different from zero at the 0.20 significance level. There is also a case of a large and positive own-price elasticity ($\hat{e}^c_{1818} = 34.3132$), which is also not statistically different from zero at the 0.20 significance level. In the Central-West region, there are two cases ($\hat{e}^c_{0707} = -19.3792$ and $\hat{e}^c_{1515} = -10.3449$). In the Central region, there are another two cases ($\hat{e}^c_{0707} = -18.0155$ and $\hat{e}^c_{1818} = -20.3480$), but the latter is not statistically different from zero at the 0.20 significance level. Finally, in the Southeast region, the last two cases are found ($\hat{e}^c_{0707} = -15.1767$ and $\hat{e}^c_{1515} = -20.9521$). Therefore, out of these fourteen extreme elastic cases, only half of them are statistically different from zero at at least 0.20 significance level ($\hat{e}^c_{0707}$ in Mexico and the Central-West, Central, and Southeast regions; and $\hat{e}^c_{1515}$ in the Northwest, Central-West and Southeast regions).

For illustration purposes, Figure 5.5 compares the Hicksian own-price elasticities across regions after removing these fourteen extreme elastic cases. The same Hicksian own-price elasticities, in different regions and in Mexico as a whole, have the same color. Figure 5.5 not only shows that there are differences in own-price elasticities across meat cuts (i.e., compare bars with different colors) but also across regions (i.e., compare bars with the same color). For example, the own-price elasticity of beefsteak ($\hat{e}^c_{0101}$) ranges from -0.9497 in the Central region to -0.6767 in the Northeast region. The own-price elasticity of pork steak ($\hat{e}^c_{0505}$) ranges from -5.2068 in the Central region to -2.4748 in the Northwest region. The own-price elasticity of chorizo ($\hat{e}^c_{0909}$) ranges from -1.9805 in the Northwest region to -0.8802 in the Northeast region. Similarly, the own-price elasticity of chicken legs, thighs and breasts ($\hat{e}^c_{1313}$) ranges from -2.1692 in the Central-West region to -0.7332 in the Northwest region. Finally, the own-price elasticity of fish ($\hat{e}^c_{1717}$) ranges from -1.2417 in the Central region to -0.6034 in the Southeast region. Additional comparisons can be made from Figure 5.5 (or Appendix, Table D.2, Table D.4, Table D.6, Table D.8, and Table D.10).

Similarly, Figure 5.6 compares the expenditure elasticities by region and with Mexico as a whole (see also Appendix, Table D.11). There is only one case in which the expenditure elasticity is negative, which suggests a case of an expenditure inferior good. That is the expenditure elasticity of shellfish in the Northwest region ($\hat{e}_{18} = -0.1106$). However, this expenditure elasticity is not statistically different from zero. Figure 5.6 not only shows that there are differences in expenditure elasticities across meat cuts (i.e., compare bars with different colors) but also across regions (i.e., compare bars with the same color). For example, the expenditure elasticity of beefsteak ($\hat{e}_{01}$) ranges from 0.8184 in the Central-West region to 1.1049 in the Central region. The expenditure elasticity of pork steak ($\hat{e}_{05}$) ranges from 0.3732 in the Southeast region to 0.5297 in the Northeast region. The expenditure elasticity of chorizo ($\hat{e}_{09}$) ranges from 0.4827 in the Northeast region to 0.7097 in the Southeast region. Similarly, the expenditure elasticity of chicken legs, thighs and breasts ($\hat{e}_{13}$) ranges from 0.5642 in the Central region to 0.9135 in the Central-West region. Finally, the expenditure elasticity of fish ($\hat{e}_{17}$) ranges from 0.6018 in the Central region to 0.9135 in the Central-West region.

Additional comparisons can be made from Appendix, Table D.11. For example, if only the beef category is considered ($\hat{e}_i, i = 1, 2, 3, 4$), the North of Mexico (Northwest and Northeast regions) seems to have the lowest beef expenditure elasticity values (i.e., the most inelastic beef cut demands). However, if only the pork expenditure elasticities are considered ($\hat{e}_i, i = 5, 6, 7, 8$), they seem to have the lowest values in the Southeast and Central-West regions. For the processed beef and pork category ($\hat{e}_i, i = 9, 10, 11, 12$), the Northwest region of Mexico seems to have the lowest expenditure elasticity values (except for $\hat{e}_{09}$). Similarly, for the chicken category ($\hat{e}_i, i = 13, 14, 15, 16$), the Central region of Mexico seem to have the lowest expenditure elasticities elasticity values (except for $\hat{e}_{14}$).

Finally, Figure 5.7, Figure 5.8, and Figure 5.9 present the empirical distributions of the Marshallian and Hicksian own-price elasticities and the expenditure elasticities respectively for Mexico as a whole. These empirical distributions provide an idea of the range of values that can be taken by the corresponding elasticities.[10] Notice how the positions of the distributions changes from one elasticity to another. This also

[10]Bootstrap confidence intervals are available upon request.

suggests differences in elasticities across meat cuts.

In summary, this section also found significant differences in Mexican meat consumption across regions. This finding is consistent with previous studies (López, 2008; Dong, Gould, and Kaiser, 2004; Gould et al., 2002; Gould and Villarreal, 2002; Dong and Gould, 2000; Golan, Perloff, and Shen, 2001; García Vega and García, 2000; Heien, Jarvis, and Perali, 1989). However, unlike previous studies, this study analyzed regional differences at the table cut level of disaggregation. Elasticities by region may help U.S. and Canadian meat exporters not only positioning meat products in the appropriate Mexican markets but also managing prices more effectively.

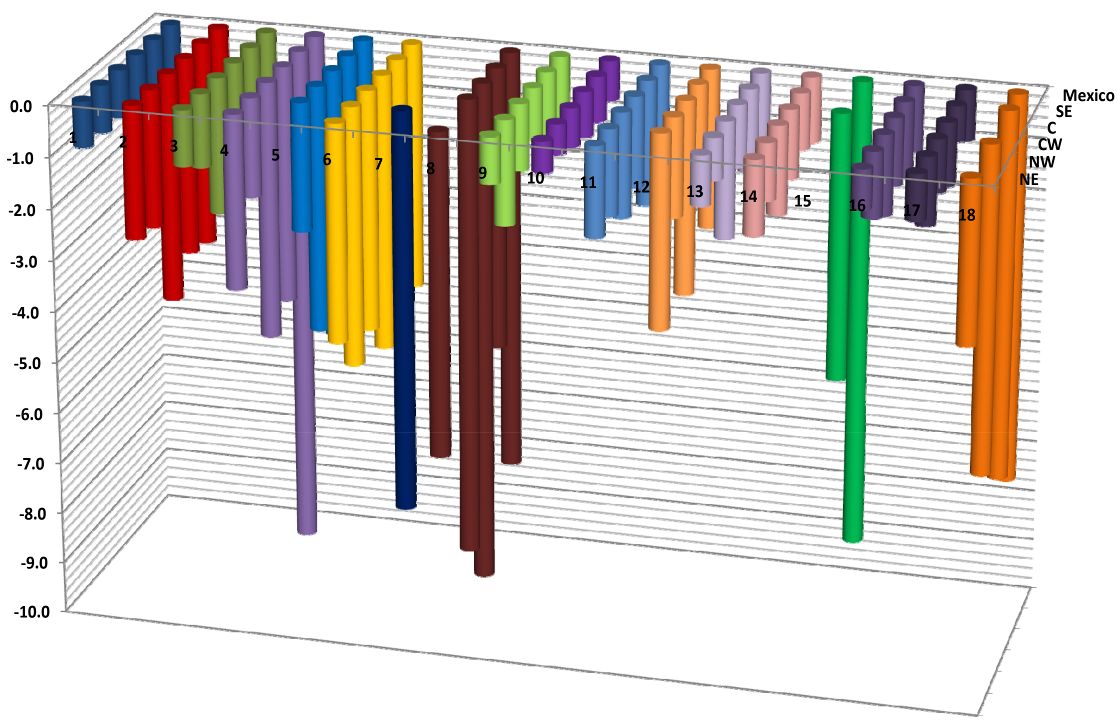


Figure 5.4: Marshallian Own-Price Elasticities by Region.

Note: Bars depict $\hat{e}_{ij}$ by region, $i = j = 1, 2, \ldots, 18$, where 1 = Beefsteak, 2 = Ground Beef, 3 = Other Beef, 4 = Beef Offal, 5 = Pork Steak, 6 = Pork Leg & Shoulder, 7 = Ground Pork, 8 = Other Pork, 9 = Chorizo, 10 = Ham, Bacon & Similar Products from Beef & Pork, 11 = Beef & Pork Sausages, 12 = Other Processed Beef & Pork, 13 = Chicken Legs, Thighs & Breasts, 14 = Whole Chicken, 15 = Chicken Offal, 16 = Chicken Ham & Similar Products, 17 = Fish, 18 = Shellfish.

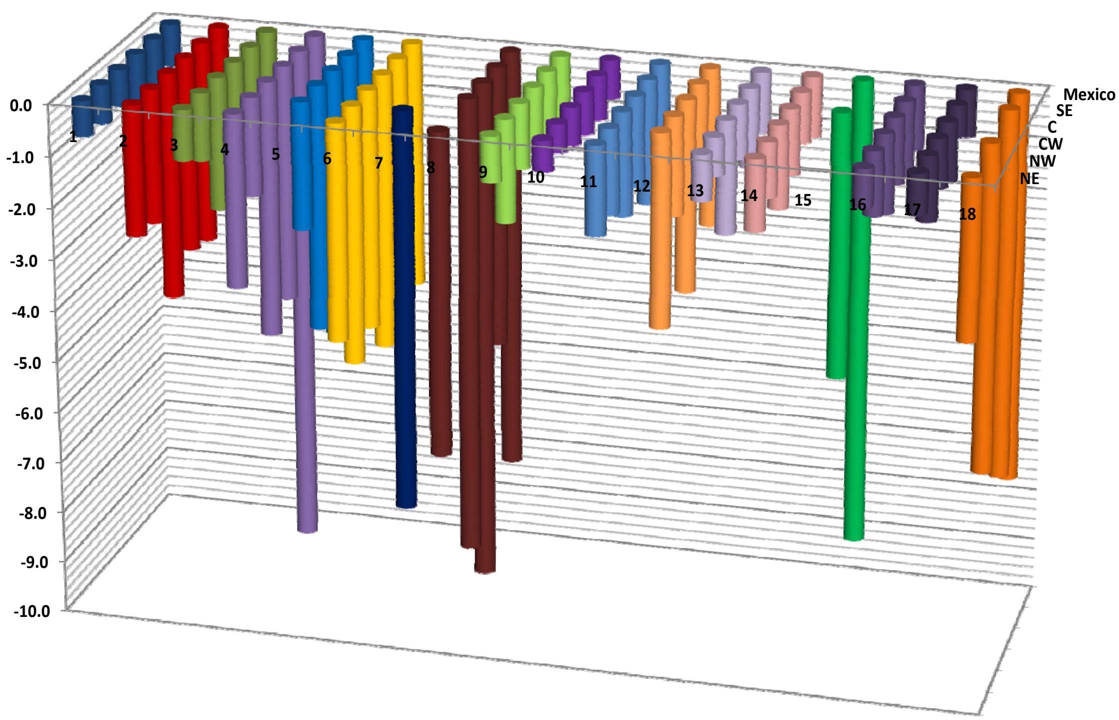


Figure 5.5: Hicksian Own-Price Elasticities by Region.

Note: Bars depict $\hat{e}^c_{ij}$ by region, $i = j = 1, 2, \ldots, 18$, where 1 = Beefsteak, 2 = Ground Beef, 3 = Other Beef, 4 = Beef Offal, 5 = Pork Steak, 6 = Pork Leg & Shoulder, 7 = Ground Pork, 8 = Other Pork, 9 = Chorizo, 10 = Ham, Bacon & Similar Products from Beef & Pork, 11 = Beef & Pork Sausages, 12 = Other Processed Beef & Pork, 13 = Chicken Legs, Thighs & Breasts, 14 = Whole Chicken, 15 = Chicken Offal, 16 = Chicken Ham & Similar Products, 17 = Fish, 18 = Shellfish.

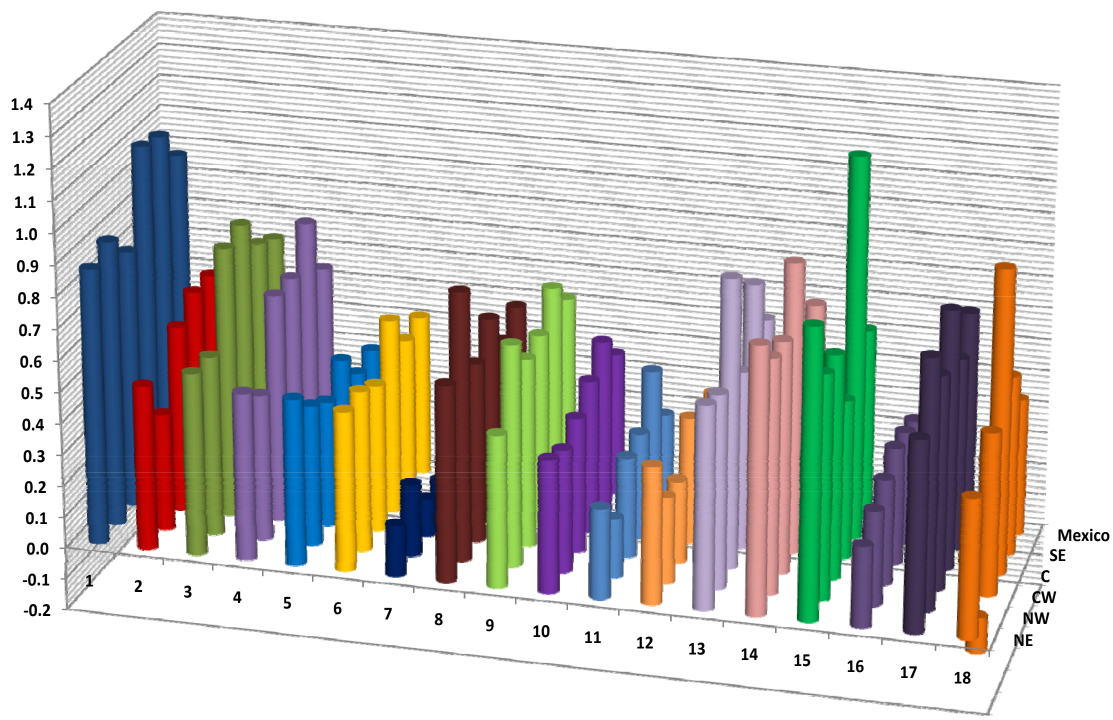


Figure 5.6: Expenditure Elasticities by Region.

Note: Bars depict $\hat{e}_i$ by region, $i = 1, 2, \ldots, 18$, where 1 = Beefsteak, 2 = Ground Beef, 3 = Other Beef, 4 = Beef Offal, 5 = Pork Steak, 6 = Pork Leg & Shoulder, 7 = Ground Pork, 8 = Other Pork, 9 = Chorizo, 10 = Ham, Bacon & Similar Products from Beef & Pork, 11 = Beef & Pork Sausages, 12 = Other Processed Beef & Pork, 13 = Chicken Legs, Thighs & Breasts, 14 = Whole Chicken, 15 = Chicken Offal, 16 = Chicken Ham & Similar Products, 17 = Fish, 18 = Shellfish.

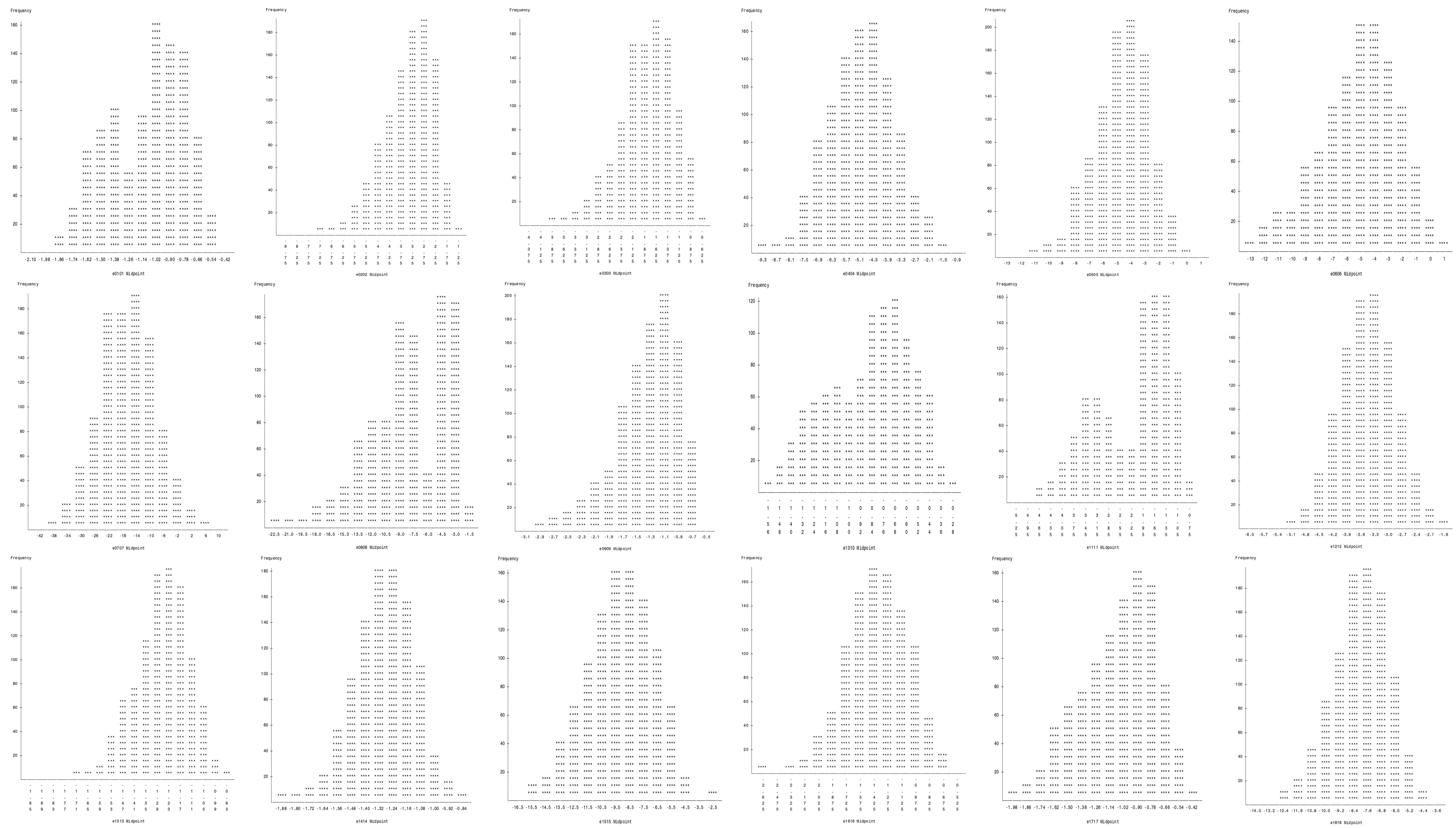


Figure 5.7: Marshallian Own-Price Elasticity Distributions.

Note: From left to right, $\hat{e}_{ij}$, $i = j = 1, 2, \ldots, 18$, where 1 = Beefsteak, 2 = Ground Beef, 3 = Other Beef, 4 = Beef Offal, 5 = Pork Steak, 6 = Pork Leg & Shoulder, 7 = Ground Pork, 8 = Other Pork, 9 = Chorizo, 10 = Ham, Bacon & Similar Products from Beef & Pork, 11 = Beef & Pork Sausages, 12 = Other Processed Beef & Pork, 13 = Chicken Legs, Thighs & Breasts, 14 = Whole Chicken, 15 = Chicken Offal, 16 = Chicken Ham & Similar Products, 17 = Fish, 18 = Shellfish.

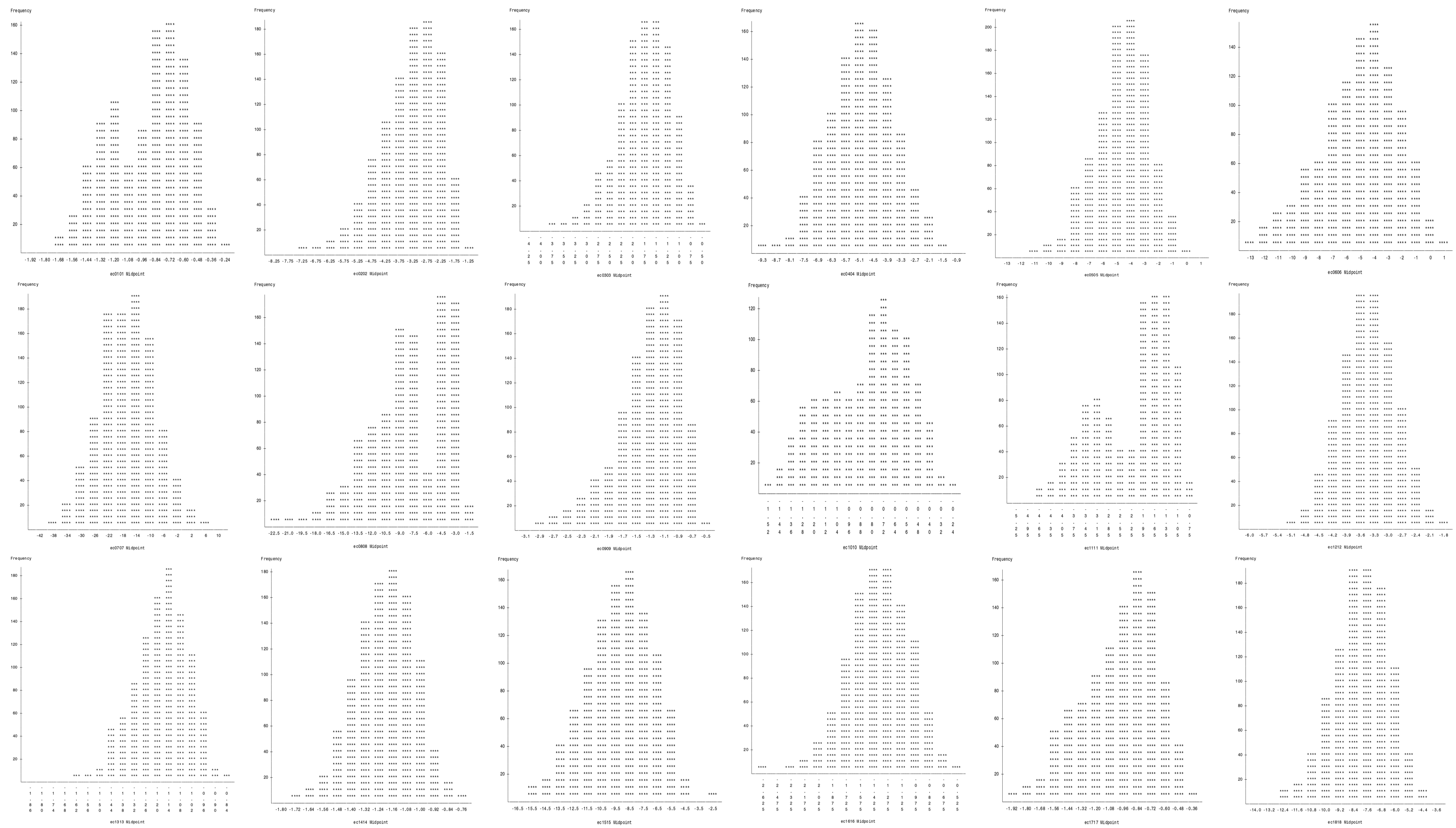


Figure 5.8: Hicksian Own-Price Elasticity Distributions.

Note: From left to right, $\hat{e}^c_{ij}$, $i = j = 1, 2, \ldots, 18$, where 1 = Beefsteak, 2 = Ground Beef, 3 = Other Beef, 4 = Beef Offal, 5 = Pork Steak, 6 = Pork Leg & Shoulder, 7 = Ground Pork, 8 = Other Pork, 9 = Chorizo, 10 = Ham, Bacon & Similar Products from Beef & Pork, 11 = Beef & Pork Sausages, 12 = Other Processed Beef & Pork, 13 = Chicken Legs, Thighs & Breasts, 14 = Whole Chicken, 15 = Chicken Offal, 16 = Chicken Ham & Similar Products, 17 = Fish, 18 = Shellfish.

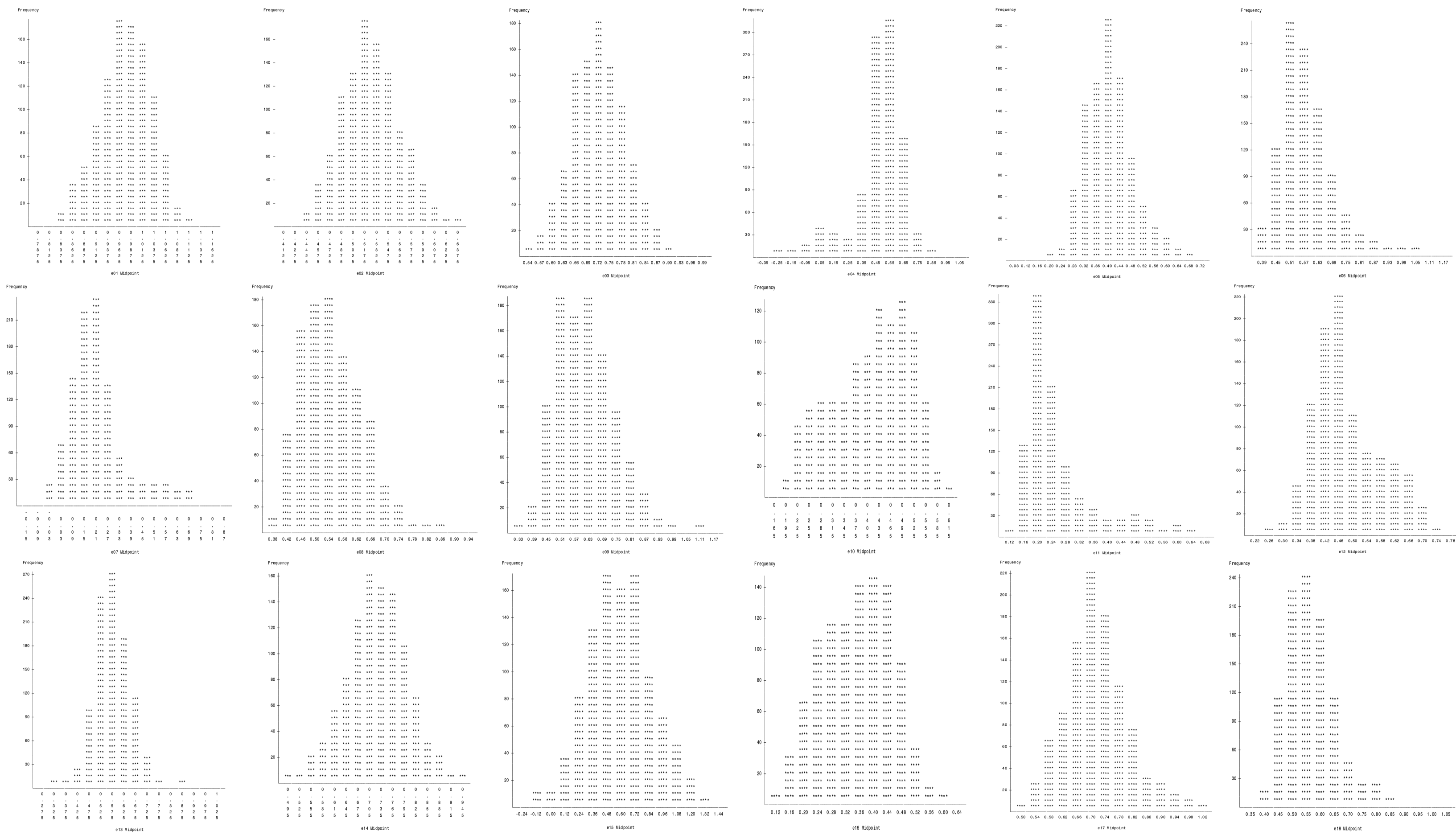


Figure 5.9: Expenditure Elasticity Distributions.

Note: From left to right, $\hat{e}_i$, $i = 1, 2, \ldots, 18$, where 1 = Beefsteak, 2 = Ground Beef, 3 = Other Beef, 4 = Beef Offal, 5 = Pork Steak, 6 = Pork Leg & Shoulder, 7 = Ground Pork, 8 = Other Pork, 9 = Chorizo, 10 = Ham, Bacon & Similar Products from Beef & Pork, 11 = Beef & Pork Sausages, 12 = Other Processed Beef & Pork, 13 = Chicken Legs, Thighs & Breasts, 14 = Whole Chicken, 15 = Chicken Offal, 16 = Chicken Ham & Similar Products, 17 = Fish, 18 = Shellfish.

5.3 Forecast and Simulation Analysis

To better estimate the effect of real per household income on Mexican meat consumption and imports, income elasticities are used, instead of expenditure elasticities. Expenditure elasticities are transformed into income elasticities by using Equation (4.14). Similar to the expenditure elasticities (Table 5.8), the income elasticities (Table 5.10) have the expected positive sign, which means that all the meat cuts are normal goods and that consumption on all meat cuts is expected to increase as the economy grows. The income elasticities range from 0.1245 for ground pork to 0.6563 for beefsteak (Table 5.10). In general, most pork cuts elasticities have lower values (therefore more necessary goods) than most beef and chicken cut elasticities, except for processed meat cuts (chorizo; ham, bacon and similar products from beef and pork; beef and pork sausages; other processed beef and pork; and chicken ham and similar products).

The income elasticities combined with the Mexican per household real GDP growth projection allows to forecast the Mexican per capita consumption by meat cut (see Section 4.3). Then, the per capita consumption by meat cut combined with the Mexican population projection allow to forecast the total Mexican consumption by meat cut (Figure 5.10, Figure 5.11 and Figure 5.12). The consumption of beef and veal, pork, and broiler by FAPRI, which is illustrated in Figure 5.10, Figure 5.11 and Figure 5.12 respectively, are the projections reported in FAPRI (2009b, p. 342) and FAPRI (2009a). On the other hand, the consumption of beef, pork and chicken (q_{beef}, q_{pork}, and $q_{chicken}$) in Figure 5.10, Figure 5.11 and Figure 5.12, are the projections obtained in this study (using FAPRI (2009b) baseline assumptions). The projections q_{beef}, q_{pork}, and $q_{chicken}$ are obtained from the sum of the corresponding meat cuts. That is, $q_{beef} = \sum_{i=1}^{4} q_i$, $q_{pork} = \sum_{i=5}^{8} q_i$, and $q_{chicken} = \sum_{i=13}^{16} q_i$. The index, in Panels (b), is computed by dividing all values in a series by its corresponding value in year 2006. Consequently, the index shows the growth rate from year 2006 to any year.

Panel (a) of Figure 5.10 indicates that Mexican beef consumption is expected to be greater than the values predicted by FAPRI (2009b, p. 342). In addition, beefsteak is expected to continue to be the most consumed beef cut, followed by other beef, ground beef and beef offal. Furthermore, Panel (b) in Figure 5.10 shows that beefsteak consumption is expected to be the fastest growing beef cut (2006-2018 growth rate of 41%), while ground beef consumption is expected to be the slowest growing beef cut (2006-2018 growth rate of 28%), and other beef and beef offal consumption are expected to have growth rates of 34% and 31% repectively. This indicates that Mexican beef consumption seems to be following the U.S. preferences for beef cuts, where the most expensive meat is consumed the most (i.e., beefsteak) and the cheapest meat is consumed the least (i.e., beef offal).

In the case of Mexican pork consumption (Figure 5.11), pork leg and shoulder is expected to continue to be the most consumed pork cut (Panel (a)), but the second fastest growing pork cut (Panel (b)). In addition, pork leg and shoulder (q_6) is expected to grow at the same rate as the total pork consumption (q_{pork}). The other three pork cuts considered, whose consumption is far much lower than the consumption of pork leg and shoulder (Panel (a)), are expected to grow at different growth rates (Panel (b)). The most rapidly growing pork cut is expected to be other pork (2006-2018 growth rate of 29%) and the slowest growing pork cut is expected to be ground pork (2006-2018 growth rate of 18%).

In the case of chicken (Figure 5.12), the consumption of chicken offal, whole chicken, and chicken legs, thighs and breasts are expected to be about the same (Panel (a)) and to grow at about the same rate, 2006-2018 growth rate of 15% (Panel (b)). Hence, unlike the beef case, Mexican chicken consumption does not seem to be following the U.S. preferences for chicken cuts, where there is high preference for chicken breasts and low preference for chicken offal. Finally, chicken ham and similar products, which is consumed at the lowest level (Panel (a)), is also expected to grow at the lowest rate (Panel (b)). Finally, our results indicate that chicken consumption is expected to be lower than what is predicted by FAPRI (2009b, p. 342).

Now, the income and the Marshallian own-price elasticities combined with the

Mexican per household real GDP growth projection and the real exchange rate growth projection allow to forecast total Mexican imports by meat cut (see Section 4.3). However, Mexican imports of beef and pork are currently not reported by meat cut.[11] Therefore, this study assumes the structure of the Mexican beef and pork consumption by meat cut is the same as the Mexican beef and pork imports by meat cut (i.e., assuming the import structure is the same as the consumption structure that is obtained from column six of Table 4.3). That is, of the total volume of Mexican beef imports in 2006, the study assumes that approximately 49.92% were beefsteak, 17.09% were ground beef, 26.01% were other beef, and 6.99% were beef offal. Similarly, of the total volume of Mexican pork imports in 2006, the study assumes that approximately 4.28% were pork steak, 78.95% were pork leg and shoulder, 1.49% were ground pork, and 15.28% were other pork. Even though this is a strong assumption that may not represent the current situation, this information is known by U.S. meat exporters. Consequently, the analysis of beef and pork imports by meat cuts could be easily modified with the real structure to obtain an even more realistic scenario. In the case of chicken, however, it is possible to recover the import structure of three meat cuts used in this study. That is, of the total volume of Mexican chicken imports in 2006, approximately 82.41% are chicken legs, thighs and breast; 8.11% is whole chicken; and 9.48% is chicken offal (see Appendix, Table A.10).

Similar to the consumption analysis, imports of beef and veal, pork and broiler by FAPRI in Figure 5.13, Figure 5.14 and Figure 5.15 respectively, are the projections reported in FAPRI (2009b, pp. 325, 327, and 329) and FAPRI (2009a); while q_{beef}, q_{pork}, and $q_{chicken}$ are the projections obtained in this study (using FAPRI (2009b) baseline assumptions). The projections q_{beef}, q_{pork}, and $q_{chicken}$ are obtained from the sum of the corresponding meat cut imports. The index shows the growth rate from year 2006 to any year.

The Mexican beef import projection presented in this study is very similar to

[11] The closest analysis that can be done using the harmonized system is presented in Appendix, Tables A.8 and Table A.9.

FAPRI (2009b, p. 325) projection from 2006 to 2014 but slightly lower (about 7%) from 2015 to 2018 (Panel (a) in Figure 5.13). On the contrary, the Mexican pork import projection in this study is moderately greater than FAPRI (2009b, p. 327) projection from 2006 to 2009 (about 9%), widely greater from 2010 to 2014 (about 38%), and slightly lower from 2015 to 2018 (about 3%), Panel (a) in Figure 5.14. Finally, the Mexican chicken import projection in this study is moderately greater than FAPRI (2009b, p. 329) projection from 2006-2009 (about 13%), and gradually becoming lower from 2011 to 2018 (1% in 2011 to 18% in 2018), Panel (a) in Figure 5.15. However, this study has the advantage of reporting import projections and growth rates of different table cuts of meats.[12]

In the case of Mexican chicken imports (Figure 5.15), chicken legs, thighs and breasts are the most imported chicken cut (Panel (a)). However, the fastest growing chicken cut is chicken offal (Panel (b)). The 2006-2018 import growth rate of chicken offal is 77%, while the import growth rates for whole chicken and chicken legs, thighs and breasts are 25% for both. In addition, chicken offal imports experience a volatile growth rate while whole chicken and chicken legs, thighs and breasts imports present smoother growth rates.

Finally, it is also possible to compute projection confidence intervals for each of the meat cut projections presented in this section. They can be obtained by using the bootstrap confidence intervals of the elasticity estimates. It is also possible to perform a sensitivity analysis based on FAPRI baseline assumptions to evaluate how Mexican consumption and imports of meat cuts change. However, it is essential to remember that in these consumption and import forecasts, the Mexican meat production trend is assumed to continue without drastic changes. Similarly, it is assumed that no radical changes in trade barriers or incentives will occur.

[12]Tables reporting consumption and import projections as well as growth rates are available upon request.

Table 5.10: Income Elasticities.

	i	$\hat{\eta}_i$
1	Beefsteak	0.6563
2	Ground Beef	0.3525
3	Other Beef	0.4895
4	Beef Offal	0.4324
5	Pork Steak	0.2632
6	Pork Leg & Shoulder	0.3467
7	Ground Pork	0.1245
8	Other Pork	0.3895
9	Chorizo	0.4173
10	Ham, Bacon & Similar Products	0.3066
11	Beef & Pork Sausages	0.1840
12	Other Processed Beef & Pork	0.2407
13	Chicken Legs, Thighs & Breasts	0.4141
14	Whole Chicken	0.4559
15	Chicken Offal	0.4121
16	Chicken Ham & Similar Products	0.2262
17	Fish	0.4700
18	Shellfish	0.2941

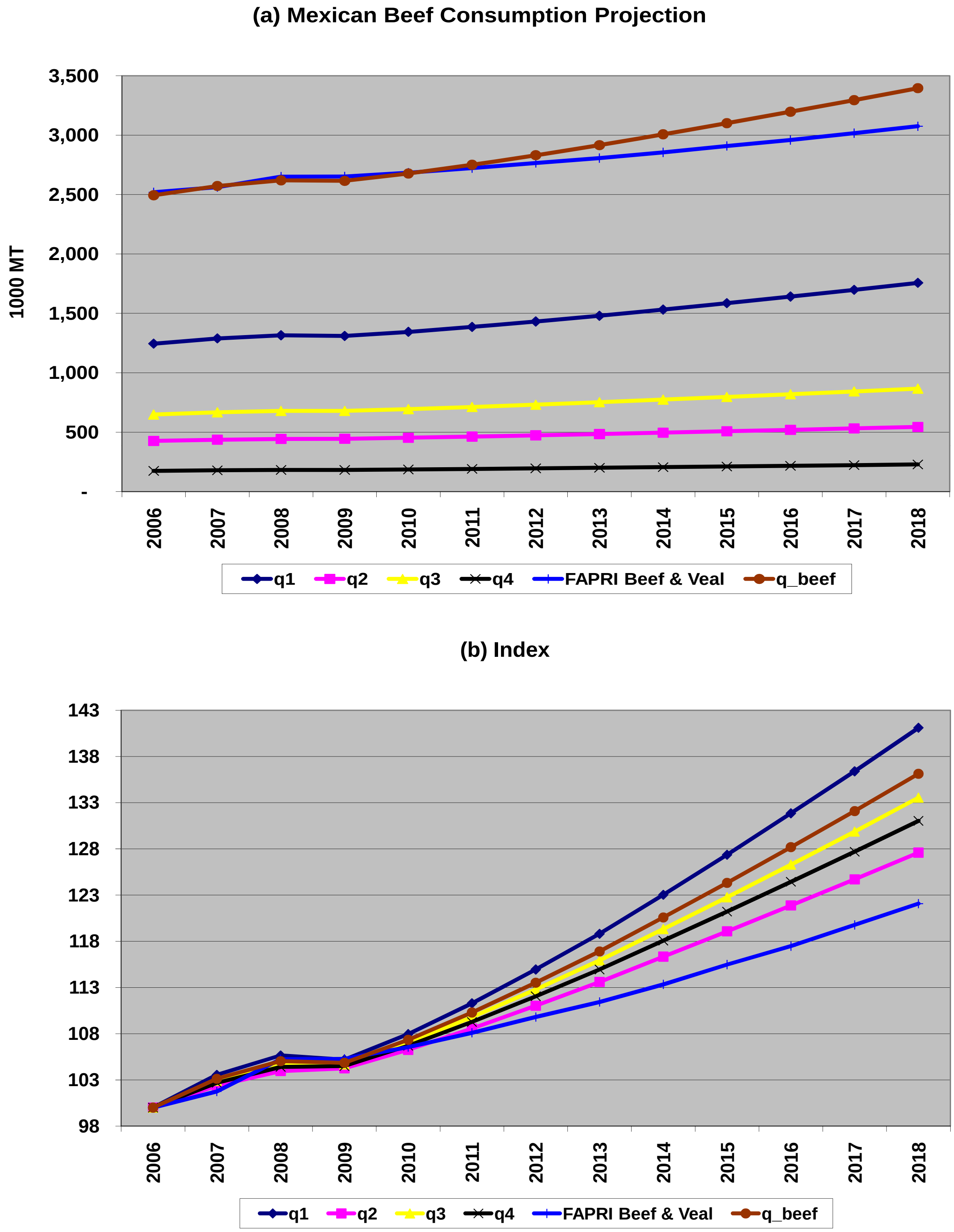
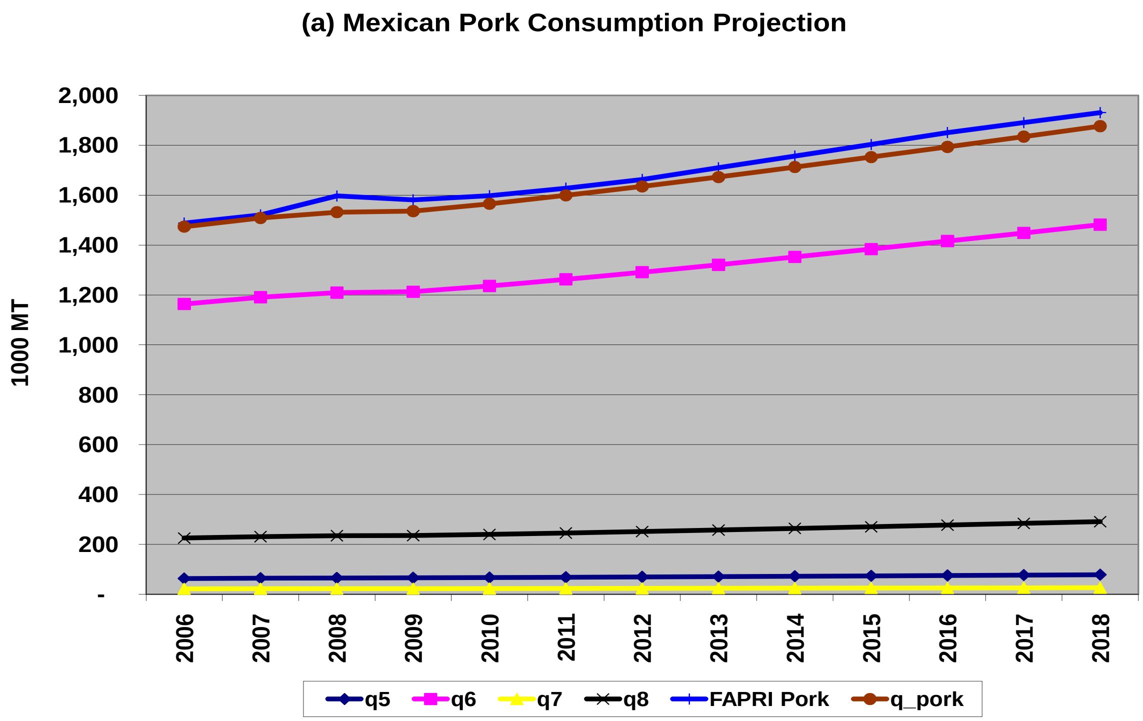


Figure 5.10: Mexican Beef Consumption Projection.

Note: FAPRI beef and veal consumption is the projection reported in FAPRI (2009b, p. 342) and FAPRI (2009a).



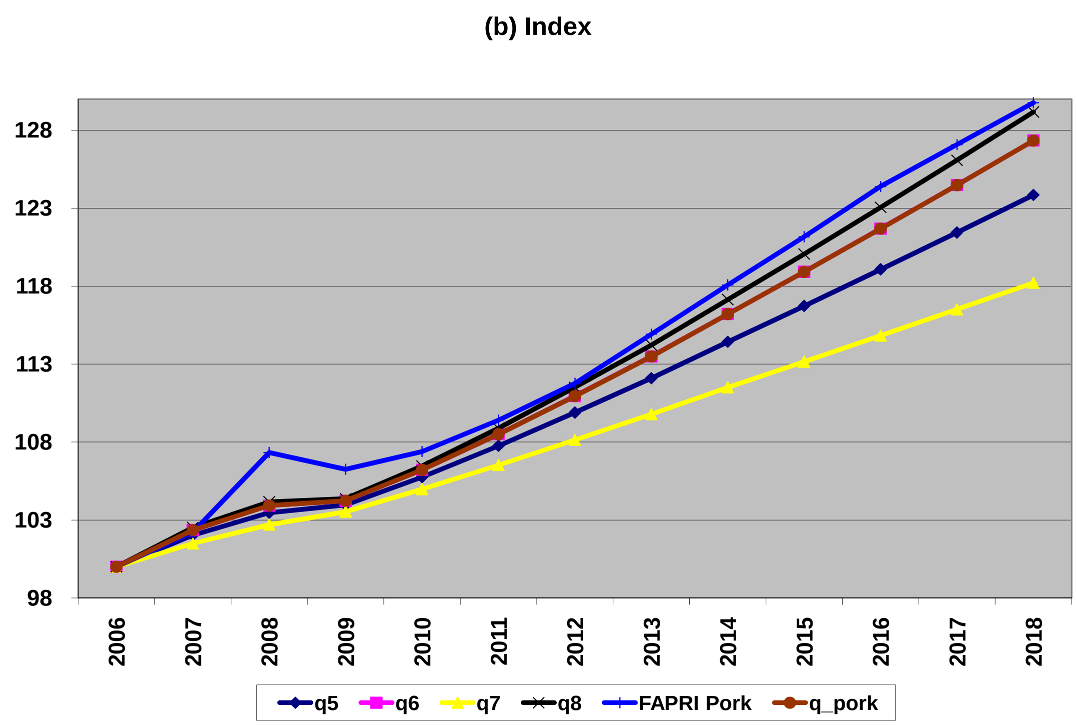


Figure 5.11: Mexican Pork Consumption Projection.

Note: FAPRI pork consumption is the projection reported in FAPRI (2009b, p. 342) and FAPRI (2009a).

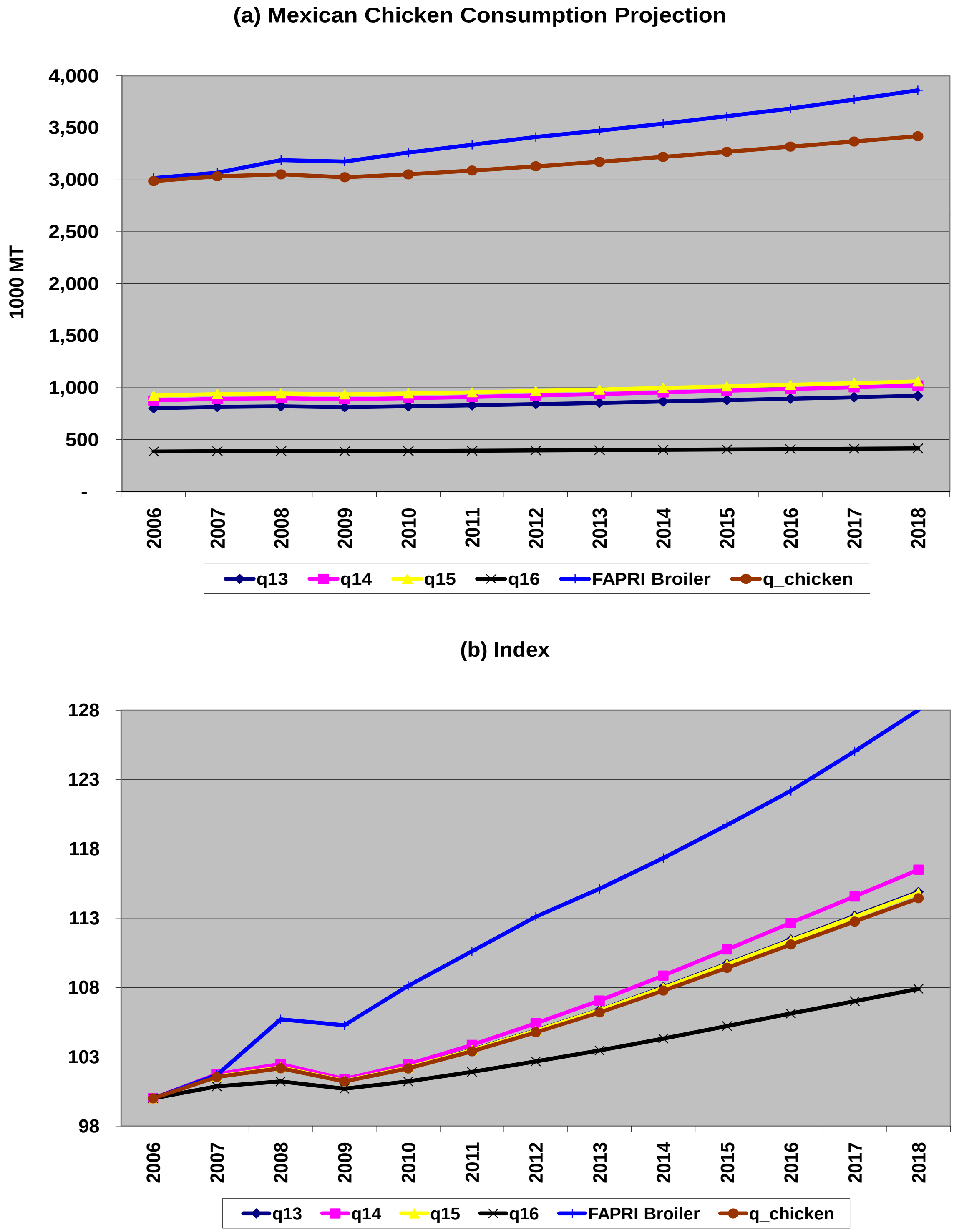
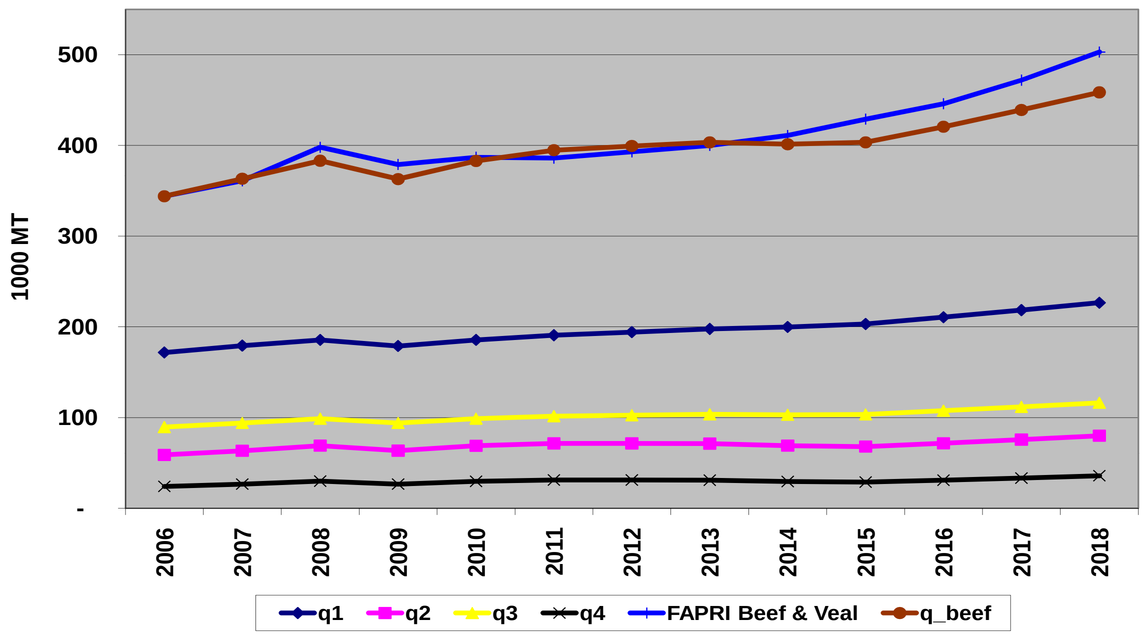


Figure 5.12: Mexican Chicken Consumption Projection.

Note: FAPRI broiler consumption is the projection reported in FAPRI (2009b, p. 342) and FAPRI (2009a).

(a) Mexican Beef Import Projection



(b) Index

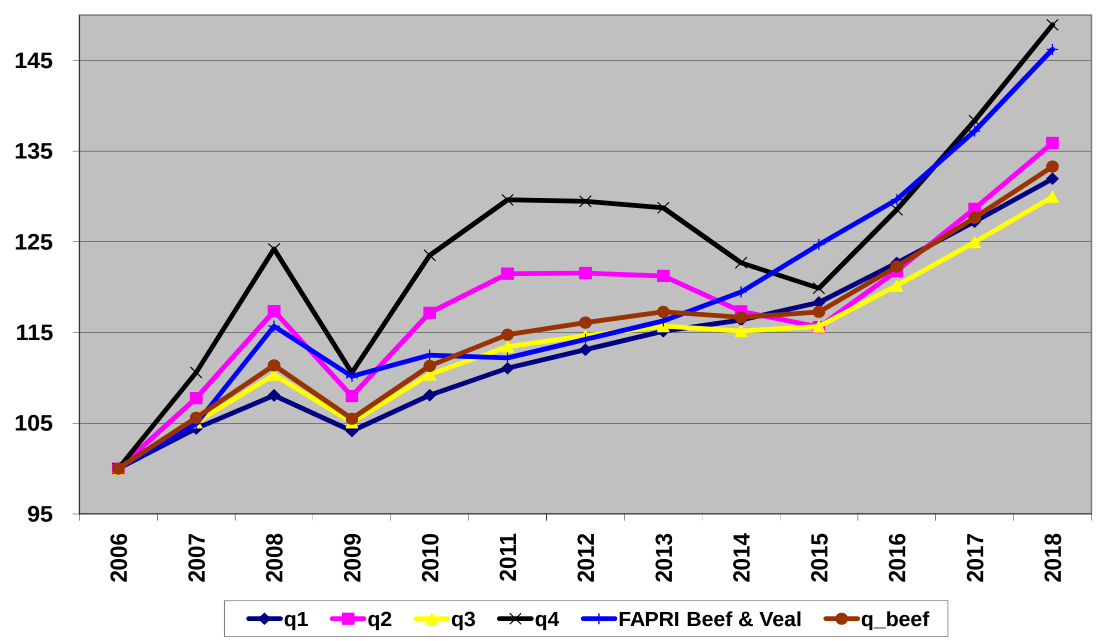


Figure 5.13: Mexican Beef Import Projection.

Note: FAPRI beef and veal imports is the projection reported in FAPRI (2009b, p. 325) and FAPRI (2009a).

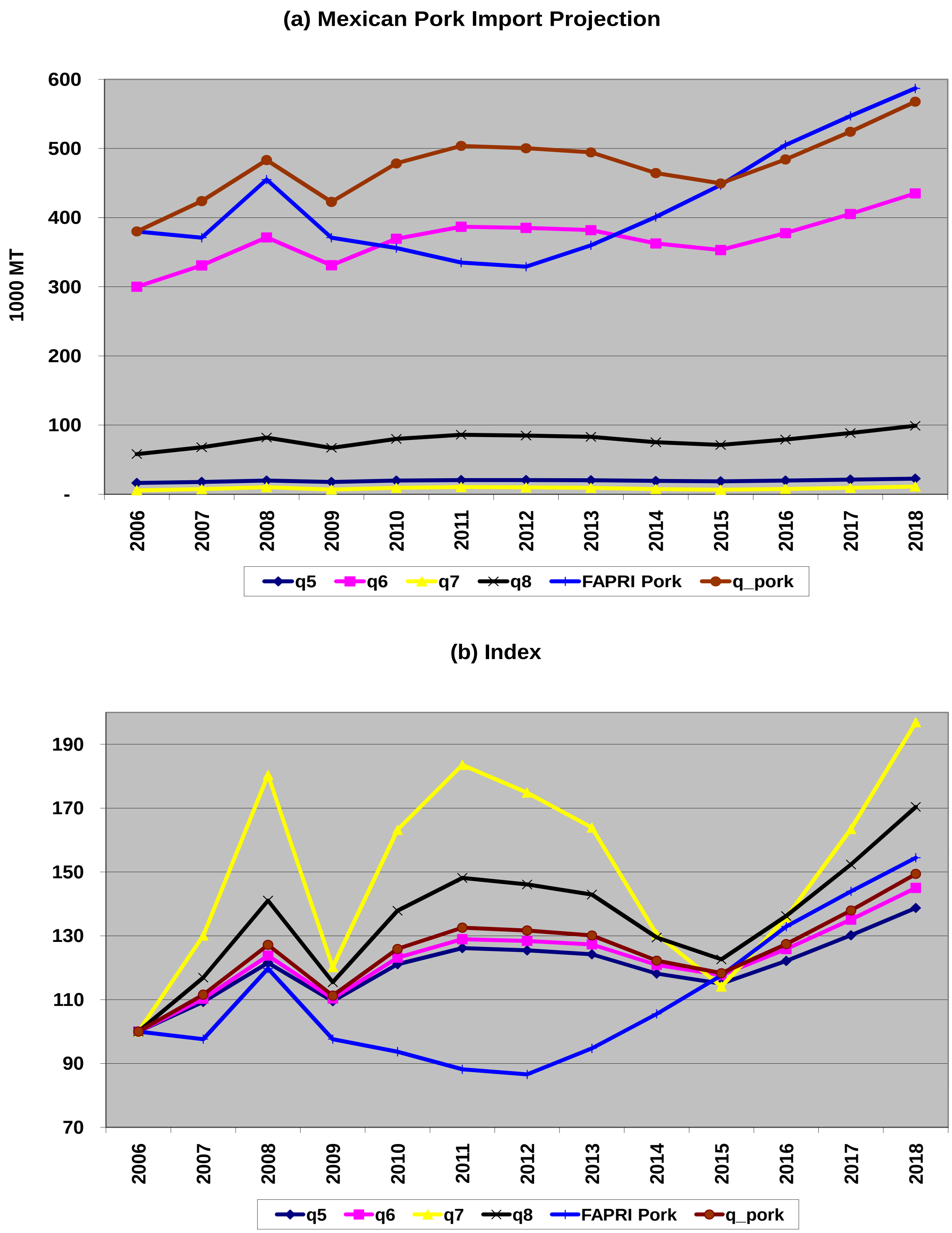


Figure 5.14: Mexican Pork Import Projection.

Note: FAPRI pork imports is the projection reported in FAPRI (2009b, p. 327) and FAPRI (2009a).

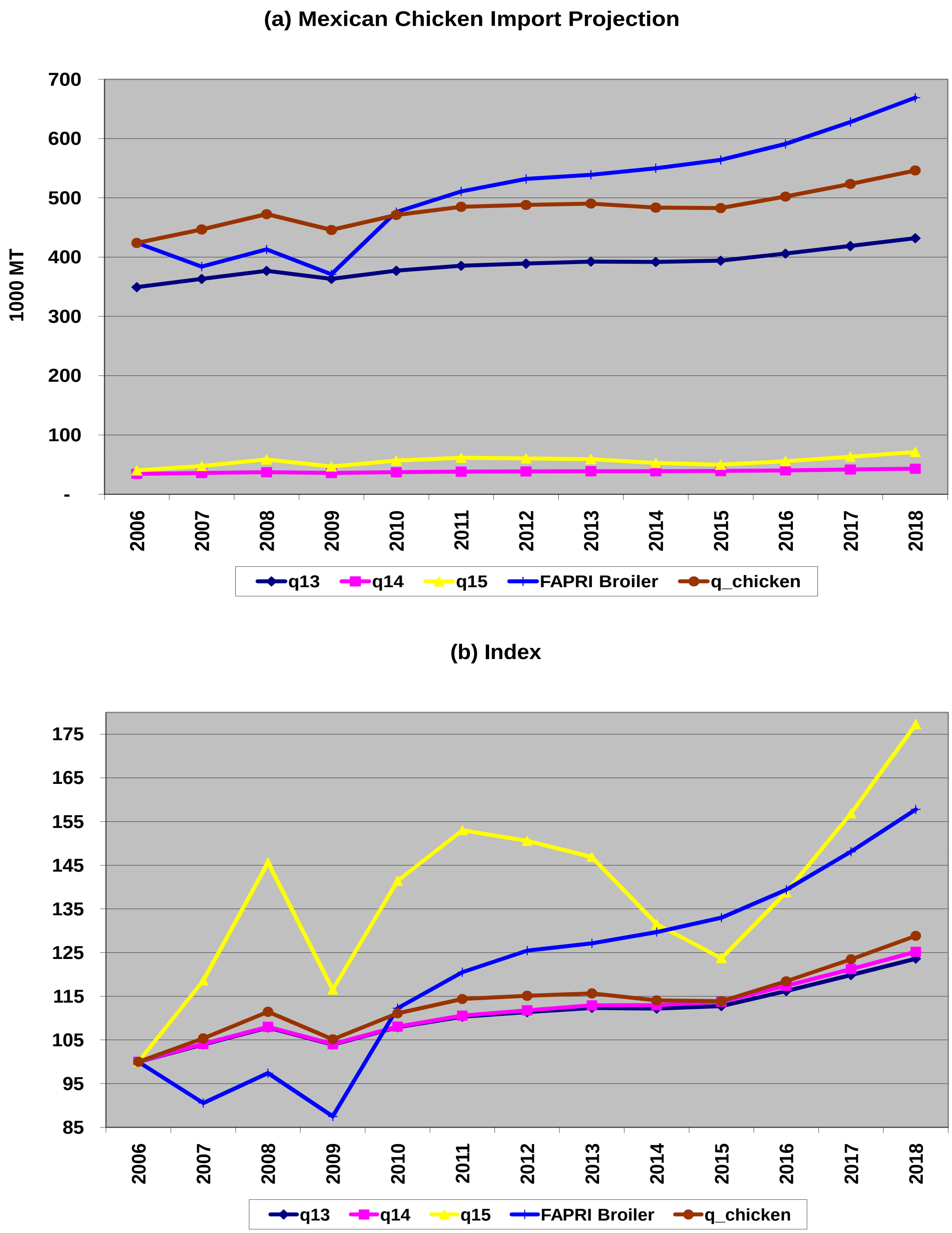


Figure 5.15: Mexican Chicken Import Projection.

Note: FAPRI broiler imports is the projection reported in FAPRI (2009b, p. 329) and FAPRI (2009a).

CHAPTER VI
CONCLUSION AND IMPLICATIONS

Mexico is becoming an important market for meat products not only because its large size, rapid growth, and meat offal preference, but also because Mexican per capita meat consumption still remains low compared to the equivalent in the United States and Canada. To appropriately understand the Mexican meat market, the study estimated Mexican meat demand parameters using a two-step censored regression model that not only incorporated stratification variables into the estimation procedure but also captured regional and urbanization level differences in the consumption of table cuts of meats. In the first step, maximum-likelihood probit estimates were obtained; while in the second step, a system of equations was estimated by using seemingly unrelated regressions. Parameter estimates were reported and their standard errors were approximated using a nonparametric bootstrap procedure. Marshallian and Hicksian price elasticities as well as expenditure and income elasticities were estimated by region at the table cut level of disaggregation, which were previously not available for Mexico. In addition, a simulation analysis of Mexican meat consumption at the table cut level was performed to explore in detail not only future trends and growth rates but also if Mexican demands for meat cuts are heterogeneous.

Expenditure and income elasticities levels indicated that Mexican consumption on all meat cuts is expected to increase as the economy grows. In addition, they suggested that all meat cuts are necessary commodities and pork cut demands are the most inelastic (excluding processed meat cuts). Moreover, several cases of substitutability and complementarity in Mexico and its five major regions were identified using the elasticity estimates. In general, further cases of (gross and net) substitutability and complementarity were identified within and across the traditional meat categories (i.e., beef, pork, chicken, and seafood). For example, *within* categories, cases of *substitutability* are found in Mexico. Ground beef is a (gross and net) substitute of beefsteak (and vice versa). Chicken ham and similar products are (gross and net) substitutes of ham, bacon and similar products from beef and pork (and vice versa). *Within* categories, cases of *complementarity* were also found in Mexico. Other beef cuts (i.e., excluding beefsteak, ground beef, and beef offal) are (gross and net) complements of beefsteak (and vice versa). Pork leg and shoulder is a (gross and net) complement of pork steak (and vice versa). *Across* categories, cases of *substitutability* are found in Mexico. Pork steak is a (gross and net) substitute of beefsteak (and vice versa). Chicken offal is a (gross and net substitute) of beef offal (and vice versa). *Across* categories, cases of *complementarity* are also found in Mexico. Fish is a (gross and net) complement of whole chicken (but not vice versa).

In addition, given that some previous studies have found chicken to be a (gross and net) substitute for beef, while others have found it to be a (gross and net) complement (see Section 5.1.3), this study clarified that this may depend on the chicken and beef cuts considered (e.g., chicken offal is a gross substitute of beef offal, but chicken legs, thighs and breasts are gross complements of beefsteak). Therefore, it is critical to analyze price elasticities at the table cut level of disaggregation.

More interestingly, Mexican consumption of table cuts of meats were found to grow at different rates within each meat category (except for the chicken category where only chicken ham and similar products have a lower growth rate). The same was also true for Mexican imports of table cuts of meats. For example, Mexican beefsteak consumption is the fastest growing meat cut within the beef category but pork steak consumption is not the fastest growing within the pork category. On the contrary, Mexican ground beef and ground pork consumption seem to be the slowest growing meat cuts within their corresponding meat category and processed meat consumption is neither the fastest growing nor the slowest growing meat cuts. Furthermore, Mexico seems to be following the U.S. preferences for beef cuts but not following the U.S. preferences for chicken cuts. Nonetheless, Mexican imports of chicken legs, thighs and breast are expected to continue to be the most imported chicken cuts.

There were also differences in the Mexican consumption of table cuts of meats among regions and between the urban and rural sectors, which is consistent with previous studies. However, unlike previous studies, this study found regional differences at the table cut level of disaggregation. It is critical to understand that elasticity estimates by region in this study were obtained from the use of binary variables for the major Mexican regions, and not from interactions of continuous and binary explanatory variables.

Given that the study found many indicators of heterogeneous demands for meat cuts, it is recommended to analyze Mexican meat consumption and trade at the table cut level. This disaggregation may also allow for projections and forecasts to be more precise. However, much effort is needed to record imports and exports at the table cut level. The current categories of the harmonized system (specially in the case of beef and pork) does not allow for an in-depth trade analysis of meat cuts. In this study, the Mexican beef and pork consumption structure by meat cut is used as the import structure to forecast meat cut imports in these two categories. Similarly, it is advised that ENIGH extends each household interview period to more than one week so that the high number of censored observations is reduced, and perhaps additional table cuts of meats could be analyzed. For this study, it would be more beneficial if ENIGH extends each household interview period (therefore reduce the number of censored observations) rather than ENIGH keeping on increasing the number of households interviewed during each survey.

There were also several methodological advantages in this study over previous studies. First, the demand parameters and elasticities as well as their corresponding standard errors can be interpreted as population estimates (or viewed as census estimates). This is because demand parameters and elasticities were calculated incorporating estimation techniques that are used in stratified sampling theory. In addition, their standard errors were approximated by using the bootstrap, which is a resampling technique that can be used to estimate standard errors of parameter estimates when other estimation techniques are inappropriate or not feasible. The bootstrap is a simple way to obtain standard errors when asymptotic theory leads to complex estimators. Second, data issues, such as censored observations and calculating the number of adult equivalents to compute per capita meat consumption, were also included in the analysis. As the study explained how to deal with some of these data issues, it also discussed the consequences of ignoring them (i.e., not using the entire target population, not adjusting for household size, and not incorporating stratification variables). In general, the study outlined a censored demand system estimation in a complex survey.

Another advantage of the study was the use of a consistent censored demand system that incorporated estimation techniques used in stratified sampling theory. For instance, the study incorporated stratification variables (strata and weight) in preliminary data preparation, in each of the two-step estimation procedure, and in computing standard errors. This was an advantage because previous studies that have used the same data source do not seem to be aware that the survey is complex. Consequently, they have treated the sample as a simple random sample, instead of a stratified sample, without doing a preliminary examination. It is important to incorporate stratification variables into the analysis because ignoring them results in incorrect standard errors of parameter estimates and in parameter estimates that may not be representative of the population or that may not capture potential differences among the subpopulations (Lohr, 1999, pp. 221-254). Moreover this study found evidence, according to DuMouchel and Duncan's (1983) test, that suggests that the use of weights is necessary when using ENIGH.

Finally, this study used data at the household level, which provides additional insights about the nature of the demand for meat. By analyzing individual households with micro-data, microeconomic models may enable better estimation of demand parameters and improvement of forecasts over those using macro-data, which assumes aggregate household behavior is the outcome of the decision of a representative household. Consequently, the demand elasticities, and the meat consumption and import projections reported in this study might be more precise than the aggregated elasticities and projections reported in some of the previous studies.

Large U.S. and Canadian exporting companies, which currently know how much of each meat cut they export to Mexico, will find this study beneficial for understanding the Mexican meat demand at the table cut level of disaggregation. In particular, this study may be useful in forecasting potential future exports to Mexico, conducting long-term investment decisions in the meat industry, or identifying regional trends in Mexican consumption and imports of specific table cuts of meats. It may also provide insight into positioning U.S. meat products in Mexican markets. That is, it may reveal where in Mexico a particular meat cut will sell better. For example, the study identified Mexican regions with the highest probability of consuming a particular meat cut. For instance, the typical household from the urban sector in the Northwest region statistically has the highest probability of consuming ground beef, other beef, chorizo, and chicken legs, thighs and breast. On the other side, the typical household from the urban sector in the Southeast region statistically has the highest probability of consuming pork steak. The study also contains information that may be relevant and useful to meat producers and Mexican policy makers in quantifying how changes in prices, income, regional location, or urbanization level may affect the consumption of a particular meat cut. Finally, elasticities by region may not only facilitate positioning meat products in appropriate Mexican markets but also managing prices more effectively.

It is also possible to obtain elasticity estimates by region by creating interactions of continuous and binary explanatory variables. However, given that this study considered table cuts of meats, creating such interactions will have significantly increased the number of variables and may have potentially decreased the number of parameters per equation that are statistically different from zero. However, it is also possible (and it is more practical and feasible than creating interactions) to compute the model within each region and urbanization level to get elasticity estimates by region and sector. Given that the study adopted a simple approach, it will be an excellent reference for future comparisons.

Similarly, it is critical to understand that, in this study, the forecasts and simulation analysis of meat consumption and import are based on elasticity estimates and FAPRI baseline assumptions. A sensitivity analysis based on FAPRI baseline assumptions could be performed to evaluate how Mexican consumption and imports of cuts of meats change. In addition, provided that most previous studies have characterized Mexico as having significant differences in food consumption patterns across regions and urbanization levels (due to economic, cultural and climatic variations), it will be very interesting to explore regional preferences for meat cuts by using a spatial dimension. That is, a spatial econometric analysis that uses meat consumption and expenditure data and incorporates household geographical location. Such analysis is interesting because spatial dependence often arises in economic processes and cross-sectional spatial data samples. In addition, a spatial econometric model can take into account spatially correlated unobservable variables that produce spatial correlation in the errors of the equations describing the economic behavior.

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APPENDIX A
PRODUCTION, CONSUMPTION, AND TRADE

Appendix A contains information about the world's largest meat consuming, producing, importing and exporting countries as well as information on Mexican imports and exports at a semi-aggregated level. It also reports the most relevant countries currently trading with Mexico. The tables in Appendix A were used in the analysis of Section 1.3 to efficiently and effectively identify trends.

Data on consumption, production, imports and exports by country (Table A.1 through Table A.7) was obtained from the Production, Supply, Distribution (PSD) online database, Economic Research Service (ERS), United States Department of Agriculture (USDA). Data on Mexican imports and exports was acquired from the Sistema de Información Arancelaria Via Internet (SIAVI) online database, Mexican Ministry of Economy. The latter Mexican governmental institution provides information on imports and exports (kg and dollars) of meat commodities at the 8-digit level of disaggregation from chapter 2 (meat and edible meat offal) of the Harmonized System. Only the most relevant meat commodities in chapter 2 of the Harmonized System were used to compute Table A.8 through Table A.10. That is, the analysis excludes exotic meats such as ovine and caprine meats, horse, dunkey, mule, etc.

Table A.1: Annual World Production, Imports, Exports and Consumption by Meat Type (1000 MT).

	1997	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**Avg. 97-06**
World Production (1000 MT CWE)[a]											
Beef[b]	49,237	48,958	49,977	50,311	49,646	51,241	50,095	51,327	52,374	53,511	50,668
Pork[c]	74,361	79,574	82,266	81,819	84,940	88,011	90,488	92,801	96,227	99,776	87,026
Poultry[d]	47,803	49,473	52,743	55,318	57,237	59,173	59,218	60,845	63,943	64,921	57,067
Total Meat	171,401	178,005	184,986	187,448	191,823	198,425	199,801	204,973	212,544	218,208	194,761
World Imports (1000 MT CWE)[a]											
Beef[b]	5,016	4,771	5,065	4,935	4,978	5,242	5,074	4,891	5,423	5,007	5,040
Pork[c]	2,587	2,658	2,891	2,960	3,195	3,871	3,962	4,172	4,342	4,232	3,487
Poultry[d]	3,992	3,809	4,251	4,245	4,581	4,861	5,025	4,768	5,517	5,627	4,668
Total Meat	11,595	11,238	12,207	12,140	12,754	13,974	14,061	13,831	15,282	14,866	13,195
World Exports (1000 MT CWE)[a]											
Beef[b]	5,795	5,439	5,724	5,746	5,670	6,274	6,339	6,496	7,092	6,996	6,157
Pork[c]	1,620	1,697	1,636	1,735	2,267	2,757	3,051	3,418	3,875	3,800	2,586
Poultry[d]	4,617	4,674	4,908	5,369	6,112	6,313	6,586	6,615	7,423	7,041	5,966
Total Meat	12,032	11,810	12,268	12,850	14,049	15,344	15,976	16,529	18,390	17,837	14,709
World Domestic Consumption (1000 MT CWE)[a]											
Beef[b]	48,275	48,496	49,818	49,536	48,716	50,277	49,049	49,874	50,770	51,509	49,632
Pork[c]	74,097	79,345	81,908	81,461	84,727	87,829	90,297	92,139	95,236	98,914	86,595
Poultry[d]	47,172	48,638	52,075	54,162	55,638	57,634	57,664	58,923	62,050	63,598	55,755
Total Meat	169,544	176,497	183,801	185,159	189,081	195,740	197,010	200,936	208,056	214,021	191,983

a. MT = metric tons and CWE = carcass weight equivalent. CWE is the weight of an animal after slaughter and removal of most internal organs, head, and skin. CWE applies only to beef and pork, poultry meat is reported by the USDA-ERS-PSD database in ready to cook equivalent.
b. Beef includes beef and veal.
c. Pork is also called swine meat.
d. Poultry includes broiler and turkey.
Note: The amounts reported in this table reflect only those countries that make up the USDA-ERS-PSD database and not all countries in the world. Any production, import, export or consumption amount represent the most important players in the world meat PSD situation, which represents over 90% of the world's situation. In addition, the list of countries that make up the USDA-ERS-PSD database changes periodically.

Source: USDA-ERS-PSD Online Database, computed by author.

Table A.2: Annual Meat Production by Country (1000 MT).

Country	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**Avg. 97-06**
China	47,778	51,756	53,660	54,911	56,611	58,670	61,389	63,773	67,421	70,850	58,682
EU-25	36,311	37,769	39,580	38,566	38,492	38,973	38,748	38,856	38,525	38,565	38,439
U.S.	34,270	35,317	36,621	37,016	37,197	38,380	38,320	38,300	39,042	40,131	37,459
Brazil	12,152	12,435	13,746	14,647	15,857	17,436	17,790	19,223	21,017	21,165	16,547
Mexico	4,239	4,348	4,690	4,883	5,070	5,185	5,354	5,651	5,832	5,999	5,125
Canada	3,224	3,481	3,788	3,915	4,057	4,227	4,149	4,523	4,569	4,390	4,032
Russia	4,108	3,889	3,748	3,727	3,757	3,879	3,952	3,980	4,177	4,359	3,958
Argentina	3,745	3,450	3,725	3,750	3,510	3,340	3,550	4,040	4,230	4,310	3,765
India	2,026	2,303	2,480	2,780	3,020	3,210	3,460	3,780	4,150	4,375	3,158
Australia	2,761	2,885	2,868	2,926	2,996	3,125	3,138	3,126	3,195	3,269	3,029
Others[a]	20,787	20,372	20,080	20,327	21,256	22,000	19,951	19,721	20,386	20,795	20,568
World[b]	171,401	178,005	184,986	187,448	191,823	198,425	199,801	204,973	212,544	218,208	194,761

a. Others = only the remaining countries that make up the USDA-ERS-PSD database. These remaining countries consist of the most important players in the world meat PSD situation, which represents over 90% of the world's situation. In addition, the list of countries that make up the USDA-ERS-PSD database changes periodically.
b. Meat production (1000 MT) includes beef (beef and veal), pork (swine meat), and poultry (broiler and turkey).

Source: USDA-ERS-PSD Online Database, computed by author.

Table A.3: Annual Meat Consumption by Country (1000 MT).

Country	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**Avg. 97-06**
China	47,529	51,599	53,757	55,067	56,464	58,567	61,291	63,282	66,766	70,319	58,464
EU-25	33,506	35,320	36,851	36,128	36,221	37,213	37,555	37,258	37,215	37,467	36,473
U.S.	31,827	33,070	34,393	34,654	34,567	36,008	35,997	36,837	37,008	37,556	35,192
Brazil	11,368	11,529	12,470	13,132	13,547	14,377	14,060	14,475	15,539	16,057	13,655
Russia	7,499	6,564	6,221	5,538	6,235	6,774	6,604	6,432	7,242	7,310	6,642
Mexico	4,759	5,046	5,495	5,870	6,107	6,335	6,530	6,794	7,045	7,304	6,129
Japan	5,349	5,367	5,477	5,585	5,484	5,526	5,580	5,456	5,588	5,624	5,504
Argentina	3,346	3,239	3,432	3,444	3,395	2,980	3,145	3,357	3,392	3,728	3,346
Canada	2,723	2,898	3,076	3,069	3,112	3,130	3,140	3,226	3,176	3,126	3,068
India	1,811	2,058	2,256	2,431	2,650	2,793	3,017	3,279	3,522	3,625	2,744
Others[a]	19,827	19,789	20,373	20,241	21,299	22,037	20,091	20,540	21,563	21,905	20,767
World[b]	169,544	176,479	183,801	185,159	189,081	195,740	197,010	200,936	208,056	214,021	191,983

a. Others = only the remaining countries that make up the USDA-ERS-PSD database. These remaining countries consist of the most important players in the world meat PSD situation, which represents over 90% of the world's situation. In addition, the list of countries that make up the USDA-ERS-PSD database changes periodically.
b. Meat consumption (1000 MT) includes beef (beef and veal), pork (swine meat), and poultry (broiler and turkey).

Source: USDA-ERS-PSD Online Database, computed by author.

Table A.4: Annual Per Capita Meat Consumption of Selected Countries (Kg).

Country	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**Avg. 97-06**
U.S.	115.30	118.55	122.01	121.65	120.09	123.81	122.51	124.10	123.42	124.01	121.61
Canada	91.20	96.19	101.18	100.00	100.41	99.97	99.27	100.95	98.42	95.96	98.38
Argentina	93.76	89.72	94.02	93.34	91.08	79.17	82.75	87.49	87.54	95.26	89.37
EU-25	74.61	78.51	81.75	79.93	79.86	81.71	82.10	81.11	80.72	81.01	80.14
Brazil	68.25	68.18	72.66	75.40	76.67	80.21	77.34	78.53	83.17	84.81	76.73
Mexico	49.99	52.09	55.84	58.86	60.56	62.27	63.69	65.75	67.57	69.34	60.78
China	38.41	41.32	42.67	43.36	44.13	45.46	47.26	48.49	50.85	53.24	45.61
Russia	50.44	44.25	42.05	37.57	42.46	46.35	45.41	44.45	50.31	51.04	45.41
Japan	42.40	42.44	43.21	43.96	43.09	43.35	43.71	42.69	43.69	43.95	43.25
India	1.83	2.04	2.19	2.32	2.49	2.58	2.74	2.94	3.10	3.15	2.56
Others[a]	20.46	20.15	20.46	20.06	20.84	21.28	19.16	19.34	20.06	20.14	20.19
World[b]	37.47	38.56	39.72	39.58	40.00	40.99	40.85	41.26	42.31	43.12	40.43

a. Others = only the remaining countries that make up the USDA-ERS-PSD database. These remaining countries consist of the most important players in the world meat PSD situation, which represents over 90% of the world's situation. In addition, the list of countries that make up the USDA-ERS-PSD database changes periodically.
b. Per capita meat consumption (kg/person) includes beef (beef and veal), pork (swine meat), and poultry (broiler and turkey).

Source: Consumption from USDA-ERS-PSD Online Database, computed by author. Population from IMF-IFS Online Database.

Table A.5: Annual Meat Imports by Country (1000 MT).

Country	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**Avg. 97-06**
Russia	3,330	2,619	2,483	1,836	2,621	2,926	2,640	2,472	3,090	2,976	2,699
Japan	2,315	2,356	2,593	2,783	2,780	2,618	2,679	2,531	2,787	2,683	2,613
U.S.	1,353	1,521	1,680	1,816	1,872	1,951	1,908	2,182	2,115	1,925	1,832
Mexico	568	756	871	1,066	1,117	1,228	1,237	1,215	1,304	1,405	1,077
EU-25	888	874	602	617	644	1,038	1,157	1,158	1,245	1,272	950
Hong Kong	396	466	585	503	519	517	537	657	619	636	544
China	386	460	671	817	624	686	730	348	269	409	540
Korea	337	209	454	573	459	687	686	470	630	517	502
Saudi Arabia	357	349	431	347	399	391	452	429	484	434	407
Canada	359	355	387	404	469	482	447	324	380	400	401
Others[a]	1,306	1,273	1,450	1,378	1,250	1,450	1,588	2,045	2,359	2,209	1,631
World[b]	11,595	11,238	12,207	12,140	12,754	13,974	14,061	13,831	15,282	14,866	13,195

a. Others = only the remaining countries that make up the USDA-ERS-PSD database. These remaining countries consist of the most important players in the world meat PSD situation, which represents over 90% of the world's situation. In addition, the list of countries that make up the USDA-ERS-PSD database changes periodically.
b. Meat imports (1000 MT) includes beef (beef and veal), pork (swine meat), and poultry (broiler and turkey).

Source: USDA-ERS-PSD Online Database, computed by author.

Table A.6: Annual Meat Exports by Country (1000 MT).

Country	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	Avg. 97-06
U.S.	3,714	3,723	3,928	4,137	4,477	4,220	4,372	3,569	4,143	4,565	4,085
Brazil	956	1,015	1,334	1,568	2,380	3,138	3,793	4,801	5,528	5,138	2,965
EU-25	2,279	2,189	2,020	1,639	1,523	1,672	1,422	1,396	1,219	992	1,635
Canada	854	921	1,101	1,250	1,384	1,573	1,450	1,621	1,760	1,676	1,359
Australia	1,188	1,279	1,281	1,351	1,418	1,381	1,279	1,407	1,427	1,434	1,345
China	635	617	574	661	771	789	828	839	924	940	758
New Zealand	510	488	443	485	496	486	558	606	589	540	520
Argentina	477	326	403	417	249	449	499	748	899	646	511
India	215	245	224	349	370	417	443	501	628	750	414
Thailand	195	274	259	304	392	427	485	200	240	280	306
Others[a]	1,009	733	701	689	589	792	847	841	1,033	876	811
World[b]	12,032	11,810	12,268	12,850	14,049	15,344	15,976	16,529	18,390	17,837	14,709

a. Others = only the remaining countries that make up the USDA-ERS-PSD database. These remaining countries consist of the most important players in the world meat PSD situation, which represents over 90% of the world's situation. In addition, the list of countries that make up the USDA-ERS-PSD database changes periodically.
b. Meat exports (1000 MT) includes beef (beef and veal), pork (swine meat), and poultry (broiler and turkey).

Source: USDA-ERS-PSD Online Database, computed by author.

Table A.7: Annual Mexican Production, Imports, Exports and Consumption by Meat Type (1000 MT).

	1997	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**Avg. 97-06**	**Share 97-06**	**Growth 97 to 06**
Mexican Production (1000 MT CWE)[a]													
Beef[b]	1,795	1,800	1,900	1,900	1,925	1,930	1,950	2,099	2,125	2,175	1,960	38%	21%
Pork[c]	940	950	994	1,035	1,065	1,085	1,100	1,150	1,195	1,200	1,071	21%	28%
Poultry[d]	1,504	1,598	1,796	1,948	2,080	2,170	2,304	2,402	2,512	2,624	2,094	41%	74%
Total Meat	4,239	4,348	4,690	4,883	5,070	5,185	5,354	5,651	5,832	5,999	5,125	100%	42%
Mexican Imports (1000 MT CWE)[a]													
Beef[b]	203	307	358	420	426	489	370	287	325	365	355	33%	80%
Pork[c]	82	144	190	276	294	325	371	458	420	450	301	28%	449%
Poultry[d]	283	305	323	370	397	414	496	470	559	590	421	39%	108%
Total Meat	568	756	871	1,066	1,117	1,228	1,237	1,215	1,304	1,405	1,077	100%	147%
Mexican Exports (1000 MT CWE)[a]													
Beef[b]	6	6	8	11	10	10	12	18	31	35	15	20%	483%
Pork[c]	39	49	53	59	61	61	48	52	59	65	55	74%	67%
Poultry[d]	3	3	5	9	9	7	1	2	1	0	4	5%	-100%
Total Meat	48	58	66	79	80	78	61	72	91	100	73	100%	108%
Mexican Consumption (1000 MT CWE)[a]													
Beef[b]	1,992	2,101	2,250	2,309	2,341	2,409	2,308	2,368	2,419	2,505	2,300	38%	26%
Pork[c]	983	1,045	1,131	1,252	1,298	1,349	1,423	1,556	1,556	1,585	1,318	22%	61%
Poultry[d]	1,784	1,900	2,114	2,309	2,468	2,577	2,799	2,870	3,070	3,214	2,511	41%	80%
Total Meat	4,759	5,046	5,495	5,870	6,107	6,335	6,530	6,794	7,045	7,304	6,129	100%	53%

a. MT = metric tons and CWE = carcass weight equivalent. CWE is the weight of an animal after slaughter and removal of most internal organs, head, and skin. CWE applies only to beef and pork, poultry meat is reported by the USDA-ERS-PSD database in ready to cook equivalent.
b. Beef includes beef and veal.
c. Pork is also called swine meat.
d. Poultry includes broiler and turkey.

Source: USDA-ERS-PSD Online Database, computed by author.

Table A.8: Annual Mexican Bovine Imports and Exports by Meat Cut (Kg).

	2002	**2003**	**2004**	**2005**	**2006**	**2007**	**Average 2002-07**
Mexican Imports (Kg)							
Bovine meat carcasses and halfcarcasses	4,183,140	1,965,257	2	106	210	90	1,024,801
Other bovine meat cuts with bone in	15,133,119	14,690,595	474,453	917,177	4,596,806	8,694,987	7,417,856
Boneless bovine meat	229,532,437	251,328,023	209,685,527	235,493,462	266,071,197	276,683,510	244,799,026
Bovine remains	56,260,784	78,100,562	54,525,104	77,437,728	81,515,099	84,617,036	72,076,052
Total bovine meat	305,109,480	346,084,437	264,685,086	313,848,473	352,183,312	369,995,623	325,317,735
Mexican Exports (Kg)							
Bovine meat carcasses and halfcarcasses	0	0	18,837	512,348	944,492	388,421	310,683
Other bovine meat cuts with bone in	416,463	998,997	2,902,683	5,596,538	8,485,894	11,100,620	4,916,866
Boneless bovine meat	1,489,396	3,680,824	7,176,903	14,008,207	15,416,589	16,729,998	9,750,320
Bovine remains	122,918	152,178	898,898	2,629,869	4,346,628	3,834,438	1,997,488
Total bovine meat	2,028,777	4,831,999	10,997,321	22,746,962	29,193,603	32,053,477	16,975,357

Note: Series were computed from chapter 2 (meat and edible meat offal) of the Harmonized System. At the 8-digit level of disaggregation, bovine meat carcasses and half-carcasses includes commodities 02011001 and 02021001. Bovine meat other cuts with bone-in includes commodities 02012099 and 02022099. Boneless bovine meat includes commodities 02013001 and 02023001. Bovine remains include commodities 02061001, 02062101, 02062201 and 02062999. All years are calendar years (January to December) except for 2002, which was reported from April to December.

Source: Mexican Ministry of Economy, SIAVI Database, computed by author.

Table A.9: Annual Mexican Swine Imports and Exports by Meat Cut (Kg).

	2002	**2003**	**2004**	**2005**	**2006**	**2007**	**Average 2002-07**
Mexican Imports (Kg)							
Swine meat carcasses and halfcarcasses	4,183,140	1,965,257	2	106	210	90	1,024,801
Swine hams, shoulders & cuts thereof, bone-in	100,668,091	171,038,812	225,607,821	209,865,565	219,926,328	218,702,754	190,968,229
Boneless swine meat	40,678,459	73,984,545	86,102,048	75,533,738	82,927,550	90,958,622	75,030,827
Swine remains	109,481,592	150,948,253	172,735,503	155,845,356	156,728,212	156,715,130	150,409,008
Total swine meat	255,011,282	397,936,867	484,445,374	441,244,765	459,582,300	466,376,596	417,432,864
Mexican Exports (Kg)							
Swine meat carcasses and halfcarcasses	199,311	231,766	243,405	351,936	166,258	127,973	220,108
Swine hams, shoulders & cuts thereof, bone-in	1,120,180	1,095,646	547,678	732,029	1,110,460	1,777,876	1,063,978
Boneless swine meat	28,823,488	34,791,035	36,475,540	43,247,006	47,008,118	58,056,298	41,400,248
Swine remains	341,868	1,200,269	1,638,334	741,095	1,299,957	503,597	954,187
Total swine meat	30,484,847	37,318,716	38,904,957	45,072,066	49,584,793	60,465,744	43,638,521

Note: Series were computed from chapter 2 (meat and edible meat offal) of the Harmonized System. At the 8-digit level of disaggregation, swine meat carcasses and half-carcasses include commodities 02031101 and 02032101. Swine hams, shoulder and cuts thereof, with bone-in include commodities 02031201 and 02032201. Boneless swine meat includes commodities 02031999 and 02032999. Swine remains include commodities 02063001, 02063099, 02064101, 02064901 and 02064999. All years are calendar years (January to December) except for 2002, which was reported from April to December.

Source: Mexican Ministry of Economy, SIAVI Database, computed by author.

Table A.10: Annual Mexican Chicken Imports and Exports by Meat Cut (Kg).

	2002	**2003**	**2004**	**2005**	**2006**	**2007**	**Average 2002-07**
Mexican Imports (Kg)							
Whole chicken	1,202,454	3,737,236	34,915	11,237,404	32,815,117	12,928,369	10,325,916
Boneless chicken	78,384,240	125,345,462	162,892,104	164,822,741	181,924,990	176,976,012	148,390,925
Chicken legs & thighs	0	111,651,017	124,563,209	127,265,519	151,473,126	130,650,381	107,600,542
Other chicken & offal	65,432,470	80,720,686	22,799,951	51,998,185	38,343,358	41,395,003	50,114,942
Total chicken	145,019,164	321,454,401	310,290,179	355,323,849	404,556,591	361,949,765	316,432,325
Mexican Exports (Kg)							
Whole chicken	0	3	0	0	17,442	0	2,908
Boneless chicken	24,325	0	264,359	0	7,620	18,562	52,478
Chicken legs & thighs	0	18,144	27,234	197,208	18,071	25,200	47,643
Other chicken & offal	187,200	1,256,674	550	149	3,628	307,542	292,624
Total chicken	211,525	1,274,821	292,143	197,357	46,761	351,304	395,652

Note: Series were computed from chapter 2 (meat and edible meat offal) of the Harmonized System. At the 8-digit level of disaggregation, whole chicken include commodities 02071101 and 02071201. Boneless chicken includes commodities 02071301 and 02071401. Chicken legs and thighs include commodities 02071303 and 02071404. Other chicken cuts and offal include commodities 02071302, 02071399, 02071402, 02071403 and 02071499. All years are calendar years (January to December) except for 2002, which was reported from April to December.

Source: Mexican Ministry of Economy, SIAVI Database, computed by author.

APPENDIX B

ELASTICITIES IN PREVIOUS STUDIES

Appendix B presents the Marshallian and Hicksian price elasticities as well as the expenditure elasticities from previous Mexican meat demand studies. In Section 5.1.3 these elasticities are indirectly compared and contrasted with this study's findings. When comparing elasticities, it is critical to remember that model functional forms, sample sizes, time periods, and assumptions influence elasticities to differ from one study to another. In general, most own-price elasticities in previous studies have been consistent with economic theory obtaining the expected negative sign. However, cross-price elasticities often vary in sign across studies, which means that some studies have found certain commodities to be substitutes while others have found them to be complements (e.g., the Marshallian beef-chicken elasticity). When more meat cuts are considered within the typical commodity groups (i.e., beef, pork, chicken, and fish), Section 5.1.3 found that this may depend on the meat cuts analyzed (e.g., chicken offal is a gross substitute of beef offal, but chicken legs, thighs and breasts are gross complements of beefsteak, Table 5.6).

Table B.1: Marshallian Beef-Price Elasticities in Mexican Meat Demand Studies.

	Model	**Period**	**Beef-Beef**	**Beef-Pork**	**Beef-Ch.**	**Beef-Fish**
López (2008)[a]	SUR	2006	-0.8889	-0.0120	0.0608	NA
Fernández (2007)[b]	LA/AIDS	1995-2005	-0.7983	-0.1019	0.0500	NA
Malaga, Pan, and Duch (2007)[c]	Censor NQUAIDS	2004	-1.2900	-0.0400	-0.0800	NA
Erdil (2006)[d]	AIDS	1961-1999	-0.4610	NA	NA	NA
Clark (2006)	Rotterdam	1970-2004	-0.5507	-0.0795	-0.2324	NA
Malaga, Pan, and Duch (2006)[e]	Censor QUAIDS	2004	-1.4300	0.0300	0.2700	NA
Dong, Gould, and Kaiser (2004)[f]	Censor AIDS	1998	-0.6276	-0.1014	0.0680	-0.0452
Golan, Perloff, and Shen (2001)[g]	Censor AIDS	1992	-1.0800	NA	NA	NA
González Sánchez (2001)[h]	AIDS	1970-1998	-0.3450	-0.1752	0.2123	NA
García Vega (1995)[i]	LA/AIDS	1971-1991	-0.3560	-0.2610	-0.1110	NA

a. López (2008) did not report elasticity estimates for beef, pork, and chicken; however, they can be easily calculated from López's (2008) Table 4.58 and Table 5.1. In addition, elasticity estimates for beef, pork and chicken can be calculated for the urban or rural sector within each Mexican region from López's (2008) Table 4.59 through Table 4.68 and Table 5.2 through Table 5.11.

b. Fernández (2007) also estimated a restricted double-log demand system of equations.

c. Malaga, Pan, and Duch (2007) also estimated censored NQUAIDS models for the years 1992, 1994, 1996, 1998, 2002.

d. Erdil (2006) did not explain whether Marshallian or Hicksian own-price elasticity. He also reported own-price elasticity of ovine meat.

e. Malaga, Pan, and Duch (2006) also estimated censored LA/AIDS and QUAIDS models for the years 1992, 1994, 1996, 1998, 2002.

f. Dong, Gould, and Kaiser (2004) extended the Amemiya-Tobin approach to demand systems estimation using an AIDS specification. They reported simulated Marshallian price elasticities of beef, pork, poultry, processed meat and seafood.

g. Golan, Perloff, and Shen (2001) use a generalized maximum entropy (GME) approach to estimate a nonlinear version of the AIDS with nonnegativity constraints. They reported elasticities for beef, pork, chicken, processed meat, and fish.

h. González Sánchez (2001) provided Marshallian price elasticites for beef, chicken, pork, and eggs from four models: AIDS with Stone index estimated by SUR, AIDS with Divisa index estimated by SUR, model of first differences estimated by SUR, and a model with one lag estimated by OLS. The Marshallian price elasticities reported correspond to the model he recommended, AIDS with Divisa index estimated by SUR.

i. LA/AIDS model estimated by SUR technique. García Vega (1995) also reported elasticity estimates using a Rotterdam model and a simple single-equation linear model for the meat market. Elasticity estimates of each demand system were reported for two estimation techniques: 3SLS and SUR. Income and Marshallian elasticity estimates of a partial equilibrium model under multiple markets (livestock, meat, and feedgrain) were reported as well.

Table B.2: Marshallian Pork-Price Elasticities in Mexican Meat Demand Studies.

	Model	**Period**	**Pork-Beef**	**Pork-Pork**	**Pork-Ch.**	**Pork-Fish**
López (2008)[a]	SUR	2006	0.0232	-0.8440	-0.0825	NA
Fernández (2007)[b]	LA/AIDS	1995-2005	-0.1718	-0.2442	-0.4295	NA
Malaga, Pan, and Duch (2007)[c]	Censor NQUAIDS	2004	0.1000	-0.7000	-0.3900	NA
Erdil (2006)[d]	AIDS	1961-1999	NA	-0.0180	NA	NA
Clark (2006)	Rotterdam	1970-2004	0.1462	-1.2536	0.1569	NA
Malaga, Pan, and Duch (2006)[e]	Censor QUAIDS	2004	0.1000	-1.5100	0.2600	NA
Dong, Gould, and Kaiser (2004)[f]	Censor AIDS	1998	-0.3670	-0.1322	-0.1056	-0.0507
Golan, Perloff, and Shen (2001)[g]	Censor AIDS	1992	NA	-0.5600	NA	NA
González Sánchez (2001)[h]	AIDS	1970-1998	-0.3406	-0.2461	-0.1719	NA
Dong and Gould (2000)[i]	Double-Hurdle	1992	NA	0.0270	NA	NA
García Vega (1995)[j]	LA/AIDS	1971-1991	-0.5790	-1.0200	0.0520	NA

a. López (2008) did not report elasticity estimates for beef, pork, and chicken; however, they can be easily calculated from López's (2008) Table 4.58 and Table 5.1. In addition, elasticity estimates for beef, pork and chicken can be calculated for the urban or rural sector within each Mexican region from López's (2008) Table 4.59 through Table 4.68 and Table 5.2 through Table 5.11.
b. Fernández (2007) also estimated a restricted double-log demand system of equations.
c. Malaga, Pan, and Duch (2007) also estimated censored NQUAIDS models for the years 1992, 1994, 1996, 1998, 2002.
d. Erdil (2006) did not explain whether Marshallian or Hicksian own-price elasticity. He also reported own-price elasticity of ovine meat.
e. Malaga, Pan, and Duch (2006) also estimated censored LA/AIDS and QUAIDS models for the years 1992, 1994, 1996, 1998, 2002.
f. Dong, Gould, and Kaiser (2004) extended the Amemiya-Tobin approach to demand systems estimation using an AIDS specification. They reported simulated Marshallian price elasticities of beef, pork, poultry, processed meat and seafood.
g. Golan, Perloff, and Shen (2001) use a generalized maximum entropy (GME) approach to estimate a nonlinear version of the AIDS with nonnegativity constraints. They reported elasticities for beef, pork, chicken, processed meat, and fish.
h. González Sánchez (2001) provided Marshallian price elasticites for beef, chicken, pork, and eggs from four models: AIDS with Stone index estimated by SUR, AIDS with Divisa index estimated by SUR, model of first differences estimated by SUR, and a model with one lag estimated by OLS. The Marshallian price elasticities reported correspond to the model he recommended, AIDS with Divisa index estimated by SUR.
i. Dong and Gould (2000) provided estimates of unit value impacts on quantity demanded of poultry and pork.
j. LA/AIDS model estimated by SUR technique. García Vega (1995) also reported elasticity estimates using a Rotterdam model and a simple single-equation linear model for the meat market. Elasticity estimates of each demand system were reported for two estimation techniques: 3SLS and SUR. Income and Marshallian elasticity estimates of a partial equilibrium model under multiple markets (livestock, meat, and feedgrain) were reported as well.

Table B.3: Marshallian Chicken-Price Elasticities in Mexican Meat Demand Studies.

	Model	**Period**	**Ch.-Beef**	**Ch.-Pork**	**Ch.-Ch.**	**Ch.-Fish**
López (2008)[a]	SUR	2006	0.0160	-0.0227	-0.5768	NA
Fernández (2007)[b]	LA/AIDS	1995-2005	-0.1373	-0.4599	-0.7277	NA
Malaga, Pan, and Duch (2007)[c]	Censor NQUAIDS	2004	-0.2000	-0.6400	-0.9200	NA
Erdil (2006)[d]	AIDS	1961-1999	NA	NA	-0.2200	NA
Clark (2006)	Rotterdam	1970-2004	-0.9942	-0.6350	-0.2747	NA
Malaga, Pan, and Duch (2006)[e]	Censor QUAIDS	2004	0.5300	0.1200	-1.4300	NA
Dong, Gould, and Kaiser (2004)[f]	Censor AIDS	1998	0.1064	-0.0274	-0.8251	-0.0818
Golan, Perloff, and Shen (2001)[g]	Cenosr AIDS	1992	NA	NA	-0.6400	NA
González Sánchez (2001)[h]	AIDS	1970-1998	-0.1121	0.0279	-0.6486	NA
Dong and Gould (2000)[i]	Double-Hurdle	1992	NA	NA	-0.1300	NA
García Vega (1995)[j]	LA/AIDS	1971-1991	-0.0150	1.0030	-0.8100	NA

a. López (2008) did not report elasticity estimates for beef, pork, and chicken; however, they can be easily calculated from López's (2008) Table 4.58 and Table 5.1. In addition, elasticity estimates for beef, pork and chicken can be calculated for the urban or rural sector within each Mexican region from López's (2008) Table 4.59 through Table 4.68 and Table 5.2 through Table 5.11.
b. Fernández (2007) also estimated a restricted double-log demand system of equations.
c. Malaga, Pan, and Duch (2007) also estimated censored NQUAIDS models for the years 1992, 1994, 1996, 1998, 2002.
d. Erdil (2006) did not explain whether Marshallian or Hicksian own-price elasticity. Additionally, he reported own-price elasticities of poultry and ovine meats.
e. Malaga, Pan, and Duch (2006) also estimated censored LA/AIDS and QUAIDS models for the years 1992, 1994, 1996, 1998, 2002.
f. Dong, Gould, and Kaiser (2004) extended the Amemiya-Tobin approach to demand systems estimation using an AIDS specification. They reported simulated Marshallian price elasticities of beef, pork, poultry, processed meat and seafood.
g. Golan, Perloff, and Shen (2001) use a generalized maximum entropy (GME) approach to estimate a nonlinear version of the AIDS with nonnegativity constraints. They reported elasticities for beef, pork, chicken, processed meat, and fish.
h. González Sánchez (2001) provided Marshallian price elasticites for beef, chicken, pork, and eggs from four models: AIDS with Stone index estimated by SUR, AIDS with Divisa index estimated by SUR, model of first differences estimated by SUR, and a model with one lag estimated by OLS. The Marshallian price elasticities reported correspond to the model he recommended, AIDS with Divisa index estimated by SUR.
i. Dong and Gould (2000) provided estimates of unit value impacts on quantity demanded of poultry and pork.
j. LA/AIDS model estimated by SUR technique. García Vega (1995) also reported elasticity estimates using a Rotterdam model and a simple single-equation linear model for the meat market. Elasticity estimates were reported of each demand system for two estimation techniques: 3SLS and SUR. Income and Marshallian elasticity estimates of a partial equilibrium model under multiple markets (livestock, meat, and feedgrain) were reported as well.

Table B.4: Hicksian Beef-Price Elasticities in Mexican Meat Demand Studies.

	Model	**Period**	**Beef-Beef**	**Beef-Pork**	**Beef-Ch.**	**Beef-Fish**
López (2008)[a]	SUR	2006	-0.6306	0.1676	0.2696	NA
Fernández (2007)[b]	LA/AIDS	1995-2005	-0.4290	0.1110	0.3180	NA
Malaga, Pan, and Duch (2007)[c]	Censor NQUAIDS	2004	-0.5900	0.6500	0.6100	NA
Clark (2006)	Rotterdam	1970-2004	-0.2612	0.4221	-0.1609	NA
Malaga, Pan, and Duch (2006)[d]	Censor QUAIDS	2004	-0.8700	0.1600	0.7100	NA
Golan, Perloff, and Shen (2001)[e]	Censor AIDS	1992	-0.5960	0.1870	0.2280	0.1660
González Sánchez (2001)[f]	AIDS	1970-1998	-0.0494	-0.0419	0.4363	NA
García Vega (1995)[g]	LA/AIDS	1971-1991	-0.0510	0.0760	-0.0250	NA

a. López (2008) did not report elasticity estimates for beef, pork, and chicken; however, they can be easily calculated from López's (2008) Table 4.58 and Table 5.1. In addition, elasticity estimates for beef, pork and chicken can be calculated for the urban or rural sector within each Mexican region from López's (2008) Table 4.59 through Table 4.68 and Table 5.2 through Table 5.11.

b. Fernández (2007) also estimated a restricted double-log demand system of equations.

c. Malaga, Pan, and Duch (2007) also estimated censored NQUAIDS models for the years 1992, 1994, 1996, 1998, 2002.

d. Malaga, Pan, and Duch (2006) also estimated censored LA/AIDS and QUAIDS models for the years 1992, 1994, 1996, 1998, 2002.

e. Golan, Perloff, and Shen (2001) use a generalized maximum entropy (GME) approach to estimate a nonlinear version of the AIDS with nonnegativity constraints. They reported elasticities for beef, pork, chicken, processed meat, and fish.

f. González Sánchez (2001) provided Hicksian price elasticites for beef, chicken, pork, and eggs from four models: AIDS with Stone index estimated by SUR, AIDS with Divisa index estimated by SUR, model of first differences estimated by SUR, and a model with one lag estimated by OLS. The Hicksian price elasticities reported correspond to the model he recommended, AIDS with Divisa index estimated by SUR.

g. LA/AIDS model estimated by SUR technique. García Vega (1995) also reported elasticity estimates using a Rotterdam model and a simple single-equation linear model for the meat market. Elasticity estimates of each demand system were reported for two estimation techniques: 3SLS and SUR. Income and Marshallian elasticity estimates of a partial equilibrium model under multiple markets (livestock, meat, and feedgrain) were reported as well.

Table B.5: Hicksian Pork-Price Elasticities in Mexican Meat Demand Studies.

	Model	**Period**	**Pork-Beef**	**Pork-Pork**	**Pork-Ch.**	**Pork-Fish**
López (2008)[a]	SUR	2006	0.3526	-0.6149	0.1838	NA
Fernández (2007)[b]	LA/AIDS	1995-2005	0.1976	-0.0312	-0.1613	NA
Malaga, Pan, and Duch (2007)[c]	Censor NQUAIDS	2004	0.2200	-0.5800	-0.2700	NA
Clark (2006)	Rotterdam	1970-2004	0.4651	-0.7009	0.2357	NA
Malaga, Pan, and Duch (2006)[d]	Censor QUAIDS	2004	0.6700	-1.3800	0.7000	NA
Golan, Perloff, and Shen (2001)[e]	Censor AIDS	1992	0.5550	-0.4180	0.0810	-0.1530
González Sánchez (2001)[f]	AIDS	1970-1998	-0.0412	-0.1167	0.0498	NA
García Vega (1995)[g]	LA/AIDS	1971-1991	0.0690	-0.3040	0.2350	NA

a. López (2008) did not report elasticity estimates for beef, pork, and chicken; however, they can be easily calculated from López's (2008) Table 4.58 and Table 5.1. In addition, elasticity estimates for beef, pork and chicken can be calculated for the urban or rural sector within each Mexican region from López's (2008) Table 4.59 through Table 4.68 and Table 5.2 through Table 5.11.

b. Fernández (2007) also estimated a restricted double-log demand system of equations.

c. Malaga, Pan, and Duch (2007) also estimated censored NQUAIDS models for the years 1992, 1994, 1996, 1998, 2002.

d. Malaga, Pan, and Duch (2006) also estimated censored LA/AIDS and QUAIDS models for the years 1992, 1994, 1996, 1998, 2002.

e. Golan, Perloff, and Shen (2001) use a generalized maximum entropy (GME) approach to estimate a nonlinear version of the AIDS with nonnegativity constraints. They reported elasticities for beef, pork, chicken, processed meat, and fish.

f. González Sánchez (2001) provided Hicksian price elasticites for beef, chicken, pork, and eggs from four models: AIDS with Stone index estimated by SUR, AIDS with Divisa index estimated by SUR, model of first differences estimated by SUR, and a model with one lag estimated by OLS. The Hicksian price elasticities reported correspond to the model he recommended, AIDS with Divisa index estimated by SUR.

g. LA/AIDS model estimated by SUR technique. García Vega (1995) also reported elasticity estimates using a Rotterdam model and a simple single-equation linear model for the meat market. Elasticity estimates of each demand system were reported for two estimation techniques: 3SLS and SUR. Income and Marshallian elasticity estimates of a partial equilibrium model under multiple markets (livestock, meat, and feedgrain) were reported as well.

Table B.6: Hicksian Chicken-Price Elasticities in Mexican Meat Demand Studies.

	Model	**Period**	**Ch.-Beef**	**Ch.-Pork**	**Ch.-Ch.**	**Ch.-Fish**
López (2008)[a]	SUR	2006	0.2714	0.1549	-0.3703	NA
Fernández (2007)[b]	LA/AIDS	1995-2005	0.4381	-0.1281	-0.3100	NA
Malaga, Pan, and Duch (2007)[c]	Censor NQUAIDS	2004	0.0700	-0.3800	-0.6500	NA
Clark (2006)	Rotterdam	1970-2004	-0.3552	0.4722	-0.1169	NA
Malaga, Pan, and Duch (2006)[d]	Censor QUAIDS	2004	0.9200	0.2100	-1.1300	NA
Golan, Perloff, and Shen (2001)[e]	Censor AIDS	1992	0.2630	0.0340	-0.4020	-0.0060
González Sánchez (2001)[f]	AIDS	1970-1998	0.2187	0.0254	-0.4702	NA
García Vega (1995)[g]	LA/AIDS	1971-1991	-0.0890	0.9210	-0.8310	NA

a. López (2008) did not report elasticity estimates for beef, pork, and chicken; however, they can be easily calculated from López's (2008) Table 4.58 and Table 5.1. In addition, elasticity estimates for beef, pork and chicken can be calculated for the urban or rural sector within each Mexican region from López's (2008) Table 4.59 through Table 4.68 and Table 5.2 through Table 5.11.

b. Fernández (2007) also estimated a restricted double-log demand system of equations.

c. Malaga, Pan, and Duch (2007) also estimated censored NQUAIDS models for the years 1992, 1994, 1996, 1998, 2002.

d. Malaga, Pan, and Duch (2006) also estimated censored LA/AIDS and QUAIDS models for the years 1992, 1994, 1996, 1998, 2002.

e. Golan, Perloff, and Shen (2001) use a generalized maximum entropy (GME) approach to estimate a nonlinear version of the AIDS with nonnegativity constraints. They reported elasticities for beef, pork, chicken, processed meat, and fish.

f. González Sánchez (2001) provided Hicksian price elasticites for beef, chicken, pork, and eggs from four models: AIDS with Stone index estimated by SUR, AIDS with Divisa index estimated by SUR, model of first differences estimated by SUR, and a model with one lag estimated by OLS. The Hicksian price elasticities reported correspond to the model he recommended, AIDS with Divisa index estimated by SUR.

g. LA/AIDS model estimated by SUR technique. García Vega (1995) also reported elasticity estimates using a Rotterdam model and a simple single-equation linear model for the meat market. Elasticity estimates of each demand system were reported for two estimation techniques: 3SLS and SUR. Income and Marshallian elasticity estimates of a partial equilibrium model under multiple markets (livestock, meat, and feedgrain) were reported as well.

Table B.7: Expenditure Elasticities in Mexican Meat Demand Studies.

	Model	**Time**	**Beef**	**Pork**	**Chicken**	**Fish**
López (2008)[a]	SUR	2006	0.6699	0.8545	0.6625	NA
Fernández (2007)[b]	LA/AIDS	95-05	0.8503	0.8506	1.3250	NA
Malaga, Pan, and Duch (2007)[c]	C. NQUAIDS	2004	1.3900	1.0500	0.7000	NA
Clark (2006)	Rotterdam	70-04	0.6833	1.4378	0.8220	NA
Erdil (2006)[d]	AIDS	61-99	0.1020	0.1640	0.4360	NA
Malaga, Pan, and Duch (2006)[e]	C. QUAIDS	2004	1.1200	1.1500	0.7800	NA
Dong, Gould, and Kaiser (2004)[f]	C. AIDS	1998	1.3059	1.1728	1.1659	1.1554
Gould and Villarreal (2002)	Expenditure	1996	0.1040	0.1000	NA	NA
Golan, Perloff, and Shen (2001)[g]	C. AIDS	1992	1.3050	1.1490	0.7450	1.2470
González Sánchez (2001)[h]	AIDS	70-98	1.6710	0.7330	1.9800	NA
Dong and Gould (2000)[i]	D.-Hurdle	1994	NA	0.2110	0.1020	NA
García Vega and García (2000)[j]	AIDS	1996	0.8800	0.8800	0.8800	0.8800
García Vega (1995)[k]	LA/AIDS	71-91	0.7280	1.5460	-0.1780	NA
Heien, Jarvis, and Perali (1989)[l]	AIDS	1977	1.3040	1.3040	1.3040	1.3040

a. López (2008) did not report elasticity estimates for beef, pork, and chicken; however, they can be easily calculated from López's (2008) Table 4.58 and Table 5.1. In addition, elasticity estimates for beef, pork and chicken can be calculated for the urban or rural sector within each Mexican region from López's (2008) Table 4.59 through Table 4.68 and Table 5.2 through Table 5.11.

b. Fernández (2007) also estimated a restricted double-log demand system of equations.

c. Malaga, Pan, and Duch (2007) also estimated censored NQUAIDS models for the years 1992, 1994, 1996, 1998, 2002.

d. Erdil (2006) reported income elasticities of bovine, ovine, poultry and pig meats.

e. Malaga, Pan, and Duch (2006) also estimated censored LA/AIDS and QUAIDS models for the years 1992, 1994, 1996, 1998, 2002.

f. Dong, Gould, and Kaiser (2004) extended the Amemiya-Tobin approach to demand systems estimation using an AIDS specification. They reported simulated expenditure elasticities of beef, pork, poultry, processed meat and seafood.

g. Golan, Perloff, and Shen (2001) use a generalized maximum entropy (GME) approach to estimate a nonlinear version of the AIDS with nonnegativity constraints. They reported elasticities for beef, pork, chicken, processed meat, and fish.

h. González Sánchez (2001) provided a graph of expenditure elasticites for beef, chicken, pork, and eggs from four models: AIDS with Stone index estimated by SUR, AIDS with Divisa index estimated by SUR, model of first differences estimated by SUR, and a model with one lag estimated by OLS. Only the values of the expenditure elasticities of the model he recommended, AIDS with Divisa index estimated by SUR, were reported.

i. Dong and Gould (2000) provided estimates of income impacts on quantity demanded of poultry and pork.

j. García Vega and García (2000) only reported expenditure elasticity for nine aggregated categories (cereals, meat, dairy products, fats, fruit, vegetables, sugar, beverages and other). The meat expenditure elasticity was adjusted for the observations with zero expenditures.

k. LA/AIDS model estimated by SUR technique. García Vega (1995) also reported elasticity estimates using a Rotterdam model and a simple single-equation linear model for the meat market. Elasticity estimates of each demand system were reported for two estimation techniques: 3SLS and SUR. Income and Marshallian elasticity estimates of a partial equilibrium model under multiple markets (livestock, meat, and feedgrain) were reported as well.

l. Heien, Jarvis, and Perali (1989) only reported expenditure elasticities for nine aggregated categories (cereals, meats, dairy products, fats, fruits, vegetables, sugars, beverages and other). For these categories they reported non-corrected and Greene (1983) and Greene (1981) corrected elasticities. Green corrected expenditure elasticity of meat is presented here and it was repeatedly reported as beef, pork, chicken and fish. Heien, Jarvis, and Perali (1989) also estimated a Tobit model for five high-protein foods (poultry, eggs, pork, beef, and beans) but did not report the expenditure elasticities.

APPENDIX C
ENCUESTA NACIONAL DE INGRESOS Y GASTOS DE LOS HOGARES (ENIGH)

Appendix C gives details on how the variables of interest in ENIGH 2006 are handled. It explains the variables from ENIGH 2006 that are used in the study and elaborates on how new variables are created or transformed. It also describes the original fifty table cuts of meats that are reported in ENIGH 2006, and discusses how they are grouped into eighteen table cuts of meats to decrease the number of censored observations.

In each survey ENIGH is usually divided into seven datasets. Table C.1 provides the number of observations from each survey from 1984 to 2006. However, this study only uses the 2006 survey. Table C.2 and Table C.3 provide more information about the 2006 survey. For example, Table C.2 lists the seven datasets that form ENIGH 2006 database while Table C.3 list the variables that are used from these datasets.

In particular, ENIGH 2006 records price, quantity, and expenditure (price times quantity) of fifty different meat cuts (A025, A026, ... , A074). Table C.4 provides a description of each meat code (A025, A026, ... , A074). ENIGH 2006 reports in Spanish a description of each meat code; therefore, they were translated into English using Figure C.1 through Figure C.4. A detailed description of additional retail cuts of meats, which are further obtained from the meat cuts illustrated in Figure C.1 through Figure C.4, can be obtained from the sources provided in the figures. In general, a very specific meat cut can be obtained from one or several different parts of an animal. For example, beefsteak (A074) can be obtained from round; while brisket and fillet steak (A075) can be obtained from chuck, brisket, rib, short loin, and round.

In Table C.3, the number of adult equivalents per household can be computed from the "*edad*" variable. This study uses the National Research Council's recommendations of the different food energy allowances for males and/or females during the life cycle as reported by Tedford, Capps, and Havlicek (1986) to compute the number of adult equivalents.

However, different from the Concentrated, Household, and Expenditure datasets, the observation unit for the Members dataset is the household member (instead of the household). Therefore, it is better to create a summary dataset for the Members dataset, where only the total number of adult equivalents per household is reported. That is, the adult equivalent has to be computed for each household member; and then, a summary dataset has to be computed (say Adult Equivalent dataset) so that only the total number of adult equivalents per household is reported (i.e., by household id).

Similarly, a summary dataset (say Summary Expenditures) is computed for the Expenditures dataset. This is required because the Expenditure dataset includes as different observations purchases of the same meat cut made at different places by the same household. That is, if during the week of interview a household purchased the same meat cut twice, but at different places; then, two transactions will be recorded and two observations will appear in the Expenditure dataset. Consequently, when a household purchased the same meat cut during the week of the interview more than once but in different places, a simple average price is computed as the meat cut price, the sum of the quantities is computed as the meat cut quantity, and expenditure is computed as price times quantity. Doing these operations will only allow one transaction per meat cut per household in the Summary Expenditure dataset.

Then, a single dataset containing the variables of interest (see Table C.3), from the seven datasets provided in ENIGH 2006 database, can be obtained by creating a query in which the datasets of interest (Concentrated, Households, Adult Equivalent, Summary Expenditures) are related by the *folio* variable. Once this dataset is obtained, new variables are computed. First, dummy variables for each education level of the household decision maker are created (i.e., *educ0*, *educ1*, *educ2*, *educ3*, *educ4*, *educ5*, *educ6*, *educ7*, *educ8*, *educ9*). Second, dummy variables for each stratum (i.e., *str1*, *str2*, *str3*, *str4*) are created from the "*estrato*" variable. Third, dummy variables for the level of urbanization (i.e., *urban* and *rural*) are created from the *estrato* variable. Following SIACON-SIAP-SAGARPA (2006), this study considers stratum 1 and stratum 2 as the urban sector, and stratum 3 and stratum 4 as the rural sector. The definitions of strata 1, 2, 3 and 4 are provided in Table C.3. Fourth, a new variable, "*state*", is derived from the "*ubica_geo*" variable by reading the first two digits of this variable (refer to Table C.3).[1] This variable provides the state the household is from. Figure C.5 provides a map of the Mexican states and the Federal District. Fifth, regional dummy variables are computed from the *state* variable. These variables are *NE*, *NW*, *CW*, *C*, and *SE*, which stand for Northeast, Northwest, Central-West, Central, and Southeast regions respectively.[2] Figure C.6 shows the Mexican geographical regions used in this study. Sixth, a new variable "*car*", recording the number of four-wheel motor vehicles per household, was generated as the sum of the variables *vehi04_01*, *vehi04_2*, and *vehi04_3*. Then a new variable "*d_car*" was created to record whether or not a household has a four-wheel motor vehicle at home. In other words, a dummy variable for *car*. Seventh, similarly, a dummy variable (*d_refri*) was created from the variable "*eqh07_20*" to record whether or not a household has a refrigerator at home. Eighth, meat consumption variables per household in kilograms per week are transformed to per capita meat consumption variables. That is, meat consumption variables per household in kilograms per week are divided by the number of adult equivalents to compute per capita meat consumption variables per household in kilograms per week (i.e., per adult-equivalent consumption per week). Similarly, the nominal meat expenditure variables per household per week in Mexican pesos are divided by the number of adult equivalents to obtain per capita nominal

[1]Alternatively, the *state* variable could have been derived from the *folio* variable. However, it is easier to program a variable from the first two digits of the *ubica_geo* variable rather than from digits 5 and 6 of the *folio* variable, which has eleven digits.

[2]This study used the same five-region definitions provided in SIACON-SIAP-SAGARPA (2006), which is is the same governmental institution that performs ENIGH. In addition, SIACON-SIAP-SAGARPA (2006) used ENIGH (2000), ENIGH (2002) and ENIGH (2004) databases. Other Mexican meat demand studies have used from three to ten regions (see Section 2.1).

meat expenditure variables in Mexican pesos (i.e., per adult-equivalent nominal meat expenditure per week). Table C.5 summarizes the resulting variables of interest.

Descriptive statistics for each meat cut, using the number of households that reported consumption of meat cuts, can be computed by conditionally subsetting the resulting single dataset (i.e., the single dataset mentioned in the previous paragraph) by a particular value of the *item* variable. That is, computing subsets of the single dataset for each meat cut (i.e., computing additional datasets for each single meat cut), and then computing descriptive statistics for each meat cut.[3]

Next, all of the single meat cut datasets are put into one dataset where the columns of this new dataset are the variables of interest (*hhid, str, a_eq, inc, educ0, educ1, educ2, educ3, educ4, educ5, educ6, educ7, educ8, educ9, wgt, str1, str2, str3, str4, urban, rural, NE, NW, CW, C, SE, d_car, d_refri*, and p_i, q_i and m_i where i stands for one of the codes $A025$, $A026$, ... , $A074$ depending on what single meat cut dataset is being considered); then, it is necessary to combine all datasets using a one-to-one match merge by household id (*hhid*). For instance, if each meat cut dataset has 31 columns (*hhid, str, a_eq, inc, educ0, educ1, educ2, educ3, educ4, educ5, educ6, educ7, educ8, educ9, wgt, str1, str2, str3, str4, urban, rural, NE, NW, CW, C, SE, d_car, d_refri*, and p_i, q_i, and m_i), a one-to-one match merge by *hhid* will produce a dataset with $50(3) + 28 = 178$ columns.[4] If all households purchased at least one meat cut,

[3]López (2008, pp. 119-120 and pp. 130-146) reported descriptive statistics for each meat cut, but he included as different observations purchases of the same meat cut at different places by the same household. López (2008, p. 120) explained that he reported descriptive statistics in that way only for the specific meat cuts ($A025$, $A026$, ... , $A074$) because purchases of the same meat cut at different places by the same household have no distortion on the descriptive statistics. Finally, prices and expenditures reported in López (2008, pp. 130-146) are in 2002 Mexican pesos (i.e., real pesos).

[4]Since the variables *hhid, str, a_eq, inc, educ0, educ1, educ2, educ3, educ4, educ5, educ6, educ7, educ8, educ9, wgt, str1, str2, str3, str4, urban, rural, NE, NW, CW, C, SE, d_car, and d_refri* provide the same information for each household, there is no need to add subscript i. Not adding subscript i and performing a one-to-one match merge by *hhid* will produce only one set of the variables *hhid, str, a_eq, inc, educ, wgt, str1, str2, str3, str4, urban, rural, NE, NW, CW, C, SE, d_car, and d_refri* in the resulting dataset.

then the number of rows of this dataset equals the number of households (i.e., 20,875 as reported on Table C.2).[5] However, if a household did not consume a particular meat cut, for instance $A025$, but consumed all others meat cuts, then a missing value appears in that row for the columns corresponding to the price of meat cut $A025$ ($p025$), per capita consumption of meat cut $A025$ ($q025$), and per capita expenditure on meat cut $A025$ ($m025$); but the corresponding numeric value for all other columns. However, some households will not consume any meat cut at all during the week of the interview and several households will only consume few (in some cases only one) meat cut during the week of the interview. Hence, the dataset will have a lot of missing observations for the corresponding columns of meat cuts that are rarely consumed; but a moderate amount of missing observations for the corresponding columns of the most frequently consumed meat cuts. Table C.6 shows the descriptive statistics of this dataset.[6]

Once again, Table C.6 was generated by allowing only one transaction per meat cut per household and then by performing a one-to-one match merge by household id to merge all the single meat cut datasets. Since $20,875$ households participated in the survey (Table C.2), this means that $20,875 - 16,909 = 3,966$ households of the total number of households that participated in the survey did not consume any meat cut at all during the week of the interview.[7] In addition, Table C.6 also shows the new number of missing observations (column "N Miss") for the price, quantity, and

[5]As it will be explained later, not all households purchased at least one meat cut.

[6]López (2008, pp. 147-150) also reported descriptive statistics of this resulting dataset, but his prices and expenditures were reported in 2002 Mexican pesos (i.e., real pesos).

[7]This study is interested in analyzing households that are meat consumers. Consequently, the 3,966 households that did not buy at least one meat cut of the fifty different meat cuts considered (including at-home and away-from-home expenditures on meat) during the one week of interview, are not considered meat consumers. Hence, they are not included in the analysis. Therefore, meat consumers are those households that buy at least one meat cut per week (at home or away from home) of the fifty different meat cuts considered in the survey. That is, if none of the household members (average household size is 4.14 members per household) bought at least one meat cut during one week (at home or away from home), the household is not a meat consumer.

expenditure of meat cut i, $i = 025, 026, \ldots, 074$, resulting from the merge of all single meat cut datasets. Clearly, the number of missing observations is extremely high compared to the total number of observations, which is 16,909. However, a missing quantity in Table C.6 is simply a decision of a household of not to purchase that particular meat cut during the week of the interview.[8] Hence, missing quantities in Table C.6 are transformed to zero quantities. Finally, it is very important to notice that the sum of weights in Table C.6 is an estimate of the total number of households in Mexico that consumed meat during the week of the interview. That is, 22.1 million households ate at least one meat cut during the week of the interview (a week between August 10 and November 24, 2006).

To reduce the high number of missing observations (Table C.6), the fifty meat cuts (Table C.4) reported by ENIGH 2006 are aggregated into eighteen table cuts (Table C.7). In order to aggregate the corresponding meat cuts in these eighteen new categories, new meat category quantities, prices and expenditures are computed as well as total meat expenditure. Meat category quantities are obtained by summing the quantities of the meat cuts in each category, while meat category prices are computed by diving meat category expenditures by meat category quantities, where meat category expenditures are obtained from the prices and quantities of the meat cuts in each category. Finally, total meat expenditure is computed as $\sum_{i=1}^{18} p_i q_i$, where 1 = beefsteak, 2 = ground beef, ... , 18 = shellfish.

Even when the number of meat cuts is reduced from fifty cuts to eighteen cuts, there are still some missing observations (censored observations), see Table 4.2. To solve the problem of censored prices (i.e., observations with missing prices), a regression imputation approach is adopted for each of the eighteen meat cuts considered

[8]There are two sources of data censoring in ENIGH 2006. First, censoring occurs because some households that participated in the survey did not consume any meat cut ($A025$, $A026$, ... , $A074$) at all during the week of interview (i.e., 3,966 households). In this study, these households are assumed to be vegetarian. Second, censoring occurs because most households did not purchase all meat cuts ($A025$, $A026$, ... , $A074$) during the week of interview (i.e., missing observations in Table C.6).

in this study. In particular, non-missing prices of each meat cut is regressed as function of a constant, total income (*inc*), dummy variables for the education level of the household decision maker (*educ0, educ1, educ2, educ3, educ4, educ5, educ6, educ7, educ8, educ9*), regional dummy variables (*NE, NW, CW and C*), stratum dummy variables (*str1, str3, str4*), the number of adult equivalent (*a_eq*), a dummy variable for car (*d_car*), and a dummy variable for refrigerator (*d_refri*). Each regression uses the SURVEYREG procedure and incorporates the variables strata and weight as documented in SAS Institute Inc. (2004, pp. 4363–4418). Table 4.2 shows the number of non-missing and missing observations, as well as the average prices in 2006 Mexican pesos per kilogram (pesos/kg) of the eighteen meat cuts considered in this study before and after price imputation. Average prices also incorporate the variables strata and weight, and are computed using the SURVEYMEANS procedure (see SAS Institute Inc., 2004, pp. 4313–4362). Table 4.3 reports the average per capita consumption per week of the 18 meat cuts considered in this study when including and excluding the zero observations. To solve the problem of censored quantities (i.e., observations with zero quantities) this study uses a censored regression model. However, this study incorporates estimation techniques from stratified sampling theory with the censored demand system of equations proposed by Shonkwiler and Yen (1999) because ENIGH is not a simple random sample and DuMouchel and Duncan's (1983) test suggests that the use of weights is necessary when working with ENIGH.

Table C.1: Observation Numbers in ENIGH Databases, 1984 to 2006.

Dataset	**Number of Observations Per Survey**									
	1984	**1989**	**1992**	**1994**	**1996**	**1998**	**2000**	**2002**	**2004**	**2006**
Concentrated (concentrado.dbf)	4,735	11,535	10,530	12,815	14,042	10,952	10,108	17,167	22,595	20,875
Households (hogares.dbf) (vivienda.dbf)	4,735	11,535	10,530	12,815	14,042	10,952	10,108	17,167	22,595	20,875
Members (poblacion.dbf) (personas.dbf)	23,985	57,289	50,862	60,353	64,916	48,110	42,535	72,602	91,738	83,624
Income (ingresos.dbf)	11,396	27,790	36,698	34,374	38,671	36,712	34,229	34,229	56,980	79,752
Expenditures (gastos.dbf)	184,843	484,709	570,494	695,704	769,975	612,207	597,187	1,029,761	1,538,676	1,348,530
Financial Transactions (erogaciones.dbf)	0	0	0	7,470	7,862	6,307	5,775	7,651	16,445	18,269
No Monetary Transactions (nomonetario.dbf)	11,191	27,059	41,926	93,410	94,108	70,825	71,321	138,015	152,910	174,490
Survey Period	Jan. to Dec.	Aug. to Nov.	Aug. to Nov.	Sep. to Dec.	Aug. to Nov.	Aug. to Nov.	Aug. to Nov.	Aug. to Nov.	Aug. to Nov.	Agu. to Nov.

Source: ENIGH 1984, ENIGH 1989, ENIGH 1992, ENIGH 1994, ENIGH 1996, ENIGH 1998, ENIGH 2000, ENIGH 2002, ENIGH 2004, and ENIGH 2006, summarized by author.

Table C.2: List of the Seven Datasets in ENIGH 2006 Database.

Dataset	Number of Records in 2006	General Description
Concentrated (concentrado.dbf)	20,875	Information about the expansion factor (number of households that a particular household represents nationally) and other variables that appear in the other six datasets.
Households (hogares.dbf)	20,875	Information about the household geographical location, household stratum, house infrastructure, utilities, home vehicles and home appliances, etc.
Members (poblacion.dbf)	83,624	Information about number of household members, relationships among household members, gender, age, city of residency, level of education, marital status, employment status, job position, if member has salary/wages, job description, weekly number of workdays, if member has social security contributions, etc.
Income (ingresos.dbf)	79,752	Information about type of employment; current income; income one, two, three, four, five and six months ago; quarterly income; etc.
Expenditures (gastos.dbf)	1,348,530	Information about items purchased, place of purchase, day of purchase, payment option, quantity, cost, price, expenditure, last month expenditure, quarterly expenditure, and frequency of purchase.
Financial Transactions (erogaciones.dbf)	18,269	Information about bank deposits, loans, credit card payments, debt with employer, interest payment, purchase of local and foreign currency, purchase of jewelries, life insurance, money inherited, purchase of houses, purchase of condominiums, purchase of land, mortgage payments, others, equipment purchases, stock investment, patent investments, etc.
No-Monetary Transactions (nomonetario.dbf)	174,490	Information about the type of expenditure, reason of purchase, day of purchase, quantity, price, expenditure, and quarterly expenditure.

Source: ENIGH 2006, summarized by author.

Table C.3: Variables Used in this Study From ENIGH 2006.

Dataset	**Variable Used**	**Variable Description**
Concentrated (concentrado.dbf)	*folio*	This variable is the household id number. It is a categorical variable of 11 digits that identifies the households. From left to right digits 1 to 4 read the year, digits 5 and 6 read the code for the Mexican state, digit 7 reads the code of the time period in which households were interviewed, digits 8 to 10 read the consecutive order of household interviews. Finally, digit 11 codifies a character variable (type of household) taking values from 0 to 9.
	hog	This is the sampling weight variable. That is, the number of households that the interviewed household represents nationally.
	ingtot	This variable is total household income in Mexican pesos (nominal pesos).
	ed_formal	This variable records the education level of the household decision maker. This variable equals "0" if no education at all, "1" if preschool, "2" if elementary school, "3" if high school, "4" if preparatory school or high school graduate, "5" if partially attended college or university, "6" if technical education or commercial college degree, "7" if bachelor degree, "8" if master's degree, and "9" if doctoral degree.
Households (hogares.dbf)	*folio*	This variable is the household id number.
	estrato	This is the stratum variable. This variable equals "1" if household location is within a population of 100,000 people or more, "2" if household location is within a population between 15,000 and 99,999 people, "3" if household location is within a population between 2,500 people and 14,999 people, and "4" if household location is within a population of less than 2,500 people.
	ubica_geo	This variable records geographical location. It is a categorical variable of 5 digits. From left to right the first two digits read the Mexican state, and the last three digits read the Mexican county.
	residentes	This is the household size variable. That is, the number of household members.

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Table C.3: *Continued*

Dataset	**Variable Used**	**Variable Description**
	vehi04_1	This variable records the number of automobiles available for home use.
	vehi04_2	This variable records the number of trucks and vans (i.e., suburbans, minivans, combi cars, etc.) available for home use.
	vehi04_3	This variable records the number of pickup or box trucks available for home use.
	eqh07_20	This variable records the number of refrigerators at home.
Members (poblacion.dbf)	*folio*	This variable is the household id number.
	edad	This variable is the age of each household member in years.
Expenditures (gastos.dbf)	*folio*	This variable is the household id number.
	clave	This variable takes the values of A025, A026, . . . , A074 which are codes for the different cuts or group of meat cuts. Refer to Table C.4.
	precio	This variable is the nominal price of “clave” in Mexican pesos per kilogram (nominal pesos/kg)
	cantidad	This variable is the quantity consumed of “clave” in kilograms per household (kg).
	gasto	This variable is the nominal expenditure on “clave” in Mexican pesos per household (nominal pesos). It is equal to the product of *precio* times *quantity*.

Source: ENIGH 2006, summarized by author.

Table C.4: Meat Cuts Reported by ENIGH 2006.

Code	Description
	Beef, Pork, Chicken and Other Meats
	(a) Beef and Veal
A025	Beefsteak: boneless rump, bottom round, top round, etc.
A026	Brisket and fillet steak
A027	Milanesa
A028	Tore shank
A029	Rib cutlet
A030	Chuck, strips for grilling and sirloin steak
A031	Meat for stewing/boiling or meat cut with bone
A032	Special cuts: t-bone, roast beef, etc.
A033	Hamburger patty
A034	Ground beef
A035	Chopped loin, chopped top and bottom round
A036	Other beef cuts: head, udder, etc.
A037	Guts/innards/viscera: heart, liver, marrow, rumen/belly, etc.
	(b) Pork
A038	Pork steak
A039	(Chopped) leg
A040	Middle leg
A041	Ground pork
A042	Ribs and pork chops (loin)
A043	Clear plate and Boston shoulder (blade/shoulder)
A044	Pinic shoulder
A045	Other pork cuts: head, upper leg, belly, spareribs, etc.

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Table C.4: *Continued*

Code	Description
A046	Guts/innards/viscera: heart, liver, kidney, etc.
	(c) Processed Beef and Pork
A047	Shredded meat
A048	Pork skin/chicharron
A049	Chorizo
A050	Smoked pork chops
A051	Crusher and dried meats
A052	Ham
A053	Bologna, embedded pork and salami
A054	Bacon
A055	Sausages
A056	Other processed meats from beef and pork: stuffing, smoked meat/dried meat, etc.
	(d) Chicken
A057	Leg, thigh and breast with bone
A058	Boneless leg, boneless thigh and boneless breast
A059	Whole chicken or in parts (except legs, thigh and breast)
A060	Guts/innards/viscera and other chicken parts: wings, head, neck, gizzard, liver, etc.
A061	Other poultry meat: hen/fowl, turkey, duck, etc.
	(e) Processed Poultry Meat
A062	Chicken sausage, ham, nuggets, bologna, etc.
	(f) Other Meats
A063	Lamb: sheep and ram

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Table C.4: *Continued*

Code	**Description**
A064	Goat and goatling
A065	Other meats: horses, iguana, rabbit, frog, deer, etc.
	Seafood
	(g) Fresh Fish
A066	Whole fish, clean and not clean (catfish, carp, tilapia, etc.)
A067	Fish fillet
	(h) Processed Fish
A068	Tuna
A069	Salmon and codfish
A070	Smoked fish, dried fish, fish nuggets and sardines
	(i) Other Fish
A071	Young eel, manta ray, eel, fish/crustaceous eggs, etc.
	(j) Shellfish
A072	Fresh shrimp
A073	Other fresh shellfish: clam, crab, oyster, octopus
	(k) Processed Shellfish
A074	Processed: smoked, packaged, breaded, dried shrimp

Source: ENIGH 2006—Clasificación de Variables, translated into English by author.

Table C.5: Variables of Interest From ENIGH 2006.

Variable	Description
hhid	Household id number. It is a categorical variable of 11 digits that identifies the households. From left to right digits 1 to 4 read the year, digits 5 and 6 read the code for the Mexican state, digit 7 reads the code of the time period in which households were interviewed, digits 8 to 10 read the consecutive order of household interviews. Finally, digit 11 codifies a character variable (type of household) taking values from 0 to 9. This is the *folio* variable in Table C.3 but renamed.
item	This variable takes the values of A025, A026, . . . , A074 which are codes for the different cuts or group of meat cuts. This is the *clave* variable in Table C.3 but renamed. Refer to Table C.4.
wgt	Sampling weight variable. That is, the number of households that the interviewed household represents nationally. This is the *hog* variable in Table C.3 but renamed.
inc	Total household income in Mexican pesos (nominal pesos). This is the *ingtot* variable in Table C.3 but renamed.
educ	Education level of the household decision maker. This variable equals "0" if no education at all, "1" if preschool, "2" if elementary school, "3" if high school, "4" if preparatory school or high school graduate, "5" if partially attended college or university, "6" if technical education or commercial college degree, "7" if bachelor degree, "8" if master's degree, and "9" if doctoral degree. This is the *ed_formal* variable in Table C.3 but renamed.
str	Stratum variable. This variable equals "1" if household location is within a population of 100,000 people or more, "2" if household location is within a population between 15,000 and 99,999 people, "3" if household location is within a population between 2,500 people and 14,999 people, and "4" if household location is within a population of less than 2,500 people. This is the *estrato* variable in Table C.3 but renamed.
str1	Dummy variable for stratum 1. This variable equals "1" if household location is within a population of 100,000 people or more, and "0" otherwise.
str2	Dummy variable for stratum 2. This variable equals "1" if household location is within a population between 15,000 and 99,999 people, and "0" otherwise.
str3	Dummy variable for stratum 3. This variable equals "1" if household location is within a population between 2,500 people and 14,999 people, and "0" otherwise.

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Table C.5: *Continued*

Variable	**Description**
str4	Dummy variable for stratum 4. This variable equals "1" if household location is within a population of less than 2,500 people, and "0" otherwise.
urban	Dummy variable for the urban households. This variable equals "1" if household location is within a population of 15,000 people or more, and "0" otherwise.
rural	Dummy variable for the rural households. This variable equals "1" if household location is within a population of 14,999 people or less, and "0" otherwise.
state	Mexican state of the household. This variable equals "1" if household state is Aguascalientes, "2" if Baja California, "3" if Baja California Sur, "4" if Campeche, "5" if Coahuila de Zaragoza, "6" if Colima, "7" if Chiapas, "8" if Chihuahua, "9" if Distrito Federal, "10" if Durango, "11" if Guanajuato, "12" if Guerrero, "13" if Hidalgo, "14" if Jalisco, "15" if Estado de México, "16" if Michoacán de Ocampo, "17" if Morelos, "18" if Nayarit, "19" if Nuevo León, "20" if Oaxaca, "21" if Puebla, "22" if Querétaro Arteaga, "23" if Quintana Roo, "24" if San Luis Potosí, "25" if Sinaloa, "26" if Sonora, "27" if Tabasco, "28" if Tamaulipas, "29" if Tlaxcala, "30" if Veracruz de Ignacio de la Llave, "31" if Yucatán, "32" if Zacatecas, "33" if the United States of America, and "34" if any other country. It should be clear that Distrito Federal (*state* = 9) is not a state, but a territory which belongs to all states. Similarly, when *state* equals "34" or "35", it refers to foreign households living in Mexico. Refer to Figure C.5.
NE	Dummy variable for the Northeast region of Mexico. This variable equals "1" if the observation belongs to the Northeast region, "0" otherwise. This region consists of the states of Chihuahua, Cohahuila de Zaragoza, Durango, Nuevo León, and Tamaulipas.
NW	Dummy variable for the Northwest region of Mexico. This variable equals "1" if the observation belongs to the Northwest region, "0" otherwise. This region consists of the states of Baja California, Sonora, Baja California Sur, and Sinaloa.
CW	Dummy variable for the Central-West region of Mexico. This variable equals "1" if the observation belongs to the Central-West region, "0" otherwise. This region consists of the states of Zacatecas, Nayarit, Aguascalientes, San Luis Potosí, Jalisco, Guanajuato, Querétaro Arteaga, Colima, and Michoacán de Ocampo.

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Table C.5: *Continued*

Variable	**Description**
C	Dummy variable for the Central region of Mexico. This variable equals "1" if the observation belongs to the Central region, "0" otherwise. This region consists of the states of Hidalgo, Estado de México, Tlaxcala, Morelos, Puebla, and Distrito Federal.
SE	Dummy variable for the Southeast region of Mexico. This variable equals "1" if the observation belongs to the Southeast region, "0" otherwise. This region consists of the states of Veracruz de Ignacio de la Llave, Yucatán, Quintana Roo, Campeche, Tabasco, Guerrero, Oaxaca, and Chiapas.
hhsize	This variable is the household size. That is, the number of household members. This is the *residentes* variable in Table C.3 but renamed.
a_eq	Number of adult equivalents.
car	Number of four-wheel motor vehicles at home.
d_car	Dummy variable for four-wheel motor vehicles at home. This variable equals "1" if the household has a four-wheel motor vehicle at home, and "0" otherwise.
refri	Number of refrigerators at home. This is the *eq07_20* variable in Table C.3 but renamed.
d_refri	Dummy variable for refrigerator. This variable equals "1" if the household has a refrigerator at home, and "0" otherwise.
p	Nominal price in Mexican pesos per kilogram (nominal pesos/kg). This is the *precio* variable in Table C.3 but renamed.
q	Per adult-equivalent consumption in kilograms (kg) per week.
m	Per adult-equivalent expenditure in Mexican pesos (nominal pesos) per week.

Table C.6: Descriptive Statistics of ENIGH 2006 Meat Cuts.

The SURVEYMEANS Procedure

Data Summary

Number of Strata	4
Number of Observations	16909
Sum of Weights	22106253

Statistics

Variable	N Miss	Minimum	Maximum	Mean	Std Error of Mean
p025	10936	3.450000	943.000000	61.376412	0.267567
q025	10936	0.014388	5.056180	0.265041	0.004033
m025	10936	0.888889	224.696629	15.813829	0.241423
p026	16738	24.800000	300.000000	72.547779	2.863587
q026	16738	0.040984	3.636364	0.291295	0.024390
m026	16738	3.379098	363.636364	21.392095	2.217308
p027	16396	12.000000	120.000000	61.441774	0.800496
q027	16396	0.028571	1.685393	0.234351	0.009527
m027	16396	1.714286	97.752809	14.244504	0.620238
p028	16860	17.500000	223.000000	47.832145	4.574427
q028	16860	0.030211	1.752809	0.378031	0.075376
m028	16860	4.434368	76.404944	15.384387	2.992538
p029	16488	6.670000	777.780000	56.558583	2.597528
q029	16488	0.016949	4.454343	0.299046	0.042560
m029	16488	1.395349	89.086860	13.950913	0.886557
p030	16634	13.330000	180.000000	59.552800	1.302662
q030	16634	0.032808	3.370787	0.351865	0.027616
m030	16634	1.312336	210.727273	20.040210	1.581068
p031	15548	4.150000	168.000000	44.714211	0.522900
q031	15548	0.033025	13.505747	0.291544	0.008762
m031	15548	1.528662	101.123596	12.036393	0.312729
p032	16869	30.000000	375.000000	73.103316	4.388912
q032	16869	0.042857	1.363636	0.337307	0.070861
m032	16869	3.322714	122.590909	23.507910	4.528076
p033	16848	11.500000	166.670000	51.929814	3.621229
q033	16848	0.043436	1.935484	0.336642	0.049957
m033	16848	1.445994	47.738693	14.316861	1.433715
p034	14011	1.000000	152.000000	55.735768	0.406418
q034	14011	0.020509	51.923077	0.203759	0.005099
m034	14011	0.601202	115.445730	10.635272	0.182762
p035	15919	3.000000	300.000000	59.704063	1.083322
q035	15919	0.019763	3.370787	0.272338	0.011790
m035	15919	0.838926	175.280899	15.451592	0.715845
p036	16668	4.910000	153.850000	54.803403	2.332382
q036	16668	0.043178	3.370787	0.244480	0.016317
m036	16668	2.003339	60.000000	12.073083	0.858011

Note: p_i, q_i, m_i, $i = 025, 026, \ldots, 074$, where 025 = A025, 026 = A026, ... , 074 = A074 (see Table C.4 and Table C.5).

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Table C.6: *Continued*

The SURVEYMEANS Procedure

Statistics

Variable	N Miss	Minimum	Maximum	Mean	Std Error of Mean
p037	16394	5.000000	100.000000	28.826685	0.847830
q037	16394	0.023502	9.049774	0.345978	0.021366
m037	16394	0.885436	135.746606	9.023370	0.515082
p038	16017	4.000000	124.850000	50.331076	0.604289
q038	16017	0.028835	3.205128	0.223072	0.009455
m038	16017	1.730104	67.408989	10.642648	0.440102
p039	16247	8.750000	140.000000	44.798510	0.724316
q039	16247	0.033113	11.428571	0.264794	0.010969
m039	16247	1.557632	182.857143	11.092369	0.380693
p040	16112	12.500000	500.000000	50.139434	0.697169
q040	16112	0.016129	2.272727	0.261178	0.012641
m040	16112	1.868460	136.363636	12.808314	0.744237
p041	16543	3.500000	120.000000	48.639076	0.968775
q041	16543	0.030581	1.910828	0.175451	0.008958
m041	16543	1.025641	53.932584	7.969800	0.360403
p042	15486	0.400000	400.000000	48.260167	0.522600
q042	15486	0.032468	26.785714	0.274093	0.035867
m042	15486	0.378788	133.333333	11.075137	0.400238
p043	16880	25.000000	4666.670000	126.468744	86.442021
q043	16880	0.007160	0.590551	0.256348	0.026089
m043	16880	4.161248	33.412912	11.718114	1.007092
p044	16842	7.900000	140.000000	38.150827	2.720245
q044	16842	0.047170	1.685393	0.247573	0.032339
m044	16842	2.056777	39.320225	8.055241	0.821859
p045	16436	6.000000	212.000000	36.918038	1.107626
q045	16436	0.019493	5.454545	0.285814	0.011503
m045	16436	1.332185	90.927273	9.500926	0.389674
p046	16884	13.330000	50.000000	26.574724	2.711384
q046	16884	0.038071	1.123596	0.238980	0.055009
m046	16884	1.268909	39.325843	6.238244	1.981387
p047	16714	6.170000	240.000000	67.335804	2.774145
q047	16714	0.023170	1.388889	0.161947	0.013656
m047	16714	1.564537	45.226131	9.410685	0.615327
p048	15096	1.000000	480.000000	70.336591	0.849031
q048	15096	0.005252	5.454545	0.111308	0.003550
m048	15096	0.338983	84.269663	6.879306	0.201701
p049	13734	0.130000	1071.430000	50.786905	0.907207
q049	13734	0.001357	11.782477	0.126517	0.003822
m049	13734	0.288248	203.718079	5.517603	0.117200
p050	16529	5.000000	456.200000	54.354419	1.680333
q050	16529	0.018685	1.984127	0.219913	0.020662
m050	16529	0.896861	67.181818	10.188837	0.668496
p051	16749	20.000000	1600.000000	162.756049	15.089380

Note: p_i, q_i, m_i, $i = 025, 026, \ldots, 074$, where 025 = A025, 026 = A026, ... , 074 = A074 (see Table C.4 and Table C.5).

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Table C.6: *Continued*

The SURVEYMEANS Procedure

Statistics

Variable	N Miss	Minimum	Maximum	Mean	Std Error of Mean
q051	16749	0.003077	2.727273	0.148293	0.051024
m051	16749	1.256732	545.454545	22.822907	10.214936
p052	13202	3.330000	1040.000000	50.751202	0.464478
q052	13202	0.003326	1.685393	0.127683	0.003153
m052	13202	0.130378	79.487185	6.167589	0.147637
p053	16515	6.000000	471.000000	39.552150	1.701603
q053	16515	0.011765	0.909091	0.126304	0.006473
m053	16515	0.487013	54.545455	4.259470	0.225450
p054	16542	10.000000	157.000000	62.757026	1.844772
q054	16542	0.006748	0.727273	0.090407	0.007656
m054	16542	0.404858	39.545455	5.072013	0.376734
p055	14525	1.000000	300.000000	31.267964	0.532688
q055	14525	0.006042	3.333333	0.178694	0.004971
m055	14525	0.139860	58.426966	4.925814	0.139792
p056	16284	4.130000	183.330000	62.027355	1.737497
q056	16284	0.006519	1.376147	0.174716	0.007205
m056	16284	0.260756	123.853211	9.836340	0.458055
p057	12907	1.780000	260.000000	33.127606	0.275200
q057	12906	0	22.471910	0.405444	0.007246
m057	12907	0.527108	168.318460	12.260849	0.216256
p058	15529	1.350000	460.000000	42.281102	0.589667
q058	15529	0.013587	5.909091	0.314146	0.007675
m058	15529	1.284202	140.449438	12.551756	0.333993
p059	11193	1.000000	360.000000	28.598186	0.287600
q059	11193	0.018625	11.423221	0.447971	0.007264
m059	11193	0.286447	198.021536	11.750972	0.183328
p060	16149	1.000000	425.000000	22.432137	0.894936
q060	16149	0.004695	6.532663	0.471931	0.056344
m060	16149	0.433526	95.454545	6.869199	0.447276
p061	16780	5.000000	200.000000	45.845211	4.581195
q061	16780	0.030035	5.617978	0.678946	0.094135
m061	16780	1.424421	157.303371	19.827763	1.916701
p062	14316	0.440000	290.000000	46.742954	0.558106
q062	14316	0.005298	8.532423	0.196946	0.005644
m062	14316	0.369004	157.988764	8.339281	0.236039
p063	16898	37.000000	120.000000	64.115804	2.014274
q063	16898	0.057870	2.352941	0.842317	0.104632
m063	16898	3.144654	112.365169	46.590702	5.114689
p064	16897	20.000000	140.000000	54.577378	13.416364
q064	16897	0.083963	0.807754	0.403425	0.102407
m064	16897	6.472492	33.900000	15.708771	1.861144
p065	16892	16.670000	90.000000	65.895874	7.381014
q065	16892	0.031726	1.123596	0.365664	0.083044

Note: p_i, q_i, m_i, $i = 025, 026, \ldots, 074$, where 025 = A025, 026 = A026, … , 074 = A074 (see Table C.4 and Table C.5).

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Table C.6: *Continued*

The SURVEYMEANS Procedure

Statistics

Variable	N Miss	Minimum	Maximum	Mean	Std Error of Mean
m065	16892	2.538071	62.500000	25.697084	8.673467
p066	15648	2.500000	300.000000	39.093670	0.902947
q066	15648	0.023866	4.494382	0.405146	0.015770
m066	15648	1.679731	210.674157	13.991166	0.695918
p067	16216	4.000000	875.000000	71.896307	1.699169
q067	16216	0.013441	2.808989	0.287611	0.012696
m067	16216	1.075269	146.067416	18.870540	0.902389
p068	14957	0.070000	630.000000	47.692540	0.604096
q068	14953	0	52.959502	0.146413	0.005929
m068	14957	0.434783	123.588090	6.294131	0.234352
p069	16890	19.700000	225.000000	89.597969	13.530365
q069	16890	0.010627	2.247191	0.237062	0.070597
m069	16890	0.637620	404.494382	24.878742	8.097645
p070	16440	4.000000	425.000000	42.557547	2.129051
q070	16433	0	2.943820	0.148417	0.012307
m070	16440	0.579151	136.363636	5.285924	0.423738
p071	16898	30.000000	140.000000	63.523216	13.989014
q071	16898	0.135747	1.235955	0.411442	0.104901
m071	16898	4.687500	63.636364	25.314022	7.434893
p072	16372	7.500000	300.000000	81.681706	2.186644
q072	16372	0.007541	3.370787	0.295148	0.019597
m072	16372	0.754148	145.454545	20.514006	0.988354
p073	16821	1.350000	469.230000	46.079446	5.409006
q073	16821	0.030211	4.938272	0.311640	0.045721
m073	16821	1.340782	104.545455	9.938295	1.473132
p074	16766	15.000000	333.330000	100.230919	6.031780
q074	16766	0.009251	0.909091	0.093814	0.010950
m074	16766	0.441826	90.909091	7.395987	0.650507
inc	0	3.020000	1059498	36384	484.694672
educ	0	1.000000	11.000000	5.072901	0.027345
str1	0	0	1.000000	0.519008	0.004320
str2	0	0	1.000000	0.146617	0.002403
str3	0	0	1.000000	0.128365	0.004194
str4	0	0	1.000000	0.206009	0.004241
urban	0	0	1.000000	0.665626	0.004875
rural	0	0	1.000000	0.334374	0.004875
NE	0	0	1.000000	0.076314	0.002375
NW	0	0	1.000000	0.131861	0.003458
CW	0	0	1.000000	0.223888	0.004566
C	0	0	1.000000	0.341810	0.005950
SE	0	0	1.000000	0.226127	0.004601
hhsize	0	0	25.000000	4.137634	0.024959
a_eq	0	0.890000	21.260000	3.987610	0.022143
car	0	0	7.000000	0.576644	0.008694
d_car	0	0	1.000000	0.424067	0.005598
refri	0	0	6.000000	0.845585	0.005054
d_refri	0	0	1.000000	0.828152	0.004796

Note: p_i, q_i, m_i, $i = 025, 026, \ldots, 074$, where 025 = A025, 026 = A026, ... , 074 = A074 (see Table C.4 and Table C.5).

Source: ENIGH 2006, computed by author.

Table C.7: Table Cuts Used in this Study.

Code	**Description**
(1) Beefsteak	
A025	Beefsteak: boneless rump, bottom round, top round, etc.
A027	Milanesa
(2) Ground Beef	
A033	Hamburger patty
A034	Ground beef
(3) Other Beef	
A026	Brisket and fillet steak
A028	Tore shank
A029	Rib cutlet
A030	Chuck, strips for grilling and sirloin steak
A031	Meat for stewing/boiling or meat cut with bone
A032	Special cuts: t-bone, roast beef, etc.
A035	Chopped loin, chopped top and bottom round
(4) Beef Offal	
A036	Other beef cuts: head, udder, etc.
A037	Guts/innards/viscera: heart, liver, marrow, rumen/belly, etc.
(5) Pork Steak	
A038	Pork steak
(6) Pork Leg & Shoulder	
A039	(Chopped) leg
A040	Middle leg
A043	Clear plate and Boston shoulder (blade/shoulder)
A044	Pinic shoulder

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Table C.7: *Continued*

Code	Description
	(7) Ground Pork
A041	Ground pork
	(8) Other Pork
A042	Ribs and pork chops (loin)
A045	Other pork cuts: head, upper leg, belly, spareribs, etc.
A050	Smoked pork chops
	(9) Chorizo
A049	Chorizo
	(10) Ham, Bacon & Similar Products From Beef & Pork
A052	Ham
A053	Bologna, embedded pork and salami
A054	Bacon
	(11) Beef & Pork Sausages
A055	Sausages
	(12) Other Processed Beef & Pork
A047	Shredded meat
A048	Pork skin/chicharron
A051	Crusher and dried meats
A056	Other processed meats from beef and pork: stuffing, smoked meat/dried meat, etc.
	(13) Chicken Legs, Thighs & Breasts
A057	Leg, thigh and breast with bone
A058	Boneless leg, boneless thigh and boneless breast

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Table C.7: *Continued*

Code	**Description**
(14) Whole Chicken	
A059	Whole chicken or in parts (except legs, thigh and breast)
(15) Chicken Offal	
A060	Guts/innards/viscera and other chicken parts: wings, head, neck, gizzard, liver, etc.
(16) Chicken Ham & Similar Products	
A062	Chicken sausage, ham, nuggets, bologna, etc.
(17) Fish	
A066	Whole fish, clean and not clean (catfish, carp, tilapia, etc.)
A067	Fish fillet
A068	Tuna
A069	Salmon and codfish
A070	Smoked fish, dried fish, fish nuggets and sardines
A071	Young eel, manta ray, eel, fish/crustaceous eggs, etc.
(18) Shellfish	
A072	Fresh shrimp
A073	Other fresh shellfish: clam, crab, oyster, octopus
A074	Processed: smoked, packaged, breaded, dried shrimp

Source: ENIGH 2006—Clasificación de Variables, translated into English by author.

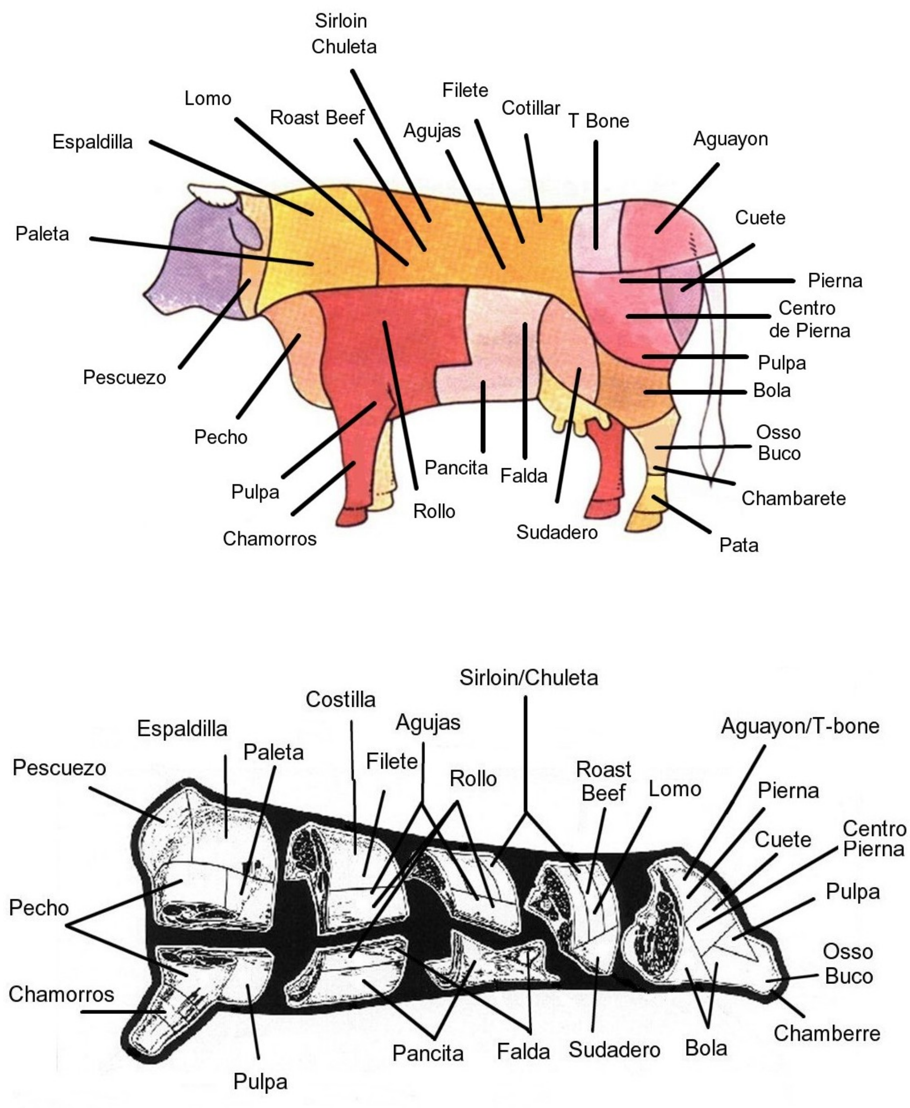


Figure C.1: Retail Cuts of Beef (Spanish).
Source: Las Recetas de la Abuela (2009).

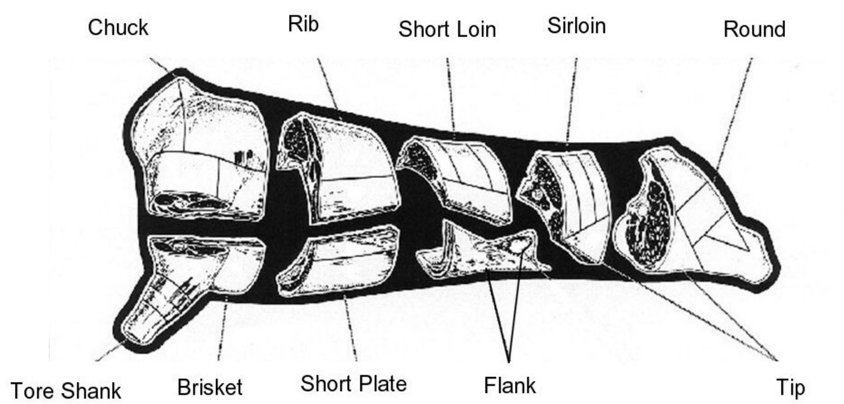
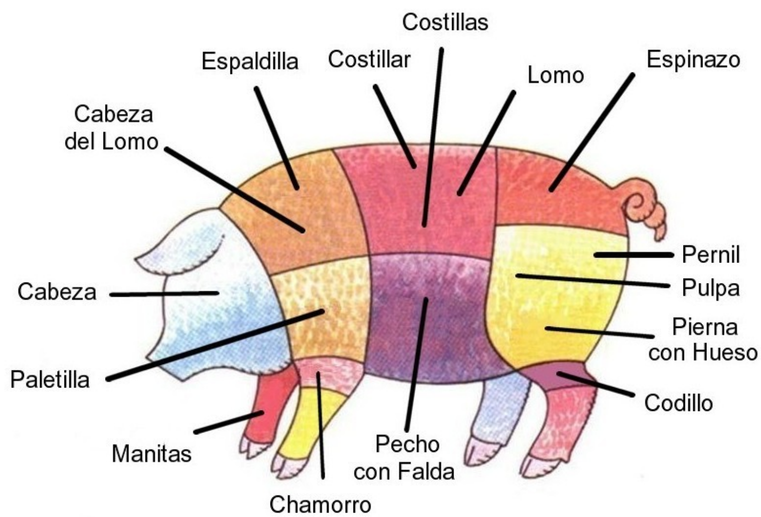


Figure C.2: Retail Cuts of Beef.
Source: Department of Animal Science, Oklahoma State University (2009).



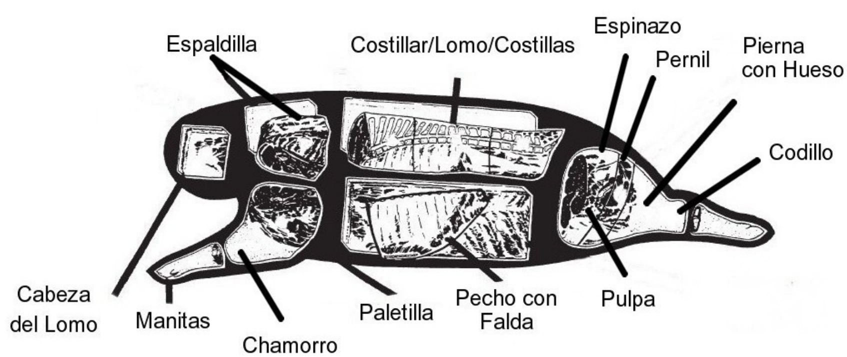


Figure C.3: Wholesale Cuts of Pork (Spanish).
Source: Las Recetas de la Abuela (2002).

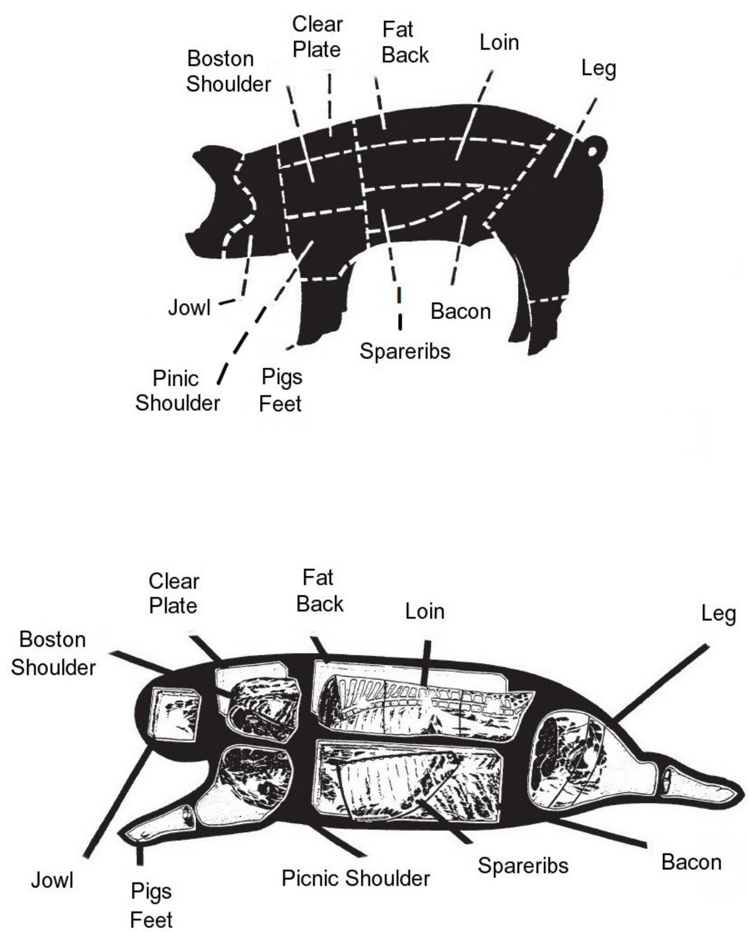


Figure C.4: Wholesale Cuts of Pork.
Source: Extension Service, Oregon State University (2009)

Figure C.5: Mexican States and the Federal District Map.

Note: 1 = Aguascalientes, 2 = Baja California, 3 = Baja California Sur, 4 = Campeche, 5 = Coahuila de Zaragoza, 6 = Colima, 7 = Chiapas, 8 = Chihuahua, 9 = Distrito Federal, 10 = Durango, 11 = Guanajuato, 12 = Guerrero, 13 = Hidalgo, 14 = Jalisco, 15 = Estado de México, 16 = Michoacán de Ocampo, 17 = Morelos, 18 = Nayarit, 19 = Nuevo León, 20 = Oaxaca, 21 = Puebla, 22 = Querétaro Arteaga, 23 = Quintana Roo, 24 = San Luis Potosí, 25 = Sinaloa, 26 = Sonora, 27 = Tabasco, 28 = Tamaulipas, 29 = Tlaxcala, 30 = Veracruz de Ignacio de la Llave, 31 = Yucatán, and 32 = Zacatecas.

Figure C.6: Mexican Geographical and Regional Map.

Note: Northeast = Chihuahua, Cohahuila de Zaragoza, Durango, Nuevo León, and Tamaulipas. Northwest = Baja California, Sonora, Baja California Sur, and Sinaloa. Central-West = Zacatecas, Nayarit, Aguascalientes, San Luis Potosí, Jalisco, Guanajuato, Querétaro Arteaga, Colima, and Michoacán de Ocampo. Central = Hidalgo, Estado de México, Distrito Federal, Tlaxcala, Morelos, and Puebla. Southeast = Veracruz de Ignacio de la Llave, Yucatán, Quintana Roo, Campeche, Tabasco, Guerrero, Oaxaca, and Chiapas.

APPENDIX D
ELASTICITY ESTIMATES BY REGION

Appendix D presents the Marshallian and Hicksian price elasticities as well as expenditure elasticities by region. These elasticities were used in Section 5.2 to compare elasticities across regions and determine differences in meat consumption patterns. The elasticity estimation procedure was explained in Section 4.2.2. Their statistical significance levels were approximated by using the bootstrap.

Table D.1: Marshallian Price Elasticities in the Northeast Region.

Table entries estimate e_{ij}.

i\j	1	2	3	4	5	6	7	8	9	10	11
1	-0.8807*	0.1586†	-0.3385*	-0.1425	0.2544	-0.3341†	-0.0211	0.0560	0.0254	0.0119	-0.0098
2	0.4477*	-2.5627*	-0.0845	-0.1208	0.3216	0.2243	0.4804	0.0676	-0.0131	0.0733	-0.0649
3	-0.9683*	0.0284	-1.0845*	0.2021‡	0.8892*	-0.4062†	-2.3404*	-0.6295*	0.0899	0.0529	0.0937
4	-1.5089*	0.3441	-0.2608	-3.3524†	-1.1540	0.6157	-1.2472	-0.1451	0.3624	-0.1804	0.4026
5	2.3490	-1.1080	-0.0677	0.1294	-11.2313	-1.7814	-3.6198	1.5743	-1.0042	-0.4470	-0.0695
6	-1.2226	-0.4799	0.0142	0.4237	-0.8081	-4.2024	0.9776	0.1920	-0.1471	-0.2861	0.0597
7	-2.2079	-0.4458	0.1965	0.2049	-1.3605	-0.6580	-11.5638	-0.2589	0.0499	0.0162	0.6724
8	-0.1662	0.3959	0.2726	0.4167	1.4207	1.4160	-1.7909	-6.2342	0.4394	-0.0167	0.5105
9	0.1199	-0.0516	0.0882	-0.1135	0.8655	-0.1629	-0.1096	-0.0495	-0.9016*	-0.3852	-0.0633
10	0.2195†	-0.6979*	0.4213	-0.1425†	0.3493	0.0984	-1.1211*	0.0696	0.0582	-0.6019*	0.2631‡
11	-0.3847*	-0.1988	0.1824*	-0.5362*	0.9574*	-0.8736*	0.8430*	0.5693*	0.0808*	-0.0448	-1.7227†
12	0.2439	-1.2940	0.4892	-2.6901	-5.5428	0.8535	-1.1370	-0.4802	0.1664	-1.0056	1.4092
13	-0.3212‡	-0.1106	0.0409	-0.3532*	0.3087	0.2049	0.9468*	0.0068	0.0539	0.1965*	-0.0158
14	0.4462†	-0.2929‡	-0.4213	-0.0357	-0.3095	-0.1051	-0.3106	-0.0868	-0.1092	-0.3495	-0.1182
15	0.1532	-0.5778	-0.0714	1.0045	0.6114	2.3547	-1.2469	0.1193	-2.4175	-2.2756	3.0495
16	-0.0391	0.1422†	0.0625	0.0527	1.5746	0.1483	-1.3038†	0.4076	0.0400	0.1083	0.1950
17	-0.0328	-0.1028	0.0571	-0.1188	0.7782*	-0.4800†	-1.4323‡	0.1085	-0.0600	0.1889‡	0.1041
18	-0.6501*	0.3987*	-0.2361	0.4791*	0.9617*	0.0113	1.0023*	-0.3155*	0.0446	0.2280*	0.3321*

Note: $i, j = 1, 2, \ldots, 18$, where 1 = Beefsteak, 2 = Ground Beef, 3 = Other Beef, 4 = Beef Offal, 5 = Pork Steak, 6 = Pork Leg & Shoulder, 7 = Ground Pork, 8 = Other Pork, 9 = Chorizo, 10 = Ham, Bacon & Similar Products from Beef & Pork, 11 = Beef & Pork Sausages, 12 = Other Processed Beef & Pork, 13 = Chicken Legs, Thighs & Breasts, 14 = Whole Chicken, 15 = Chicken Offal, 16 = Chicken Ham & Similar Products, 17 = Fish, 18 = Shellfish. Number of bootstrap resamples = 1,000. Bootstrap significance levels of 0.05, 0.10 and 0.20 are indicated by asterisks (*), double daggers (‡) and daggers (†) respectively.

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Table D.1: *Continued*

Table entries estimate e_{ij}.

i\j	12	13	14	15	16	17	18
1	-0.0568	-0.2029*	-0.0308	0.0592	-0.1759	-0.0332	-0.5894*
2	-0.0941	-0.0291	0.1759	0.1869*	-0.1835†	-0.0597	-1.0032*
3	-0.1206	-0.1871*	0.0240	0.2989†	0.0472	-0.1148	-0.5112*
4	-0.8086	-0.4503	-0.3463	0.5252	-0.1392	-1.2176†	0.7383
5	0.2532	0.1033	-0.9406	0.2390	2.2270	-0.0730	-0.5547
6	0.7084	0.0951	-0.4592	0.0240	0.1445	0.1693	0.2075
7	-1.5361	-0.1861	-0.4202	-0.2928	-0.5727	-0.4180	-0.3838
8	-0.5512	-0.2438	-0.4034	0.1244	-0.7901	-0.2473	0.2046
9	0.3462	-0.0941	-0.1724†	-0.3345*	-0.1460	-0.0510	0.1903
10	0.1868	0.0877	0.1135†	-0.5920*	0.1279†	0.1167	0.2228†
11	-0.3382*	-0.0094	-0.1854‡	-0.3471	0.1726	0.2846*	0.1960
12	-12.0059	1.6891	-0.2312	-3.6255	1.7913	0.1402	1.9028
13	0.1151	-0.9688*	-0.1596*	-0.0107	0.1567‡	0.0721‡	-0.1523
14	-0.0218	-0.0019	-1.4192*	0.3393	-0.1438	-0.9365	-0.2538
15	0.1021	-0.0132	-0.3408	-17.5961	1.2530	-0.3697	-1.4206
16	0.0477	0.1399	0.0314	0.1554	-0.7602‡	0.0381	0.0222
17	0.0539	-0.0406	0.1211	0.2678*	0.1109	-0.8751*	0.4418
18	-0.3973*	-0.0702	-0.0274	0.3208*	0.2632	0.0893‡	-3.1103*

Note: $i, j = 1, 2, \ldots, 18$, where 1 = Beefsteak, 2 = Ground Beef, 3 = Other Beef, 4 = Beef Offal, 5 = Pork Steak, 6 = Pork Leg & Shoulder, 7 = Ground Pork, 8 = Other Pork, 9 = Chorizo, 10 = Ham, Bacon & Similar Products from Beef & Pork, 11 = Beef & Pork Sausages, 12 = Other Processed Beef & Pork, 13 = Chicken Legs, Thighs & Breasts, 14 = Whole Chicken, 15 = Chicken Offal, 16 = Chicken Ham & Similar Products, 17 = Fish, 18 = Shellfish. Number of bootstrap resamples = 1,000. Bootstrap significance levels of 0.05, 0.10 and 0.20 are indicated by asterisks (*), double daggers (‡) and daggers (†) respectively.

Table D.2: Hicksian Price Elasticities in the Northeast Region.

Table entries estimate e^c_{ij}.

i\j	1	2	3	4	5	6	7	8	9	10	11
1	-0.6767*	0.2199‡	-0.1941*	-0.1243	0.2564	-0.3205†	-0.0177	0.0766	0.0642‡	0.0506	0.0156
2	0.5695*	-2.5261*	0.0017	-0.1099	0.3228	0.2325	0.4824	0.0799	0.0101	0.0964†	-0.0498
3	-0.8332*	0.0690	-0.9890*	0.2142‡	0.8905*	-0.3971†	-2.3382*	-0.6158*	0.1155	0.0785†	0.1105
4	-1.3850‡	0.3814	-0.1731	-3.3413†	-1.1528	0.6240	-1.2452	-0.1326	0.3859	-0.1569	0.4180
5	2.4726	-1.0708	0.0198	0.1405	-11.2301	-1.7731	-3.6177	1.5868	-0.9807	-0.4236	-0.0541
6	-1.1043	-0.4444	0.0979	0.4342	-0.8069	-4.1945	0.9796	0.2039	-0.1246	-0.2637	0.0744
7	2.1699	-0.4344	0.2234	0.2083	-1.3601	-0.6555	-11.5632	-0.2551	0.0571	0.0234	0.6771
8	-0.0210	0.4396	0.3754	0.4297	1.4222	1.4257	-1.7885	-6.2195	0.4670	0.0108	0.5286
9	0.2325†	-0.0177	0.1679†	-0.1035	0.8666	-0.1554	-0.1078	-0.0381	-0.8802*	-0.3639	-0.0493
10	0.3181*	-0.6683‡	0.4910	-0.1337†	0.3503	0.1050	-1.1195*	0.0795	0.0770	-0.5832*	0.2754‡
11	-0.3179‡	-0.1787	0.2297*	-0.5302*	0.9581*	-0.8692*	0.8441*	0.5761*	0.0935*	-0.0321	-1.7144†
12	0.3452	-1.2635	0.5609	-2.6810	-5.5418	0.8603	-1.1353	-0.4699	0.1856	-0.9864	1.4218
13	-0.1717	-0.0656	0.1468*	-0.3398*	0.3101	0.2149	0.9492*	0.0219	0.0823†	0.2249*	0.0028
14	0.6422†	-0.2339‡	-0.2825	-0.0181†	-0.3076	-0.0920	-0.3074	-0.0669	-0.0719	-0.3124	-0.0938
15	0.3661	-0.5137	0.0793	1.0236	0.6134	2.3689	-1.2434	0.1408	-2.3770	-2.2352	3.0761
16	0.0202	0.1601†	0.1045	0.0580	1.5752	0.1523	-1.3028†	0.4136	0.0513	0.1196	0.2024
17	0.1076	-0.0605	0.1565‡	-0.1063	0.7795*	-0.4706†	-1.4300‡	0.1227	-0.0333	0.2155*	0.1216
18	-0.5476‡	0.4295*	-0.1636	0.4882*	0.9627*	0.0181	1.0040*	-0.3052‡	0.0641	0.2475*	0.3449*

Note: $i, j = 1, 2, \ldots, 18$, where 1 = Beefsteak, 2 = Ground Beef, 3 = Other Beef, 4 = Beef Offal, 5 = Pork Steak, 6 = Pork Leg & Shoulder, 7 = Ground Pork, 8 = Other Pork, 9 = Chorizo, 10 = Ham, Bacon & Similar Products from Beef & Pork, 11 = Beef & Pork Sausages, 12 = Other Processed Beef & Pork, 13 = Chicken Legs, Thighs & Breasts, 14 = Whole Chicken, 15 = Chicken Offal, 16 = Chicken Ham & Similar Products, 17 = Fish, 18 = Shellfish. Number of bootstrap resamples = 1,000. Bootstrap significance levels of 0.05, 0.10 and 0.20 are indicated by asterisks (*), double daggers (‡) and daggers (†) respectively.

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Table D.2: *Continued*

Table entries estimate e^c_{ij}.

i\j	12	13	14	15	16	17	18
1	-0.0404	-0.0892‡	0.0270	0.0626	-0.0869	0.0923	-0.5032*
2	-0.0843	0.0388	0.2104	0.1889*	-0.1304	0.0153	-0.9517*
3	-0.1097	-0.1118†	0.0622†	0.3012†	0.1061	-0.0318	-0.4541*
4	-0.7987	-0.3812	-0.3112	0.5272	-0.0851	-1.1413†	0.7907
5	0.2631	0.1722	-0.9056	0.2410	2.2809	0.0030	-0.5025
6	0.7179	0.1610	-0.4257	0.0259	0.1961	0.2421	0.2575
7	-1.5330	-0.1650	-0.4094	-0.2922	-0.5561	-0.3946	-0.3678
8	-0.5395	-0.1628	-0.3623	0.1268	-0.7268	-0.1580	0.2659
9	-0.3372	-0.0314	-0.1405	-0.3326*	-0.0969	0.0183	0.2379
10	0.1947	0.1427	0.1415*	-0.5903*	0.1709†	0.1774	0.2644†
11	-0.3328*	0.0279	-0.1665‡	-0.3460	0.2017	0.3257*	0.2242
12	-11.9977	1.7456	-0.2025	-3.6239	1.8355	0.2025	1.9455
13	0.1271	-0.8855*	-0.1172*	-0.0083	0.2219*	0.1641*	-0.0891
14	-0.0060	0.1074*	-1.3637*	0.3426	-0.0583	-0.8158	-0.1710
15	0.1192	0.1055	-0.2805	-17.5926	1.3459	-0.2387	-1.3307
16	0.0524	0.1730	0.0482	0.1564	-0.7343‡	0.0746	0.0473
17	0.0652	0.0377	0.1608	0.2701*	0.1721‡	-0.7886‡	0.5011†
18	-0.3890‡	-0.0131	0.0017	0.3225*	0.3079	0.1524*	-3.0671*

Note: $i, j = 1, 2, \ldots, 18$, where 1 = Beefsteak, 2 = Ground Beef, 3 = Other Beef, 4 = Beef Offal, 5 = Pork Steak, 6 = Pork Leg & Shoulder, 7 = Ground Pork, 8 = Other Pork, 9 = Chorizo, 10 = Ham, Bacon & Similar Products from Beef & Pork, 11 = Beef & Pork Sausages, 12 = Other Processed Beef & Pork, 13 = Chicken Legs, Thighs & Breasts, 14 = Whole Chicken, 15 = Chicken Offal, 16 = Chicken Ham & Similar Products, 17 = Fish, 18 = Shellfish. Number of bootstrap resamples = 1,000. Bootstrap significance levels of 0.05, 0.10 and 0.20 are indicated by asterisks (*), double daggers (‡) and daggers (†) respectively.

Table D.3: Marshallian Price Elasticities in the Northwest Region.

Table entries estimate e_{ij}.

i\j	1	2	3	4	5	6	7	8	9	10	11
1	-0.9204*	0.1755	-0.4613*	-0.1278	0.2876	-0.3983	-0.0164	0.0809	0.0412	0.0136	-0.0111
2	0.2885*	-2.6667*	-0.1090	-0.0522	0.3622	0.3387	0.2204	0.1467	-0.0255	0.0396	-0.0839
3	-0.9723*	0.0368	-1.4271*	0.1715‡	0.9559*	-0.4586	-1.9729*	-0.8644*	0.1409	0.0559	0.1087
4	-1.0440‡	0.1426	-0.2719	-1.9066†	-1.2138	0.5405	-0.5896†	-0.1394	-0.0391	-0.1588	0.2285
5	0.3116	-0.7529	0.2108	-0.3824	-2.4768	-1.1426	-1.1263	0.4106	-0.3054	-0.8282	0.2339
6	-1.2591	-0.5214	0.0178	0.3695	-0.8630	-4.9957	0.8177	0.3095	-0.2326	-0.3119	0.0624
7	-2.9224	-0.6069	0.3429	0.4656	-1.3660	-1.0056	-7.7553	-0.6439	-0.2009	0.2029	1.1267
8	-0.1615	1.0295	0.7422	0.3280	2.4784	3.5718	-3.4705	-18.3578	1.8331	0.3530	1.2436
9	0.1835	-0.0860	0.1667	-0.1174	1.3268	-0.3185	-0.1009	-0.1149	-2.0084*	-0.6259	-0.1075
10	0.1991†	-0.7005†	0.5417	-0.0897†	0.4379	0.0811	-0.8151*	0.0817	0.0953	-0.5672*	0.2697†
11	-0.3081*	-0.0978†	0.1661*	-0.2983†	0.8349*	-0.5943†	0.1535†	0.5490*	0.0686‡	0.0116	-1.6522‡
12	0.1293	-0.6238†	0.1047	-0.8001*	-2.0443*	0.0691	0.2739	-0.3347	0.1120	-0.4892	0.1726
13	-0.3182‡	-0.1640	0.0581	-0.2837*	0.3241	0.1736	0.8398*	0.0414	0.0791	0.2117*	-0.0216
14	0.3619†	-0.2092‡	-0.5983	0.0357	-0.4592	-0.2290	-0.2412	-0.2021	-0.1626	-0.3857	-0.1073
15	0.0873	-0.2690	-0.0326	0.5660	0.6204	1.6635	-1.0886	0.1452	-3.0144*	-2.2455	2.2723
16	-0.0657	0.2289†	0.0253	0.1310†	2.0131	0.2230	-1.4353‡	0.7695	0.0572	0.1020	0.2783
17	-0.0383	-0.1019	0.0679	-0.0847	1.0786	-0.7617	-1.6555†	0.2138	-0.0864	0.2728	0.1417
18	3.4125	-1.2564	3.4114	1.9220	0.3626	-2.0750	4.1288	1.4307	0.2084	0.2002	-1.1002

Note: $i, j = 1, 2, \ldots, 18$, where 1 = Beefsteak, 2 = Ground Beef, 3 = Other Beef, 4 = Beef Offal, 5 = Pork Steak, 6 = Pork Leg & Shoulder, 7 = Ground Pork, 8 = Other Pork, 9 = Chorizo, 10 = Ham, Bacon & Similar Products from Beef & Pork, 11 = Beef & Pork Sausages, 12 = Other Processed Beef & Pork, 13 = Chicken Legs, Thighs & Breasts, 14 = Whole Chicken, 15 = Chicken Offal, 16 = Chicken Ham & Similar Products, 17 = Fish, 18 = Shellfish. Number of bootstrap resamples = 1,000. Bootstrap significance levels of 0.05, 0.10 and 0.20 are indicated by asterisks (*), double daggers (‡) and daggers (†) respectively.

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Table D.3: *Continued*

Table entries estimate e_{ij}.

i\j	12	13	14	15	16	17	18
1	-0.0610	-0.2008*	-0.0304	0.0701	-0.2093	-0.0349	-0.9737
2	0.0130	0.0092	0.1638	0.0990‡	-0.0717	-0.0830	-0.8168*
3	-0.1247	-0.1784*	0.0220	0.3346†	0.0553	-0.1170	-0.7985*
4	-0.8239	-0.2738‡	-0.2629	0.4369	-0.0844	-1.0093	0.6170
5	-0.4702	-0.2727	-0.4939	0.4482	0.2066	0.0682	-1.7473
6	0.7566†	0.0911	-0.4389	0.0213	0.1773	0.1686	0.3966
7	-1.8111	-0.2651	-0.4045	-0.2645	-1.1431	-0.5101	-0.4967
8	-0.8728	-0.1838	-0.4622	-0.0279	-1.3327	-0.3551	1.8674
9	-0.5342†	-0.1367	-0.2407†	-0.5464*	-0.2899	-0.0727	0.3604
10	0.1471	0.0802	0.0968†	-0.6263‡	0.1142	0.1229	0.2326
11	-0.0436†	0.0028	-0.0429†	-0.3057†	0.2666	0.1668‡	0.8578
12	-3.7392*	0.4537†	-0.0308	-0.9103	0.3323	0.0343	0.4835
13	0.0971	-0.8054*	-0.1442*	0.0072	0.1654*	0.0747‡	-0.3681
14	-0.0634	-0.0200	-1.1071*	0.3735	-0.2311	-0.8434	-0.5810
15	0.1674	-0.0565	-0.2452	-15.6209*	1.1649†	-0.3797	-1.2911
16	0.0507	0.1544	0.0276	0.1246	-1.2413*	0.0331	0.3578
17	0.0628	-0.0478	0.1439	0.3638	0.1339	-1.2957*	1.1151*
18	-3.2889	0.4593	0.0115	0.4995	-5.5950	0.5752	34.3129

Note: $i, j = 1, 2, \ldots, 18$, where 1 = Beefsteak, 2 = Ground Beef, 3 = Other Beef, 4 = Beef Offal, 5 = Pork Steak, 6 = Pork Leg & Shoulder, 7 = Ground Pork, 8 = Other Pork, 9 = Chorizo, 10 = Ham, Bacon & Similar Products from Beef & Pork, 11 = Beef & Pork Sausages, 12 = Other Processed Beef & Pork, 13 = Chicken Legs, Thighs & Breasts, 14 = Whole Chicken, 15 = Chicken Offal, 16 = Chicken Ham & Similar Products, 17 = Fish, 18 = Shellfish. Number of bootstrap resamples = 1,000. Bootstrap significance levels of 0.05, 0.10 and 0.20 are indicated by asterisks (*), double daggers (‡) and daggers (†) respectively.

Table D.4: Hicksian Price Elasticities in the Northwest Region.

Table entries estimate e^c_{ij}.

i\j	1	2	3	4	5	6	7	8	9	10	11
1	-0.7465*	0.3373*	-0.2739*	-0.1106	0.2917	-0.3775	-0.0137	0.0952	0.0771	0.0555	0.0390
2	0.3596*	-2.6005*	-0.0324	-0.0452	0.3639	0.3472	0.2215	0.1525	-0.0108	0.0567	-0.0634
3	-0.8624*	0.1391	-1.3087*	0.1824‡	0.9585*	-0.4455†	-1.9712*	-0.8553*	0.1637	0.0824†	0.1404
4	-0.9549‡	0.2255	-0.1759	-1.8978†	-1.2117	0.5511	-0.5882†	-0.1321	-0.0207	-0.1373	0.2542†
5	0.3975	-0.6730	0.3034	-0.3739	-2.4748	-1.1323	-1.1249	0.4177	-0.2876	-0.8074	0.2587
6	-1.1610	-0.4301	0.1235	0.3792	-0.8607	-4.9840	0.8192	0.3175	-0.2123	-0.2883	0.0907
7	-2.8783	-0.5658	0.3905	0.4700	-1.3650	-1.0003	-7.7546	-0.6402	-0.1918	0.2135	1.1395
8	0.0022	1.1817	0.9185	0.3442	2.4822	3.5914	-3.4680	-18.3444	1.8670	0.3925	1.2908
9	0.3188‡	0.0399	0.3124	-0.1041	1.3300	-0.3023	-0.0988	-0.1038	-1.9805*	-0.5932	-0.0685
10	0.2741‡	-0.6307†	0.6225	-0.0823	0.4397	0.0901	-0.8140*	0.0879	0.1108	-0.5491*	0.2913‡
11	-0.2716*	-0.0638†	0.2055*	-0.2947†	0.8358*	-0.5899†	0.1540†	0.5520*	0.0762‡	0.0205	-1.6417‡
12	0.1821	-0.5746†	0.1616	-0.7949*	-2.0430*	0.0754	0.2747	-0.3304	0.1229	-0.4765	0.1878
13	-0.2003	-0.0543	0.1851‡	-0.2721*	0.3269	0.1877	0.8416*	0.0510	0.1035†	0.2402*	0.0124
14	0.5045†	-0.0765†	-0.4447	0.0497	-0.4559	-0.2119	-0.2390	-0.1904	-0.1331	-0.3513	-0.0662
15	0.2236	-0.1422	0.1142	0.5795	0.6236	1.6798	-1.0865	0.1564	-2.9862*	-2.2126	2.3116
16	-0.0078	0.2828†	0.0877	0.1368†	2.0145	0.2299	-1.4344‡	0.7742	0.0692	0.1160	0.2951
17	0.1138	0.0397	0.2319	-0.0697	1.0822	-0.7436	-1.6531†	0.2263	-0.0550	0.3096	0.1855
18	3.3913	-1.2761	3.3885†	1.9199	0.3621	-2.0775	4.1285	1.4289	0.2040	0.1951	-1.1063

Note: $i, j = 1, 2, \ldots, 18$, where 1 = Beefsteak, 2 = Ground Beef, 3 = Other Beef, 4 = Beef Offal, 5 = Pork Steak, 6 = Pork Leg & Shoulder, 7 = Ground Pork, 8 = Other Pork, 9 = Chorizo, 10 = Ham, Bacon & Similar Products from Beef & Pork, 11 = Beef & Pork Sausages, 12 = Other Processed Beef & Pork, 13 = Chicken Legs, Thighs & Breasts, 14 = Whole Chicken, 15 = Chicken Offal, 16 = Chicken Ham & Similar Products, 17 = Fish, 18 = Shellfish. Number of bootstrap resamples = 1,000. Bootstrap significance levels of 0.05, 0.10 and 0.20 are indicated by asterisks (*), double daggers (‡) and daggers (†) respectively.

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Table D.4: *Continued*

Table entries estimate e^c_{ij}.

i\j	12	13	14	15	16	17	18
1	-0.0296	-0.0944‡	0.0267	0.0805	-0.1550	0.0268	-0.9763
2	0.0259	0.0527	0.1872†	0.1033‡	-0.0495	-0.0578	-0.8178*
3	-0.1049	-0.1111†	0.0581†	0.3412†	0.0896	-0.0780	-0.8002*
4	-0.8079	-0.2192†	-0.2336	0.4423	-0.0565	-0.9777	0.6156
5	-0.4547	-0.2201	-0.4657	0.4534	0.2334	0.0987	-1.7486
6	0.7742†	0.1511	-0.4067	0.0272	0.2079	0.2033	0.3951
7	-1.8031	-0.2381	-0.3900	-0.2619	-1.1293	-0.4944	-0.4973
8	-0.8433	-0.0836	-0.4084	-0.0180	-1.2816	-0.2971	1.8650
9	-0.5098†	-0.0539	-0.1963†	-0.5383*	-0.2477	-0.0247	0.3584
10	0.1607	0.1261	0.1214‡	-0.6218‡	0.1376†	0.1495	0.2314
11	-0.0370†	0.0252	-0.0309†	-0.3035†	0.2780	0.1797‡	0.8572
12	-3.7296*	0.4861*	-0.0134	-0.9071	0.3488	0.0531	0.4827
13	0.1183	-0.7332*	-0.1055*	0.0142	0.2023*	0.1165*	-0.3699
14	-0.0377	0.0673‡	-1.0603*	0.3821	-0.1866	-0.7928	-0.5831
15	0.1920	0.0269	-0.2004	-15.6128*	1.2074†	-0.3313	-1.2931
16	0.0611	0.1898	0.0467	0.1281	-1.2232*	0.0537	0.3570
17	0.0902	0.0454	0.1939	0.3729	0.1814	-1.2417*	1.1128*
18	-3.2928	0.4463	0.0045	0.4982	-5.6016	0.5677	34.3132

Note: $i, j = 1, 2, \ldots, 18$, where 1 = Beefsteak, 2 = Ground Beef, 3 = Other Beef, 4 = Beef Offal, 5 = Pork Steak, 6 = Pork Leg & Shoulder, 7 = Ground Pork, 8 = Other Pork, 9 = Chorizo, 10 = Ham, Bacon & Similar Products from Beef & Pork, 11 = Beef & Pork Sausages, 12 = Other Processed Beef & Pork, 13 = Chicken Legs, Thighs & Breasts, 14 = Whole Chicken, 15 = Chicken Offal, 16 = Chicken Ham & Similar Products, 17 = Fish, 18 = Shellfish. Number of bootstrap resamples = 1,000. Bootstrap significance levels of 0.05, 0.10 and 0.20 are indicated by asterisks (*), double daggers (‡) and daggers (†) respectively.

Table D.5: Marshallian Price Elasticities in the Central-West Region.

Table entries estimate e_{ij}.

i\j	1	2	3	4	5	6	7	8	9	10	11
1	-0.9436*	0.1660†	-0.3956*	-0.1309	0.0978†	-0.2598*	-0.2000	0.0209	0.0098	-0.0087	-0.0191
2	0.4569*	-4.4337*	-0.1479	-0.1028	0.6117	0.5845†	0.4448	0.2252	-0.0308	0.0658	-0.1195
3	-1.7540*	0.5580	-2.6376*	0.1961	1.8163‡	-0.6123	-5.5472*	-1.4639‡	0.3282	0.0568	0.5010†
4	-2.0955	0.5431	-0.3989	-4.9841	-1.7711	1.0411	-1.8680	-0.2651	0.6266	-0.2776	0.5593
5	0.7756	-0.7732†	0.0873	-0.2470	-4.7654‡	-1.2809	-1.8210	0.7555	-0.4304	-0.6420*	0.1063
6	-1.1230*	-0.4883†	0.0155	0.4195†	-0.8680	-4.6568‡	0.9811‡	0.2011	-0.1568	-0.2963†	0.0579
7	-1.9426	-0.4573	0.1880	-0.1955	-2.1542	-0.6843	-19.3798†	-0.0758	0.3559	-0.2367	0.4062
8	-0.1383	0.5024	0.3244	0.3655†	1.5689†	1.9086	-2.1358	-8.8904†	0.6143	0.0673	0.5507
9	0.1561	-0.0769	0.1199	-0.1193	1.1844	-0.2987	-0.1027	-0.0956	-1.2835*	-0.5612	-0.0819
10	0.2350†	-0.7647*	0.4324*	-0.2112	0.2303	0.1693	-1.3581*	0.1063	0.0522†	-0.7496*	0.2650*
11	-0.4466*	-0.2303	0.2286*	-0.6356*	1.2675*	-1.1723*	0.8677‡	0.8461*	0.1012*	-0.0407	-2.0079†
12	0.1182	-0.5775*	0.0465	-0.8204*	-1.7768*	-0.0166	0.4953	-0.2923	0.0745	-0.4571*	0.0386
13	-0.4366	-0.0089‡	0.0478	-0.5733*	0.4873	0.5320‡	1.1440	-0.0845‡	0.0914	0.2847	-0.0089
14	0.4530†	-0.4042	-0.2520†	-0.1682	-0.0101	0.1151	-0.2684	0.0588	-0.0939	-0.2463‡	-0.1153
15	0.0908	-0.3078	-0.0321	0.7176	0.6369	1.8457	-1.3308	0.1362	-2.2515‡	-2.2966	2.0564
16	-0.0774	0.2767	0.0063	0.2063†	2.3403*	0.2713	-2.0573*	0.8395†	0.0441	0.1072	0.2784†
17	-0.0352	-0.1130	0.0627	-0.1219	0.9845*	-0.6765	-1.7458*	0.1660	-0.0694	0.2404†	0.1121
18	-1.0169*	0.6113*	-0.5305‡	0.4037*	1.2319*	0.1912	0.8225*	-0.5872†	0.0476	0.2790*	0.4542*

Note: $i, j = 1, 2, \ldots, 18$, where 1 = Beefsteak, 2 = Ground Beef, 3 = Other Beef, 4 = Beef Offal, 5 = Pork Steak, 6 = Pork Leg & Shoulder, 7 = Ground Pork, 8 = Other Pork, 9 = Chorizo, 10 = Ham, Bacon & Similar Products from Beef & Pork, 11 = Beef & Pork Sausages, 12 = Other Processed Beef & Pork, 13 = Chicken Legs, Thighs & Breasts, 14 = Whole Chicken, 15 = Chicken Offal, 16 = Chicken Ham & Similar Products, 17 = Fish, 18 = Shellfish. Number of bootstrap resamples = 1,000. Bootstrap significance levels of 0.05, 0.10 and 0.20 are indicated by asterisks (*), double daggers (‡) and daggers (†) respectively.

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Table D.5: *Continued*

Table entries estimate e_{ij}.

i\j	12	13	14	15	16	17	18
1	-0.0214	-0.2842*	-0.0378	0.0211	-0.1281*	-0.0367	-0.4696*
2	0.0145	0.0216	0.3340	0.1045†	-0.1208	-0.1302	-0.9804*
3	-0.2017†	-0.5183*	-0.0053	0.2902	0.2305	-0.2902	-0.6559†
4	-0.7280	-0.8462	-0.5750	0.5457	-0.2388	-1.6487	1.2438
5	-0.1391	-0.1942	-0.6601†	0.2225	0.8141†	0.0215	-0.9514†
6	0.4278*	0.1195	-0.5171*	0.0201	0.1537	0.1589*	0.1896
7	-1.1316†	-0.1600	-0.6514	-0.3457	-0.2044	-0.4225	-0.7092
8	-0.3516	-0.2611	-0.4310†	0.0546	-0.9067	-0.2270	0.4544
9	-0.2968†	-0.1656	-0.2611†	-0.3087*	-0.2709	-0.0601	0.2228
10	0.1647	0.1135	0.1475†	-0.4469*	0.2007	0.0930*	0.4048
11	-0.2111*	-0.0099	-0.2184‡	-0.3014	0.2836	0.3058*	0.4272
12	-1.9184*	0.4914*	-0.0169	-0.4097	0.1858	0.0239	0.1880
13	0.1436	-2.2288*	-0.2813‡	-0.0508	0.2931†	0.0877	0.0631*
14	0.0363	0.0427	-1.6940*	0.1848*	0.0053	-0.8028*	0.0282
15	0.1010	-0.0707	-0.3125	-10.3498*	1.2341	-0.3583	-1.0189
16	0.0350	0.2391	0.0360	0.0756	-1.5287*	0.0322	0.3659
17	0.0382	-0.0599	0.1613	0.2185*	0.1401	-1.0139*	0.6425*
18	-0.1384	-0.1602	-0.0393	0.2524*	0.8397	0.0577	-6.3271*

Note: $i, j = 1, 2, \ldots, 18$, where 1 = Beefsteak, 2 = Ground Beef, 3 = Other Beef, 4 = Beef Offal, 5 = Pork Steak, 6 = Pork Leg & Shoulder, 7 = Ground Pork, 8 = Other Pork, 9 = Chorizo, 10 = Ham, Bacon & Similar Products from Beef & Pork, 11 = Beef & Pork Sausages, 12 = Other Processed Beef & Pork, 13 = Chicken Legs, Thighs & Breasts, 14 = Whole Chicken, 15 = Chicken Offal, 16 = Chicken Ham & Similar Products, 17 = Fish, 18 = Shellfish. Number of bootstrap resamples = 1,000. Bootstrap significance levels of 0.05, 0.10 and 0.20 are indicated by asterisks (*), double daggers (‡) and daggers (†) respectively.

Table D.6: Hicksian Price Elasticities in the Central-West Region.

Table entries estimate e^c_{ij}.

i\j	1	2	3	4	5	6	7	8	9	10	11
1	-0.7157*	0.2049‡	-0.3500*	-0.1248	0.1106†	-0.2225*	-0.1963	0.0707‡	0.0399*	0.0373†	0.0002
2	0.6218*	-4.4056*	-0.1150	-0.0984	0.6209	0.6115†	0.4476	0.2612	-0.0090	0.0991	-0.1056
3	-1.5150*	0.5988†	-2.5898*	0.2025	1.8297‡	-0.5731	-5.5432*	-1.4117‡	0.3598	0.1050	0.5212†
4	-1.8942	0.5775	-0.3587	-4.9787	-1.7598	1.0741	-1.8647	-0.2212	0.6531	-0.2370	0.5763
5	0.8869	-0.7542†	0.1095	-0.2440	-4.7592‡	-1.2627	-1.8191	0.7798	-0.4158	-0.6195*	0.1158
6	-0.9923*	-0.4660†	0.0416	0.4230*	-0.8607	-4.6354‡	0.9833‡	0.2297	-0.1395	-0.2700†	0.0689
7	-1.9092	-0.4516	0.1947	-0.1946	-2.1523	-0.6788	19.3792†	-0.0685	0.3603	-0.2299	0.4090
8	0.0207	0.5295	0.3561	0.3698†	1.5778†	1.9346	-2.1332	-8.8556	0.6353	0.0993	0.5641
9	0.3234†	-0.0483	0.1534	-0.1148	1.1938	-0.2713	-0.0999	-0.0591	-1.2614*	-0.5275	-0.0678
10	0.3546*	-0.7443*	0.4563*	-0.2080	0.2370	0.1889	-1.3561*	0.1324	0.0680‡	-0.7255*	0.2751*
11	-0.3576‡	-0.2152	0.2464*	-0.6333*	1.2725*	-1.1577*	0.8692‡	0.8655*	0.1129*	-0.0228	-2.0004†
12	0.1912	-0.5650*	0.0611	-0.8184*	-1.7727*	-0.0046	0.4965	-0.2764	0.0841	-0.4424*	0.0447
13	-0.1822	0.0345‡	0.0987	-0.5665*	0.5016	0.5737‡	1.1482	-0.0289†	0.1250	0.3360†	0.0126
14	0.6573*	-0.3693	-0.2112	-0.1627	0.0013	0.1485	-0.2651	0.1034	-0.0670	-0.2051*	-0.0981
15	0.2882	-0.2741	0.0073	0.7229	0.6480	1.8780	-1.3275	0.1793	-2.2255‡	-2.2568	2.0731
16	0.0156	0.2926	0.0249	0.2088†	2.3455*	0.2865	-2.0557*	0.8598†	0.0563	0.1260	0.2863†
17	0.1530	-0.0809	0.1003	-0.1168	0.9950*	-0.6457†	-1.7426*	0.2071	-0.0446	0.2784‡	0.1280
18	-0.8735‡	0.6358*	-0.5018‡	0.4075†	1.2399†	0.2147	0.8249*	-0.5559†	0.0665	0.3079†	0.4663†

Note: $i, j = 1, 2, \ldots, 18$, where 1 = Beefsteak, 2 = Ground Beef, 3 = Other Beef, 4 = Beef Offal, 5 = Pork Steak, 6 = Pork Leg & Shoulder, 7 = Ground Pork, 8 = Other Pork, 9 = Chorizo, 10 = Ham, Bacon & Similar Products from Beef & Pork, 11 = Beef & Pork Sausages, 12 = Other Processed Beef & Pork, 13 = Chicken Legs, Thighs & Breasts, 14 = Whole Chicken, 15 = Chicken Offal, 16 = Chicken Ham & Similar Products, 17 = Fish, 18 = Shellfish. Number of bootstrap resamples = 1,000. Bootstrap significance levels of 0.05, 0.10 and 0.20 are indicated by asterisks (*), double daggers (‡) and daggers (†) respectively.

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Table D.6: *Continued*

Table entries estimate e^c_{ij}.

i\j	12	13	14	15	16	17	18
1	0.0184	-0.2308*	0.0753†	0.0267	-0.0959*	0.0470	-0.4333*
2	0.0433	0.0602	0.4158†	0.1086†	-0.0975	-0.0697	-0.9541*
3	-0.1600	-0.4622‡	0.1133	0.2961	0.2642	-0.2025	-0.6178
4	-0.6928	-0.7990	-0.4751	0.5507	-0.2104	-1.5748	1.2759
5	-0.1197	-0.1681	-0.6049†	0.2253	0.8298†	0.0623	-0.9337
6	0.4506*	0.1501	-0.4523*	0.0233	0.1721	0.2068*	0.2104
7	-1.1258†	-0.1522	-0.6348	-0.3449	-0.1997	-0.4103	-0.7038
8	-0.3238	-0.2238	-0.3521	0.0586	-0.8843	-0.1687	0.4797
9	-0.2676	-0.1263	-0.1780	-0.3045*	-0.2473	0.0013	0.2495
10	0.1856	0.1416†	0.2068*	-0.4439*	0.2176	0.1370*	0.4238
11	-0.1956*	0.0109	-0.1743†	-0.2992	0.2961	0.3384*	0.4414
12	-1.9057*	0.5086*	0.0194	-0.4079	0.1961	0.0507	0.1997
13	0.1880†	-2.1692*	-0.1551	-0.0445	0.3290†	0.1811	0.1037*
14	0.0719	0.0906	-1.5926*	0.1899*	0.0341	-0.7278*	0.0607
15	0.1355	-0.0245	-0.2145	-10.3449*	1.2620	-0.2858	-0.9875
16	0.0512	0.2609†	0.0822	0.0779	-1.5156*	0.0663	0.3807
17	0.0711	-0.0158	0.2547	0.2232*	0.1667	-0.9448*	0.6724*
18	-0.1134	-0.1266	0.0318	0.2560*	0.8600	0.1104	-6.3043*

Note: $i, j = 1, 2, \ldots, 18$, where 1 = Beefsteak, 2 = Ground Beef, 3 = Other Beef, 4 = Beef Offal, 5 = Pork Steak, 6 = Pork Leg & Shoulder, 7 = Ground Pork, 8 = Other Pork, 9 = Chorizo, 10 = Ham, Bacon & Similar Products from Beef & Pork, 11 = Beef & Pork Sausages, 12 = Other Processed Beef & Pork, 13 = Chicken Legs, Thighs & Breasts, 14 = Whole Chicken, 15 = Chicken Offal, 16 = Chicken Ham & Similar Products, 17 = Fish, 18 = Shellfish. Number of bootstrap resamples = 1,000. Bootstrap significance levels of 0.05, 0.10 and 0.20 are indicated by asterisks (*), double daggers (‡) and daggers (†) respectively.

Table D.7: Marshallian Price Elasticities in the Central Region.

Table entries estimate e_{ij}.

i\j	1	2	3	4	5	6	7	8	9	10	11
1	-1.1531*	0.2111†	-0.4878*	-0.1641	0.1269	-0.2931†	-0.2249	0.0285	0.0131	-0.0089	-0.0212
2	0.4871*	-3.8371*	-0.1248	-0.1295	0.4571	0.3742	0.5150	0.1420	-0.0215	0.0841	-0.0866
3	-1.4913*	0.2843	-2.0795*	0.2460	1.4271*	-0.5596	-4.2276*	-1.1733*	0.2102	0.0701	0.2765
4	-1.9248*	0.5183	-0.3683	-4.6191*	-1.4868	0.8399†	-1.6888	-0.2268	0.5499	-0.2605	0.4860
5	0.9421	-0.8812†	0.0809	-0.2347	-5.2140‡	-1.2564†	-2.0470†	0.8396†	-0.4810†	-0.6872†	0.0938
6	-1.3979†	-0.6226	0.0158	0.5109	-0.9056	-5.3797	1.1058	0.3471	-0.1839	-0.3724	0.0534
7	-1.7507	-0.4276	0.1703	-0.2187	-1.8646	-0.5403	-18.0162†	-0.0416	0.3311	-0.2459	0.3273
8	-0.1316	0.6376	0.3846	0.3457†	1.5852‡	2.0113†	-2.5387	-9.8240†	0.7292	0.1518	0.6202
9	0.1776	-0.1025	0.1009	0.0413	0.8353†	-0.4540†	0.1079	-0.1477	-1.0248*	-0.6467†	-0.0910
10	0.2561‡	-0.7885*	0.3959*	-0.2872	0.0286	0.2023	-1.5399†	0.1166	0.0319	-0.8684*	0.2592‡
11	-0.4210*	-0.2335†	0.2198*	-0.6151*	1.0988*	-0.9964*	0.8667‡	0.7514*	0.0922*	-0.0461	-1.7689†
12	0.1706	-0.8838	0.1122	-1.3110	-2.6001	0.0727	0.4854	-0.3956	0.1045	-0.6950	0.1737
13	-0.2394*	0.0494	0.0217	-0.3375*	0.2493†	0.3130	0.5404*	-0.0734	0.0490	0.1549*	-0.0007
14	0.4566†	-0.3530†	-0.4507	-0.0582†	-0.2850	-0.0848	-0.3228	-0.0853	-0.1171	-0.3889	-0.1117
15	0.0109	0.1246	0.0297	0.2705	0.5327	0.4553	-1.3444	0.1047	-1.4813	-2.0720	0.8149
16	-0.0561	0.2276	0.0821	0.0946	2.2096‡	0.2189	-1.8613*	0.6883	0.0563	0.1598	0.2460†
17	-0.0380	-0.1206	0.0650	-0.1242	1.0010‡	-0.6681†	-1.9177‡	0.1745	-0.0674	0.2748†	0.1155
18	-2.6324	1.4186	-1.7037	-0.0076	1.7695	0.8317	-0.1213	-1.2609	0.0320	0.4106	0.9647

Note: $i, j = 1, 2, \ldots, 18$, where 1 = Beefsteak, 2 = Ground Beef, 3 = Other Beef, 4 = Beef Offal, 5 = Pork Steak, 6 = Pork Leg & Shoulder, 7 = Ground Pork, 8 = Other Pork, 9 = Chorizo, 10 = Ham, Bacon & Similar Products from Beef & Pork, 11 = Beef & Pork Sausages, 12 = Other Processed Beef & Pork, 13 = Chicken Legs, Thighs & Breasts, 14 = Whole Chicken, 15 = Chicken Offal, 16 = Chicken Ham & Similar Products, 17 = Fish, 18 = Shellfish. Number of bootstrap resamples = 1,000. Bootstrap significance levels of 0.05, 0.10 and 0.20 are indicated by asterisks (*), double daggers (‡) and daggers (†) respectively.

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Table D.7: *Continued*

Table entries estimate e_{ij}.

i\j	12	13	14	15	16	17	18
1	-0.0330	-0.3051*	-0.0357	0.0211	-0.1669†	-0.0473	-0.6868*
2	-0.0424	-0.0150	0.2150	0.1029‡	-0.2007	-0.0986	-1.3811*
3	-0.1770†	-0.3648‡	0.0141	0.2206	0.1473	-0.2257	-0.8449‡
4	-0.7863	-0.6822	-0.4049†	0.3768	-0.2225	-1.5980†	1.3161
5	-0.1472	-0.1584	-0.5661†	0.1752‡	1.0179	0.0166	-1.1329†
6	0.6620*	0.1240	-0.4725	0.0083	0.2247	0.1873	0.4432
7	-1.2375	-0.1208	-0.4678	-0.2465	-0.1426	-0.4098	-0.7702
8	-0.4511	-0.2069	-0.3349†	0.0214	-0.9803†	-0.2543†	0.7882
9	-0.3777*	-0.1671	-0.1926‡	-0.1997*	-0.4939*	-0.0458	-0.0948
10	0.2545	0.0957	0.1241‡	-0.3415*	0.2598	0.0711†	0.6616
11	-0.2584*	-0.0098	-0.1703‡	-0.2143	0.2552	0.3133*	0.3958
12	-3.7557*	0.7306*	-0.0372	-0.5845*	0.4498	0.0458	0.5246
13	0.1090	-1.2052*	-0.1236*	-0.0310	0.1738*	0.0477‡	0.1594
14	-0.0089	0.0035	-1.3441*	0.1884	-0.1542	-0.9811‡	-0.3002
15	0.1747	-0.1252	-0.1459	-5.1443*	0.8922	-0.3804	-0.1721
16	0.0495	0.2207	0.0376	0.1099	-1.2985*	0.0509	0.0933
17	0.0488	-0.0575	0.1362	0.1791‡	0.1503	-1.2175*	0.8507*
18	0.4450	-0.3920	-0.0530	0.2424	3.1034	-0.0673	-20.3552

Note: $i, j = 1, 2, \ldots, 18$, where 1 = Beefsteak, 2 = Ground Beef, 3 = Other Beef, 4 = Beef Offal, 5 = Pork Steak, 6 = Pork Leg & Shoulder, 7 = Ground Pork, 8 = Other Pork, 9 = Chorizo, 10 = Ham, Bacon & Similar Products from Beef & Pork, 11 = Beef & Pork Sausages, 12 = Other Processed Beef & Pork, 13 = Chicken Legs, Thighs & Breasts, 14 = Whole Chicken, 15 = Chicken Offal, 16 = Chicken Ham & Similar Products, 17 = Fish, 18 = Shellfish. Number of bootstrap resamples = 1,000. Bootstrap significance levels of 0.05, 0.10 and 0.20 are indicated by asterisks (*), double daggers (‡) and daggers (†) respectively.

Table D.8: Hicksian Price Elasticities in the Central Region.

Table entries estimate e^c_{ij}.

i\j	1	2	3	4	5	6	7	8	9	10	11
1	-0.9497*	0.2682‡	-0.4125*	-0.1452	0.1437	-0.2702†	-0.2177	0.0951	0.0527†	0.0663	0.0046
2	0.6063*	-3.8036*	-0.0807	-0.1184	0.4670	0.3876	0.5192	0.1811	0.0017	0.1281†	-0.0715
3	-1.3294*	0.3298	-2.0195*	0.2611	1.4405*	-0.5414	-4.2219*	-1.1202*	0.2417	0.1299	0.2970†
4	-1.7918*	0.5557	-0.3190	-4.6067*	-1.4758	0.8549†	-1.6841	-0.1832	0.5759	-0.2114	0.5029
5	1.0295	-0.8567†	0.1132	-0.2266	-5.2068‡	-1.2466†	-2.0439†	0.8683†	-0.4640	-0.6550†	0.1049
6	-1.2840†	-0.5907	0.0579	0.5215	-0.8962	-5.3669	1.1099	0.3845	-0.1617	-0.3303	0.0679
7	-1.7294	-0.4216	0.1782	-0.2168	-1.8629	-0.5379	-18.0155‡	-0.0347	0.3352	-0.2380	0.3300
8	-0.0111	0.6714	0.4292	0.3569†	1.5951‡	2.0249†	-2.5344	-9.7845†	0.7527	0.1963	0.6355
9	0.2911‡	-0.0706	0.1429	0.0519	0.8447†	-0.4412	0.1119	-0.1104	-1.0027*	-0.6048†	-0.0766
10	0.3454*	-0.7634*	0.4290*	-0.2789	0.0360	0.2124	-1.5368†	0.1459	0.0494	-0.8354*	0.2705‡
11	-0.3595‡	-0.2162	0.2426*	-0.6094*	1.1039*	-0.9895*	0.8689‡	0.7716*	0.1042*	-0.0234	-1.7611†
12	0.2446	-0.8630	0.1396†	-1.3041	-2.5940	0.0811	0.4880	-0.3714	0.1190	-0.6677	0.1831
13	-0.1355†	0.0785	0.0601	-0.3278*	0.2579†	0.3247	0.5440*	-0.0393	0.0693†	0.1932*	0.0125
14	0.6259‡	-0.3054†	-0.3880	-0.0425†	-0.2711	-0.0657	-0.3168	-0.0298	-0.0841	-0.3264	-0.0902
15	0.1040	0.1508	0.0641	0.2792	0.5404	0.4658	-1.3411	0.1352	-1.4631	-2.0376	0.8267
16	0.0125	0.2468	0.1075	0.1010	2.2153‡	0.2266	-1.8589*	0.7108†	0.0697	0.1851	0.2547†
17	0.1131	-0.0782	0.1209	-0.1101	1.0135*	-0.6511†	-1.9123‡	0.2241	-0.0379	0.3306‡	0.1347
18	-2.4553	1.4683	-1.6381	0.0089	1.7841	0.8516	-0.1150	-1.2028	0.0665	0.4760	0.9872

Note: $i, j = 1, 2, \ldots, 18$, where 1 = Beefsteak, 2 = Ground Beef, 3 = Other Beef, 4 = Beef Offal, 5 = Pork Steak, 6 = Pork Leg & Shoulder, 7 = Ground Pork, 8 = Other Pork, 9 = Chorizo, 10 = Ham, Bacon & Similar Products from Beef & Pork, 11 = Beef & Pork Sausages, 12 = Other Processed Beef & Pork, 13 = Chicken Legs, Thighs & Breasts, 14 = Whole Chicken, 15 = Chicken Offal, 16 = Chicken Ham & Similar Products, 17 = Fish, 18 = Shellfish. Number of bootstrap resamples = 1,000. Bootstrap significance levels of 0.05, 0.10 and 0.20 are indicated by asterisks (*), double daggers (‡) and daggers (†) respectively.

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Table D.8: *Continued*

Table entries estimate e^c_{ij}.

i\j	12	13	14	15	16	17	18
1	0.0281	-0.0389	0.0411	0.0503	-0.1333	0.0522	-0.6785*
2	-0.0067	0.1409	0.2600†	0.1200*	-0.1810	-0.0403	-1.3763*
3	-0.1285	-0.1529	0.0753	0.2438	0.1741	-0.1465	-0.8383‡
4	-0.7464	-0.5081	-0.3547†	0.3959	-0.2005	-1.5329†	1.3215
5	-0.1210	-0.0441	-0.5332†	0.1877‡	1.0323	0.059 3	-1.1293†
6	0.6961*	0.2730	-0.4295	0.0246	0.2436	0.2430	0.4478
7	-1.2311	-0.0929	-0.4598	-0.2435	-0.1391	-0.3994	-0.7693
8	-0.4149	-0.0492	-0.2894	0.0386	-0.9604†	-0.1953	0.7931
9	-0.3436*	-0.0185	-0.1497†	-0.1834*	-0.4751*	0.0098	-0.0902
10	0.2814	0.2126‡	0.1578*	-0.3287*	0.2746	0.1148†	0.6653
11	-0.2400*	0.0708	-0.1470‡	-0.2055	0.2653	0.3434*	0.3982
12	-3.7335*	0.8275*	-0.0093	-0.5739*	0.4620	0.0820	0.5276
13	0.1401	-1.0693*	-0.0843*	-0.0162	0.1910*	0.0985*	0.1636
14	0.0419	0.2251*	-1.2801*	0.2126	-0.1262	-0.8983‡	-0.2933
15	0.2026	-0.0034	-0.1108	-5.1310*	0.9076	-0.3349	-0.1684
16	0.0701	0.3105	0.0635	0.1197	-1.2872*	0.0845	0.0961
17	0.0941	0.1402	0.1932	0.2008‡	0.1753	-1.1436*	0.8568*
18	0.4981	-0.1603	0.0138	0.2678	3.1327	0.0193	-20.3480

Note: $i, j = 1, 2, \ldots, 18$, where 1 = Beefsteak, 2 = Ground Beef, 3 = Other Beef, 4 = Beef Offal, 5 = Pork Steak, 6 = Pork Leg & Shoulder, 7 = Ground Pork, 8 = Other Pork, 9 = Chorizo, 10 = Ham, Bacon & Similar Products from Beef & Pork, 11 = Beef & Pork Sausages, 12 = Other Processed Beef & Pork, 13 = Chicken Legs, Thighs & Breasts, 14 = Whole Chicken, 15 = Chicken Offal, 16 = Chicken Ham & Similar Products, 17 = Fish, 18 = Shellfish. Number of bootstrap resamples = 1,000. Bootstrap significance levels of 0.05, 0.10 and 0.20 are indicated by asterisks (*), double daggers (‡) and daggers (†) respectively.

Table D.9: Marshallian Price Elasticities in the Southeast Region.

Table entries estimate e_{ij}.

i\j	1	2	3	4	5	6	7	8	9	10	11
1	-1.0845*	0.2048	-0.4489*	-0.2710	0.1878	-0.3375	-0.1464†	0.0475	0.0225	-0.0005	-0.0203
2	0.4754‡	-3.9687*	-0.1264	-0.2000	0.4895	0.4183	0.4662	0.1677	-0.0273	0.0833	-0.1091
3	-1.2456*	0.1718	-1.6340*	0.3775	1.2162*	-0.5134	-3.2342*	-1.0441*	0.1875	0.0684	0.2259
4	-2.4583*	0.7459	-0.4344	-9.8008*	-1.6661	1.0605†	-2.1658	-0.3058	1.0942	-0.3276	0.7900
5	0.6396	-0.6704†	0.0754	-0.3585	-3.7107†	-0.9784	-1.4222†	0.6187	-0.3947†	-0.5935†	0.1038
6	-1.1418*	-0.5034†	0.0107	0.6717‡	-0.7076	-4.6627†	0.8135†	0.3620	-0.1774	-0.3167†	0.0428
7	-1.7658	-0.4223	0.1682	-0.1939	-1.7212	-0.5666	-15.1776‡	-0.1026	0.3051	-0.1894	0.4405
8	-0.1356	0.2907	0.2052	0.6053*	1.1239*	1.0607*	-1.1806†	-5.5384*	0.3490	-0.0640	0.3769†
9	0.2221	-0.1334	0.1051	0.2295	0.8599†	-0.6625	0.2327	-0.2201	-1.3079*	-0.8461	-0.1360
10	0.2646†	-0.9382	0.5375	-0.3226	0.4052	0.1404	-1.3601*	0.1111	0.0848	-0.8844*	0.3433
11	-0.5279	-0.3922	0.2953	-1.4566	1.3854	-1.5455	1.6859	1.0946	0.1705	-0.1366	-2.4358
12	0.1234	-0.6162‡	0.0439	-1.4011*	-1.7205*	-0.0238	0.4994	-0.3014	0.0856	-0.5129*	0.0326
13	-0.3443†	-0.0382	0.0396	-0.7287*	0.3587	0.3466†	0.8816*	-0.0475	0.0783	0.2451*	-0.0104
14	0.3115†	-0.3050	-0.1127	-0.2470	0.0782	0.1296	-0.1556	0.0849	-0.0614	-0.1399‡	-0.0872
15	0.1504	-0.5515	-0.0580	1.9119	0.9053	2.7177	-1.8516	0.2059	-3.8627	-3.7620	3.6584
16	-0.0662	0.2515	0.0373	0.2531	2.1594*	0.2301	-1.8015*	0.7646	0.0549	0.1346	0.2926†
17	-0.0316	-0.1192	0.0642	-0.2205	0.7727*	-0.4820‡	-1.2921*	0.1262	-0.0788	0.2091‡	0.1077
18	-1.1544*	0.6806*	-0.6355†	0.5053*	1.1395*	0.2555	0.5653*	-0.6347‡	0.0454	0.2911*	0.5481*

Note: $i, j = 1, 2, \ldots, 18$, where 1 = Beefsteak, 2 = Ground Beef, 3 = Other Beef, 4 = Beef Offal, 5 = Pork Steak, 6 = Pork Leg & Shoulder, 7 = Ground Pork, 8 = Other Pork, 9 = Chorizo, 10 = Ham, Bacon & Similar Products from Beef & Pork, 11 = Beef & Pork Sausages, 12 = Other Processed Beef & Pork, 13 = Chicken Legs, Thighs & Breasts, 14 = Whole Chicken, 15 = Chicken Offal, 16 = Chicken Ham & Similar Products, 17 = Fish, 18 = Shellfish. Number of bootstrap resamples = 1,000. Bootstrap significance levels of 0.05, 0.10 and 0.20 are indicated by asterisks (*), double daggers (‡) and daggers (†) respectively.

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Table D.9: *Continued*

Table entries estimate e_{ij}.

i\j	12	13	14	15	16	17	18
1	-0.0374	-0.3202*	-0.0421	0.0458	-0.1989	-0.0366	-0.6399
2	-0.0261	-0.0069	0.2764	0.1656	-0.1864	-0.0897	-1.1061‡
3	-0.1352	-0.3295*	0.0214	0.3370	0.1115	-0.1475	-0.6530‡
4	-0.8298	-0.9856	-0.6046†	0.8118	-0.3167	-1.5917‡	1.5286
5	-0.1417	-0.1656	-0.5287‡	0.2478	0.7021	0.0174	-0.7949
6	0.5389*	0.1085	-0.4625‡	0.0025	0.2077	0.1180†	0.3810
7	-1.1402	-0.1502	-0.5318	-0.3775	-0.2624	-0.3303	-0.5807
8	-0.3172	-0.2661†	-0.3650*	0.1153	-0.7663*	-0.1645	0.0641
9	-0.4467	-0.2321	-0.2755	-0.3758‡	-0.7367	-0.0367	-0.2623
10	0.1812	0.1351	0.1571	-0.6878	0.2060	0.1160	0.3401
11	-0.5482	-0.0319	-0.4217	-0.4714	0.1660†	0.3990	-0.1847
12	-2.2619*	0.4874*	-0.0148	-0.5357‡	0.1883†	0.0213	0.1757
13	0.1214	-1.6193*	-0.2071*	-0.0421	0.2362‡	0.0625	-0.0096
14	0.0439	0.0399	-1.0937*	0.1400*	0.0540	-0.4550*	0.1040
15	0.1643	-0.0902	-0.4653	-20.9676*	2.0101	-0.4729	-1.6364
16	0.0424	0.2307	0.0385	0.1343	-1.4547*	0.0335	0.2288
17	0.0401	-0.0500	0.1306	0.2493*	0.1405†	-0.6737*	0.4371‡
18	-0.0581	-0.1809	-0.0379	0.3098*	1.1394	0.0305	-7.1793*

Note: $i, j = 1, 2, \ldots, 18$, where 1 = Beefsteak, 2 = Ground Beef, 3 = Other Beef, 4 = Beef Offal, 5 = Pork Steak, 6 = Pork Leg & Shoulder, 7 = Ground Pork, 8 = Other Pork, 9 = Chorizo, 10 = Ham, Bacon & Similar Products from Beef & Pork, 11 = Beef & Pork Sausages, 12 = Other Processed Beef & Pork, 13 = Chicken Legs, Thighs & Breasts, 14 = Whole Chicken, 15 = Chicken Offal, 16 = Chicken Ham & Similar Products, 17 = Fish, 18 = Shellfish. Number of bootstrap resamples = 1,000. Bootstrap significance levels of 0.05, 0.10 and 0.20 are indicated by asterisks (*), double daggers (‡) and daggers (†) respectively.

Table D.10: Hicksian Price Elasticities in the Southeast Region.

Table entries estimate e^c_{ij}.

i\j	1	2	3	4	5	6	7	8	9	10	11
1	-0.9211*	0.2443†	-0.3683*	-0.2499	0.2214	-0.2916	-0.1379	0.1370	0.0547	0.0283	-0.0089
2	0.5725*	-3.9453*	-0.0786	-0.1874	0.5094	0.4455	0.4713	0.2208	-0.0082	0.1004	-0.1023
3	-1.1307*	0.1996	-1.5773*	0.3923	1.2398*	-0.4812	-3.2283*	-0.9812*	0.2102	0.0887	0.2339
4	-2.3314*	0.7766	-0.3719	-9.7844*	-1.6400	1.0961†	-2.1593	-0.2363	1.1192	-0.3053	0.7989
5	0.6957	-0.6568	0.1031	-0.3512	-3.6992†	-0.9626	-1.4193†	0.6494†	-0.3836†	-0.5836	0.1077
6	-1.0671*	-0.4853†	0.0476	0.6813‡	-0.6923	-4.6417†	0.8174†	0.4029	-0.1626	-0.3036†	0.0480
7	-1.7472	-0.4178	0.1774	-0.1915	-1.7174	-0.5614	-15.1767‡	-0.0924	0.3087	-0.1861	0.4418
8	-0.0567	0.3098	0.2441	0.6155*	1.1401*	1.0828*	-1.1765†	-5.4951*	0.3645	-0.0501	0.3824†
9	0.3288	-0.1076	0.1577	0.2433	0.8819†	-0.6325	0.2382	-0.1617	-1.2869*	-0.8273	-0.1286
10	0.3477†	-0.9181	0.5785	-0.3118	0.4222	0.1637	-1.3558*	0.1566	0.1012	-0.8698*	0.3491
11	-0.4564	-0.3749	0.3306	-1.4474	1.4001	-1.5254	1.6896	1.1337	0.1846	-0.1240	-2.4309
12	0.1688	-0.6052‡	0.0663	-1.3952*	-1.7112*	-0.0111	0.5018	-0.2765	0.0946	-0.5049*	0.0358
13	-0.2267	-0.0097	0.0976	-0.7135‡	0.3828	0.3796†	0.8877*	0.0169	0.1015	0.2659*	-0.0022
14	0.3897*	-0.2861	-0.0741	-0.2369	0.0943	0.1515	-0.1515	0.1278	-0.0459	-0.1261‡	-0.0818
15	0.3332	-0.5073	0.0321	1.9355	0.9428	2.7690	-1.8422	0.3060	-3.8267	-3.7298	3.6712
16	-0.0121	0.2646	0.0639	0.2601	2.1705*	0.2453	-1.7986*	0.7942†	0.0655	0.1442	0.2964†
17	0.0598	-0.0971	0.1092†	-0.2087	0.7915*	-0.4563†	-1.2874*	0.1763	-0.0608	0.2252*	0.1141
18	-1.0687‡	0.7013*	-0.5932†	0.5164*	1.1571*	0.2796	0.5698*	-0.5878†	0.0623	0.3062*	0.5541*

Note: $i, j = 1, 2, \ldots, 18$, where 1 = Beefsteak, 2 = Ground Beef, 3 = Other Beef, 4 = Beef Offal, 5 = Pork Steak, 6 = Pork Leg & Shoulder, 7 = Ground Pork, 8 = Other Pork, 9 = Chorizo, 10 = Ham, Bacon & Similar Products from Beef & Pork, 11 = Beef & Pork Sausages, 12 = Other Processed Beef & Pork, 13 = Chicken Legs, Thighs & Breasts, 14 = Whole Chicken, 15 = Chicken Offal, 16 = Chicken Ham & Similar Products, 17 = Fish, 18 = Shellfish. Number of bootstrap resamples = 1,000. Bootstrap significance levels of 0.05, 0.10 and 0.20 are indicated by asterisks (*), double daggers (‡) and daggers (†) respectively.

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Table D.10: *Continued*

Table entries estimate e^c_{ij}.

i\j	12	13	14	15	16	17	18
1	0.0214	-0.2018*	0.2087*	0.0597	-0.1639	0.0890	-0.5898
2	0.0088	0.0633	0.4254†	0.1739	-0.1656	-0.0151	-1.0764†
3	-0.0939	-0.2463†	0.1977‡	0.3468	0.1361	-0.0592	-0.6179‡
4	-0.7841	-0.8937	-0.4099	0.8226	-0.2895	-1.4941‡	1.5675
5	-0.1215	-0.1249	-0.4426†	0.2526	0.7141	0.0605	-0.7777
6	0.5658*	0.1626	-0.3478†	0.0089	0.2237	0.1755‡	0.4039
7	-1.1335	-0.1367	-0.5032	-0.3759	-0.2584	-0.3159	-0.5750
8	-0.2888	-0.2089	-0.2439†	0.1220	-0.7494*	-0.1038	0.0883
9	-0.4083	-0.1548	-0.1118	-0.3667‡	-0.7139	0.0454	-0.2296
10	0.2111	0.1953	0.2847	-0.6808	0.2238	0.1799	0.3655
11	-0.5225	0.0199	-0.3121	-0.4654	0.1813†	0.4540	-0.1628
12	-2.2455*	0.5203*	0.0549	-0.5318‡	0.1980†	0.0562	0.1896
13	0.1637†	-1.5341*	-0.0266	-0.0321	0.2614*	0.1529*	0.0264
14	0.0721	0.0966	-0.9736*	0.1466*	0.0708	-0.3948*	0.1280
15	0.2301	0.0422	-0.1847	-20.9521*	2.0493	-0.3323	-1.5804
16	0.0618	0.2699	0.1215	0.1389	-1.4431*	0.0751	0.2454
17	0.0730	0.0163	0.2710†	0.2571*	0.1601†	-0.6034*	0.4652‡
18	-0.0273	-0.1188	0.0937	0.3171*	1.1578	0.0964‡	-7.1531*

Note: $i, j = 1, 2, \ldots, 18$, where 1 = Beefsteak, 2 = Ground Beef, 3 = Other Beef, 4 = Beef Offal, 5 = Pork Steak, 6 = Pork Leg & Shoulder, 7 = Ground Pork, 8 = Other Pork, 9 = Chorizo, 10 = Ham, Bacon & Similar Products from Beef & Pork, 11 = Beef & Pork Sausages, 12 = Other Processed Beef & Pork, 13 = Chicken Legs, Thighs & Breasts, 14 = Whole Chicken, 15 = Chicken Offal, 16 = Chicken Ham & Similar Products, 17 = Fish, 18 = Shellfish. Number of bootstrap resamples = 1,000. Bootstrap significance levels of 0.05, 0.10 and 0.20 are indicated by asterisks (*), double daggers (‡) and daggers (†) respectively.

Table D.11: Expenditure Elasticities by Region.

Table entries estimate e_i.

	i	*NE*	*NW*	*CW*	*C*	*SE*	Mexico	Min.	Max.
1	Beefsteak	0.8742*	0.9057*	0.8184*	1.1049*	1.0867*	0.9733*	0.8184	1.1049
2	Ground Beef	0.5222*	0.3704*	0.5922*	0.6475*	0.6453*	0.5228*	0.3704	0.6475
3	Other Beef	0.5787*	0.5724*	0.8583*	0.8796*	0.7639*	0.7260*	0.5724	0.8796
4	Beef Offal	0.5313†	0.4641	0.7229	0.7228†	0.8438†	0.6413*	0.4641	0.8438
5	Pork Steak	0.5297	0.4477	0.3996*	0.4745‡	0.3732	0.3904*	0.3732	0.5297
6	Pork Leg & Shoulder	0.5069	0.5108	0.4694*	0.6184	0.4970*	0.5141*	0.4694	0.6184
7	Ground Pork	0.1627	0.2301	0.1200	0.1157	0.1238	0.1846	0.1157	0.2301
8	Other Pork	0.6221	0.8524	0.5710*	0.6548*	0.5250*	0.5776*	0.5250	0.8524
9	Chorizo	0.4827‡	0.7047*	0.6009*	0.6167*	0.7097	0.6190*	0.4827	0.7097
10	Ham, Bacon & Similar B&P	0.4225*	0.3906*	0.4296*	0.4855*	0.5528	0.4547*	0.3906	0.5528
11	Beef & Pork Sausages	0.2863*	0.1905†	0.3193*	0.3343*	0.4752	0.2728*	0.1905	0.4752
12	Other Processed Beef & Pork	0.4342	0.2752	0.2622	0.4023	0.3019*	0.3570*	0.2622	0.4342
13	Chicken Legs, Thighs & Breasts	0.6409*	0.6139*	0.9135*	0.5642*	0.7824*	0.6142*	0.5642	0.9135
14	Whole Chicken	0.8404	0.7426	0.7335*	0.9199*	0.5205*	0.6761*	0.5205	0.9199
15	Chicken Offal	0.9125	0.7099	0.7088	0.5055*	1.2158*	0.6112*	0.5055	1.2158
16	Chicken Ham & Similar Products	0.2544	0.3018	0.3337*	0.3727	0.3600†	0.3354*	0.2544	0.3727
17	Fish	0.6018*	0.7926†	0.6759*	0.8210*	0.6085*	0.6970*	0.6018	0.8210
18	Shellfish	0.4392*	-0.1106	0.5148*	0.9619	0.5699*	0.4361*	-0.1106	0.9619

Note: Number of bootstrap resamples = 1,000. Bootstrap significance levels of 0.05, 0.10 and 0.20 are indicated by asterisks (*), double daggers (‡) and daggers (†) respectively.