How Meat Demand Elasticities Vary with Price, Income, and Product Category

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Abstract: As U.S. beef and pork prices approached record high levels in 2014, industry analysts expressed surprised at consumer response. Because the relative price swings have occurred only recently, traditional approaches to demand analysis that rely on historical data series may be less useful than is typically the case. Employing one of the largest and longest-running choice experiments, we analyze data on 110,295 choices made by 12,255 consumers observed over a year-long time period coinciding with historically high meat prices. Our findings reveal non-linear demands for meat products, with demand being more inelastic at higher prices. Ground beef, steak, and pork chop demands are more sensitive to changes in chicken breast price than the reverse. Moreover, cross-price elasticities between disaggregate meat products shrink as prices rise. Consumers' incomes significantly affect demand inter-relationships. Higher income consumers are more likely to choose steak and chicken breasts and are less likely to choose ground beef, chicken wings, and deli ham than are lower income consumers. High income consumers tend to be less responsive to own-price changes and more responsive to cross-price changes than lower income consumers. This analysis provides estimates of structural demand parameters that help explain current meat expenditure patterns, and the results have implications for the assumption of linearity often invoked in policy analyses.

Keywords: beef, chicken, choice experiment, heterogeneous consumers, meat demand, mixed logit, non-linear elasticities, pork

JEL Codes: Q11, Q18, D12, C83

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A confluence of events related to drought, high feed prices, disease, and growing global demand led to unprecedented rises in the prices of beef and pork in the U.S. Figure 1 provides some perspective on the recent changes. The Bureau of Labor Statistics reports ground beef prices were 54% higher (an annual increase of over 10%) and steak prices were 43% higher (an annual increase of 8.6%) in January 2015 as compared to January 2010. Pork chop and ham prices were 30% and 39% higher than they were in 2010 despite recent declines. By contrast, in January 2015, chicken prices were only about 10% higher than five previous (experiencing annual increases of only 1-2%). Although meat demand is one of the most studied issues in the agricultural economics literature (e.g., see the review in Unnevehr et al., 2010), prior demand estimates were generally obtained using historical disappearance data on aggregated products for "representative households" that lie outside the range of prices recently witnessed.

Industry observers have expressed surprise about how consumers have responded to recent price changes (Ishmael, 2014). In particular, expenditures for beef and pork have not fallen as much as some people expected given the high prices. Industry analysts have asked "where is the tipping point" when consumers will stop buying beef and pork (Rutherford, 2014), but it may be that demand elasticities are more non-linear than previously realized. Moreover, relative price swings would have seemed to have favored chicken over beef and pork, and yet there does not seem to be a high degree of substitution in the current market environment. Such observations raise the possibility that cross-price elasticities have changed or are lower at higher price levels. Finally, these meat price swings have occurred during and following a serious and prolonged economic recession. Amid contemporary discussions of income inequality have come questions about which segments of the population have been most affected by price increases and how substitution patterns might differ for the rich and the poor. Questions of income and price-sensitivities in light of current market outcomes diverging from expectations motivate this study.

One challenge faced in meat demand analysis is data quality and availability (Brester and Wohlgenant, 1993). Aggregate disappearance data are often used, but these data may not be perfectly correlated with actual consumption, are typically limited to aggregate categories, do not yield much information on heterogeneity in preferences, and are necessarily constrained by historical price ranges (Piggott and Marsh, 2004; Tonsor, Mintert, and Schroeder, 2010). Scanner data can provide more information on differential responses across different consumer types in a more timely manner, but for fresh meat, these data are typically "random weight" items, meaning one only observes the number of units sold without knowing the products' weights (Taylor and Tonsor, 2013). Either type of these data also pose challenges associated with endogeneity, aggregation, unobserved promotions and quality variation, measurement error, and frequency of observation (Lensing and Purcell, 2006). Many of these problems can be overcome with carefully designed choice experiments. Choice experiments have their own drawbacks, but coupling insights from timely choice experiment surveys with pre-existing insights from secondary data might provide a deeper understanding of the current meat demand environment.[1]

The overall purpose of this article is to determine consumer demand for cut-specific meat products in light of recent market conditions. Specifically, we aim to determine how: 1) own- and cross-price elasticities vary with the market price, 2) consumers substitute between different

[1] Possible drawbacks of choice experiments include the possibility for hypothetical bias , particularly in the propensity to choose the "none" option, framing effects resulting from the need to specify particular options and attribute levels and display them in a particular format, and selection effects that might arise if the survey sample doesn't match the population of interest. Overviews of the method and discussions of advantages and disadvantages of choice experiments can be found in Carlsson (2011), Holmes and Adamowicz (2003), and Louviere, Hensher, and Swait (2000).

cuts of meat at different price levels, 3) price sensitivities and substitution patterns vary across consumers with different incomes, and 4) models assuming linearity in price effects or restrictive substitution patterns mis-state consumer responses to meat price changes. To address these issues, we bring to bear what is perhaps one of the largest and longest-running choice experiments. We utilize data on 110,295 choices made by 12,255 consumers who responded to choice experiments conducted over a year-long time period concurrent with the historically high beef and pork prices.

The next section briefly reviews the research on meat demand and situates our work in that body of literature. Then, we describe our data and econometric methods. The penultimate section discusses results, and the last section concludes.

Synthesis of Existing Literature

Meat demand is complex and evolving as demand drivers emerge and change over time. Multiple factors work to collectively shape meat demand including traditional economic determinants such as relative prices and income as well as non-traditional determinants such as health, nutrition, and food safety information; changing product characteristics and new product developments; and shifts in consumer demographics and lifestyles (Tonsor, Mintert, and Schroder, 2010). Over time, new dimensions of demand may arise and the relative importance of previously examined determinants may adjust in response to new information and economic conditions. For example, the rise of high-protein diets, discovery of new health risks, or shifts in household work-home time allocation may alter structural demand parameters. Similarly, as meat prices change, so may the accuracy of elasticity estimates derived from past market situations. Hence, on-going demand estimation is important for informed decision-making by industry stakeholders and policy makers.

A large body of prior research has sought to investigate meat demand determinants (e.g., see Bryant and Davis 2008 or Gallett 2010 for integrative quantitative reviews of prior demand estimates). Unnevehr et al. (2010) and Piggott and Marsh (2011) provide some historical context for this work, much of which arose during a period in which researchers debated whether the fall (rise) in per-capita beef (poultry) consumption resulted from a change in relative prices or a shift in preferences (i.e., a structural shift). Prior research has identified a variety of potential demand shifters including food safety and product recall news (Mazzocchi, 2006; Piggott and Marsh, 2004; Marsh, Schroeder, and Mintert, 2004; Burton and Young, 1996), health and dietary information (Rickertsen, Kristofersson, and Lothe, 2003; Brown and Schrader, 1990; Chang and Kinnucan, 1991), and advertising (Brester and Schroeder, 1995; Kinnucan et al., 1997; Rickertsen, 1998; Piggott et al., 1996; Park and Capps, Jr., 2002).

More broadly, there are large literatures that have touched on some of the same themes of the present analysis, albeit using traditional demand systems with historical time series data. For example, researchers have studied separability between disaggregate meat products and aggregate categories (Eales and Unnevehr, 1988; Moschini, Moro, and Green 1994; Nayga and Capps, 1994), structural change (Eales and Unnevehr, 1988, 1993; Rickertsen, 1996; Moschini and Meilke, 1989; Davis, 1997), product aggregation (Brester and Wohlgenant, 1991; Schulz, Schroeder, and Xia, 2012; Coffey, Schroeder, and Marsh, 2010), and functional form (Banks, Blundell, and Lewbel, 1997; Beach and Holt, 2001; Golan, Perloff, and Shen, 2001; Kastens and Brester, 1996), among others.

More recently, the literature has expanded to include data from consumer experiments and surveys, often choice experiments. Beyond examining topical issues associated with credence attributes (e.g. Alfnes and Rickertsen, 2003; Lusk, Norwood, and Pruitt, 2006; Lusk, Roosen, and Fox, 2003), methodological inquiries applied to meat demand issues have focused on hypothetical bias (Lusk and Schroeder, 2004), beliefs and consumer inferences (Lusk et al., 2014), and the effects of question format (Carlsson et al., 2007; Gao and Schroeder, 2009; Tonsor, 2011), just to name a few. It is important to note that most of these studies provide "snap-shot" assessments, as they are conducted only at one point in time with a given set of study participants.

While this existing work provides a wealth of insights into meat demand, we are unaware of research conducted in the current era of high meat prices, focusing on own- and cross-price elasticities, disaggregated meat products, and income-effects.

Methods

The data utilized in this study come from the Food Demand Survey (FooDS) project that began in May 2013. FooDS tracks consumer preferences, food expenditures, price expectations, and awareness and concern for a variety of food issues. FooDS is an on-line survey with a sample size of at least 1,000 individuals each month. The survey is delivered on the 10th of the month unless that date falls on a weekend, in which case it is moved to the next closest Monday. The requisite sample size is typically acquired within three days. The data collected do not constitute a panel because a new sample is drawn each month; however, precisely the same questions are posed each month. The survey is administered to an opt-in panel maintained by Survey Sampling International, and participants receive points worth about $1.50 for participating.

Participants can redeem accumulated points for cash or various goods like frequent flyer miles, electronics, or sports equipment.

We make use of the data collected from the year-long time period from June 2013 through June 2014. We omitted the May 2013 data because the order of appearance of the products used in the choice experiment were not randomized in that initial survey as they were in all the remaining issuances, and we stopped in June 2014 so that we could begin to estimate the models reported here. The final dataset used for this analysis consists of 110,290 choices made by 12,255 people. The appendix shows the demographic make-up of the sample and compares it to the US population. The levels of income, age, gender, ethnicity, region of residence, household size, and food stamp participation in our FooDS sample is very similar to that for the general U.S. population; the largest divergence is for education as our sample has more college graduates (45%) than the US population (28%).

The data that serve as the focal point of this analysis come from a choice experiment delivered each month. As noted earlier, choice experiments are widely used in the meat demand literature, but their applications in the economics literature often focus on estimating willingness-to-pay for specific quality attributes rather than estimating demand elasticities or substitution patterns *per se*. Choice experiments have been found to yield results that are predictive of and broadly consistent with actual retail purchasing patterns (Brooks and Lusk, 2010; Chang, Lusk, and Norwood, 2009; Louviere, Hensher, and Swait, 2000), though as with all surveys there are concerns with the extent to which people will actually behave as they say they will – a problem in choice experiments that seems to be most related to the decision of whether to buy or not rather than which product to buy conditional on a choice (Lusk and Schroeder, 2004).

In our choice experiment, each subject answered nine choice questions like the one illustrated in figure 2. Preceding the set of questions was the verbiage: "Imagine you are at the grocery store buying the ingredients to prepare a meal for you or your household. For each of the nine questions that follow, please indicate which meal you would be most likely to buy." Each of the choice questions was identical except the prices varied across each question. Each question had nine options (two beef, two pork, two chicken, two non-meat, and one "no purchase" alternative) and the price of each option was varied at three levels. For each meat type, we chose a higher-value product (steak, pork chop, chicken breast) and a lower-value product (ground beef, deli ham, and chicken wing) to investigate substitution not only across meat species but also within species. We purposely included two non-meat products in the choice experiment to allow for shifts out of meat to not be necessarily forced into the no-purchase option as this more accurately reflects grocery store experiences.

Rather than presenting respondents with choices involving all possible price combinations that could exist, we selected a subset of choices (or a fractional factorial design) such that the prices of each choice alternative were uncorrelated with each other alternative (i.e., there is no multicollinearity). This so-called "main effects orthogonal fractional factorial design" (see Louviere, Hensher, and Swait, 2000; Lusk and Norwood, 2005) required 27 choices. The 27 choices were blocked into three sets of nine, and each person was randomly assigned to one of the three blocks. The design is able to identify non-linearity in the price effect (because there are three levels) and it allows the price effects to vary for each alternative. When implementing the survey, the order in which the alternatives were presented was randomly varied across respondents (e.g., some people saw ground beef as the first in the set, others saw chicken breast first in the set, etc.). The mid-point of the price levels for each product were chosen to be roughly similar to market prices when the project was initiated, and the higher and lower levels were \$1.50 above and below the mid-point.[2] The appendix shows the precise price levels used for each alternative, compares them to actual retail prices over this time period, and shows the full experimental design.

Econometric Methods

We analyze the choice data through the lenses of a random utility model (McFadden, 1973). In particular, consumer *i* derives the following utility from choice option *j*: $U_{ij} = V_{ij} + \varepsilon_{ij}$. If the ε_{ij} follow a Type I extreme value distribution and are independently and identically distributed across *i* and *j*, then the conventional multinomial logit model (MNL) results:

(1) $$\text{Prob}(i \text{ chooses } j) = \frac{e^{V_{ij}}}{\sum_{k=1}^{9} e^{V_{ik}}}.$$

The MNL imposes restrictive substitutions pattern across alternatives that are particularly undesirable in this application (all cross-price elasticities for an alternative are identical due to the independence of irrelevant alternatives (IIA) property of the MNL). Moreover, many applications of random utility models utilize functional forms for V_{ij} (the deterministic component of utility function) that assume that the marginal utility of a price change is constant (i.e., the utility function is linear in price) and is identical for all alternatives. Fortunately, one can rely on the simple structure in (1) and relax the restrictive assumptions by modifying V_{ij}.

There are a variety of ways to relax the assumptions of the MNL, and we consider several approaches. It is useful to begin by considering the most basic utility specification:

[2] We chose to vary the difference in prices for each alternative by an equal amount (\$1.50) which could have produced a different result than varying prices by equal percentage amounts. We varied the prices using the same levels (not same percentages) because in the discrete choices models we consider, choices are driven by the differences in levels of attributes (not proportional differences). See Hanley et al. (2005) for evidence that choice of price levels has no influence on resulting implications.

(2) $V_{ij} = \beta_j + \alpha p_j,$

where p_j is the price of alternative j, α is the marginal utility of a price change, and β_j is an alternative specific constant indicating the utility of option j relative to the utility of the "no purchase" option which is normalized to zero for identification purposes. Some simple modifications to the utility function can allow more flexible price response patterns. For example, price responsive can be allowed to vary across alternatives by adding a j subscript to α, and by adding quadratic terms:

(3) $V_{ij} = \beta_j + \alpha_j p_j + \delta_j p_j^2.$

While adding a quadratic term (versus say a logarithmic term) might produce undesirable predictions (i.e., at some point the estimates will suggest people prefer paying higher prices), over the price ranges we consider here, we do not observe such anomalies, and as such we stick with this approximation. Although (3) is less restrictive than (2), the IIA property is still imposed.

We consider three different approaches to relax the IIA property. The first is the universal or mother logit (McFadden, Tye, and Train, 1977; Timmermans, Borgers, and van de Waerden, 1991) with quadratic price effects. The mother logit not only includes the price of alternative *j* in alternative *j*'s utility function but the price of all other alternatives in the choice set. The mother logit has the advantage of being easy to estimate while allowing highly flexible substitution patterns. It is specified as:

(4) $V_{ij} = \beta_j + \sum_{t=1}^{8} \alpha_{jt} p_t + \delta_j p_j^2.$

Despite its flexibility and ease of estimation, the mother logit may yield estimates that are inconsistent with utility maximization, and it results in a proliferation of parameters (in our case 56 more parameters than equation 3).

As a result, we also consider an error-component model (ECM) (DeJong et al., 2003; Scarpa, Ferrini, and Willis, 2005), which has the advantage of relaxing IIA in a more parsimonious manner while explicitly modeling the panel nature of the data (i.e., each person answered 9 choice questions, and it is assumed that their preferences are correlated over the choices). In general, the ECM can be written as:

(5) $$V_{ij} = \beta_j + \alpha_j p_j + \delta_j p_j^2 + \epsilon_{ij},$$

where ϵ_{ij} is a mean-zero Normally distributed error component for person i and alternative j. We parsimoniously summarize the error component in (5) with a single term, ϵ_{ij}, but in practice we consider specifications in which this term is made up of several additive error components that enter the utility function for multiple alternatives. In particular, we consider error components for: 1) all food products vs. the "none" alternative, 2) all meat products vs. non-meat products, 3) the two beef product alternatives, 4) the two pork product alternatives, 5) the two chicken product alternatives, 6) higher value meat products (steak, pork chop, chicken breast), and 7) lower value meat products (ground beef, deli ham, chicken wing). With the addition of just seven additional parameters (relative to equation 3), the ECM allows a much richer possibility of substitution possibilities. Still, the ECM requires the analyst to make judgment calls about how the error components enter the utility functions, which may not properly reflect consumers' preferences.

The final specification we consider is the mixed logit model, also known as the random parameter logit (RPL). The most general form of the RPL we consider is:

(6) $$V_{ij} = \left(\beta_j + \sum_{t=1}^{8} \omega_{jt} d_{it}\right) + \alpha_j p_j + \delta_j p_j^2 ,$$

where $d_{it} \sim N(0,1)$ and ω_{jt} are the elements of the lower-triangle of the Cholesky decomposition associated with the covariance matrix of the random parameters. Equation (6) posits a specification in which the eight alternative specific constants are distributed multivariate normal and in which correlations between each alternative specific constant are estimated. If the off-diagonals of the Cholesky matrix are assumed zero, then each alternative specific constant, β_j, is independently distributed. The advantage of the RPL is that, according to McFadden and Train (2000), it can approximate any random utility model to any degree of accuracy. However, the fully-correlated version of the model requires 60 parameters and, given our large sample size, is quite slow to estimate (requiring several days to reach convergence).

Given the robust set of models considered, we took the following approach for model selection. First, using the entire data set, we estimated the MNL, mother logit, ECM, and RPL models for utility specifications that included and excluded quadratic price effects, and except for the mother logit, models that assumed alternative-specific and alternative-independent price effects. The MNL and mother logit were estimated using conventional maximum likelihood estimation, whereas the ECM and RPL were estimated using simulated maximum likelihood techniques using 200 individual-specific quasi-random Halton draws (see Train (2009) for discussion on discrete choice estimation using simulation). Likelihood ratio tests are used to test the appropriateness of each utility specification within each model approach (i.e., whether $\alpha_j = \alpha \; \forall \; j$ and whether $\delta_j = 0$). In addition, a likelihood ratio test is used to determine whether the RPL model should include independent or correlated alternative-specific constants (i.e., whether $\omega_{jt} = 0 \; \forall \; j \neq t$). The Akaike Information Criteria (AIC) is used to select across the preferred MNL, mother logit, ECM, and RPL models. Finally, for the preferred specification, we split the sample into three income categories: low income (<\$40,000 in annual household income), middle income (between \$40,000 and \$99,999 in annual household income), and high income (≥ \$100,000 in annual household income), and re-estimate the preferred specification for each income category.[3] Likelihood ratio tests are used to test the hypothesis that the model parameters are identical for each income category.

Results

For the MNL, mother logit, ECM, and RPL models, likelihood ratio tests strongly reject the assumption of constant marginal utility in favor of including quadratic effects. Likelihood ratio tests also reject the assumption of alternative-independent price effects in favor of alternative-specific price effects. Thus, no matter the model specification (MNL, mother logit, ECM, or RPL), the data support non-linear price effects that vary with the type of product. Across specifications, the AIC suggests that the preferred specification is the RPL model with quadratic price effects and correlated alternative-specific constants. Moreover, within the RPL specification, likelihood ratio tests reject the assumptions of uncorrelated alternative specific constants and zero quadratic effects. The appendix shows the log-likelihood function and AIC values for each model as well as details on the likelihood ratio tests.

Table 1 reports the results for the preferred specification for the aggregate pooled model and for the three income classes. All parameters are of expected sign, and the results indicate significant differences in price responsiveness across different meat products, statistically significant quadratic price effects, and large covariances between random parameters (the appendix reports the correlation coefficients between random parameters implied by the variance-covariance estimates in table 1). To provide some insight into interpretation of

[3] In addition to income, it is possible to include other demographics like age, gender, and household size which might affect preferences. We do not do this here for several reasons. First, the RPL models allow for taste heterogeneity across households. So, heterogeneity is not ignored (it is a key aspect of the RPL model), rather it is not linked to observable demographics. Second, the addition of demographic variables quickly leads to parameter proliferation. For example, assume five additional demographic variables were considered. There are eight alternative specific constants (plus one normalized to zero), eight linear price effects, and eight quadratic price effects. This would mean an additional 5*(8+8+8)=120 coefficients would be estimated. While our sample size is sufficient to undertake this activity, succinctly report and summarize these findings would be a challenge.

estimates, consider the pooled model. The first coefficient in the model, 6.295, implies that the "average" consumer receives 6.295 more utils from ground beef than from buying nothing (the "none" option). Likewise, the "average" consumer receives 7.534 more utils from steak than "none." Thus, steak provides 7.532-6.295=1.239 more utils than ground beef (ignoring price differences). The price coefficients provide the marginal utility of a price change. A $1 increase in the price of ground beef, for example, causes a -1.437+0.094*$p_{ground\ beef}$ change in the utility derived from the ground beef option. Although the mean preference for ground beef over "none" is 6.295, the estimated variance is 11.122, meaning there is significant heterogeneity across consumers. We would expect 68% of consumers to have a preference for ground beef that is within $\pm\sqrt{11.122} = 3.335$ of the mean, 6.295.

Comparing the sum of the log likelihood function values from the three income category models to the pooled model in table 1 yields a chi-squared value of 1256.95 with 120 degrees of freedom, which yields a p-value of less than 0.001. Thus, the hypothesis that the model parameters are the same for all income categories is firmly rejected. Preferences differ by income.

Comparing across the linear price effect estimates, high income consumers are less responsive to own-price changes for every type of food than are low income consumers, with middle income consumers falling in between the two. Recognizing that comparisons of individual parameters across models could be confounded with differences in error variance, table 2 reports the estimated market shares for each income class of consumers at the median prices for each product used in the choice experiment (shares are calculated by plugging the estimated coefficients associated with equation (6) into using equation (1); see the appendix for more detail). Higher income consumers are almost twice as likely to choose steak (the most expensive product in the set) than are lower income consumers. In addition, the estimated market share of chicken breast is six percentage points higher for high vs. low income consumers. By contrast, low income consumers are more likely to choose lower-priced products such as ground beef, chicken wings, and rice and beans than are richer consumers, suggesting these products are inferior goods. Although there is nothing in the model that would require such an outcome, the market share of middle income consumers falls between that of low and high income for every alternative (except pasta). This finding, coupled with the results of the likelihood ratio test, suggests income is an important and predictable driver of meat preferences.

Also of interest in table 2 is the result that low income consumers are more likely to choose the "no purchase" alternative than are higher income consumers. This finding suggests some caution in utilizing conditional demand systems (which simply re-allocate a fixed level of expenditure among products in the assumed separability set when prices rise) to compare consumption patterns of richer and poorer consumers. This result is also interesting in light of rising prices and amidst the recent recession. Specifically, the lower-income segment is likely representing a declining share of total consumption for meat products. Given our finding of different elasticities by income segment, this is important for understanding the current, aggregate meat demand landscape.

Figure 3 utilizes the estimates in table 1 to construct demand curves for four meat products for each income category over the range of prices used in the experimental design. The first thing to note about the demand curve for each product and income class is that they are convex (as implied by the positive quadratic effects in table 1). This implies that demand becomes more inelastic as prices rise. Price changes in the upper-end of the price distribution do not change the quantity demanded as much as price changes in the lower-end of the price distribution. This phenomenon helps explain the surprise expressed by some analysts at the lack of reduction in beef and pork expenditures despite higher prices.

For some products, like pork chops, there are not marked differences in the demand curves for low, middle, and high income consumers (except at high price levels). For other products like steak, income changes result in large shifts in demand. In all cases, but perhaps most easily seen for ground beef, the demand curves for high income consumers are more inelastic than that for low-income consumers.

Whereas figure 3 illustrates relative responsiveness to own-price changes, figure 4 uses the estimated model for middle income consumers (representing the largest share of consumers at 43.5%) to illustrate cross-price demand responses for steak and chicken breast. The top panel reveals that a drop in price for chicken breast has a much larger impact on steak demand than an equivalent increase in ground beef price. This demand inter-relationship is consistent with the observed reduction in the share of meat purchases that have come from beef over the past thirty to forty years as the price of chicken has substantively fallen in relative terms. However, as the bottom panel of table 5 shows, demand for chicken breast is virtually unaffected by large price increases for steak or ground beef. This result is consistent with observations in the current market environment suggesting that consumers have not substituted in large numbers toward chicken despite much high beef prices.

It is useful to illustrate the potential bias inherent in more restrictive models that assume linear price effects or uncorrelated alternative-specific constants. Figure 5 shows the implied demand curves for ground beef associated with the preferred specification for middle income consumers (the third column of results in table 1) and compares it to RPL models that assume linear price effects or uncorrelated random parameters (the appendix shows the estimates for these rejected models). When all prices are at the median level used in the experimental design (which is $3.50 for ground beef), there is not much difference in the implied market shares across the competing models. However, as prices increase or decrease, the bias grows. The models assuming linear price effects under-state the quantity demanded (or market share) at both low and high prices. It is important to note that even the specifications that assume linear price effects still imply demand curves with some degree of curvature because of the non-linear form of the logit formula in equation (1). Not only does the assumption of constant marginal price effects yield biased estimates of the slope of the demand curve, as figure 5 also shows, the assumption also has implications for understanding cross-price demand responses. In particular, when the price of chicken breast falls, the RPL model with uncorrelated random parameters suggests a more dampened demand shift than actually results. Allowing random parameter correlation yields a more accurate depiction of the cross-price demand response, but the lack of curvature in the price effects yields biased estimates – this time at the mid-point of the price for ground beef rather than at the extremes.

The own- and cross-price demand responses can be more systematically investigated by investigating elasticities. Because of the non-linear nature of the demand curves, table 3 reports elasticities implied by a price increase, and table 4 reports elasticities implied by a price decrease. The reported elasticities are arc elasticities calculated by determining how a constant percentage price increase for each product changes the estimated market share (determined via equation 1), starting from the mid-points of the prices for each product utilized in the experimental design (the appendix provides more detail on how elasticities are calculated and shows qualitatively similar results associated with a constant dollar increase for each product).

Before discussing the results, we note that it is a bit of a challenge to directly compare our elasticities with those present in the extant literature because prior analyses typically provide elasticities aggregated over all cuts within a species and over all markets. We have product-level demands observed from a choice question format that places people in a single, store market environment (where demand is likely to be more elastic). That said, the estimates in table 3 are not outside the realm of that reported in prior literature. For example, the own-price elasticities of demand for steak we estimate are between -1.67 and -1.84, depending on income class, which can be compared with the estimate of -1.88 in Taylor and Tonsor (2013) obtained using scanner data.

We find ground beef demand is more elastic than steak, which is consistent with the findings of Brester and Wohlgenant (1991) and Coffey, Schroeder, and Marsh (2010) but opposite of that found by Capps (1989), Nayga and Capps (1994), and Taylor and Tonsor (2013). Table 3 indicates pork chop demand to be more elastic than ham. This is consistent with the findings of Capps (1989) and Coffey, Schroeder, and Marsh (2010) but differs from the findings of Nayga and Capps (1994).[4] Our estimates suggesting chicken breast demand is less elastic than ground beef, steak, and pork chop demand is consistent with Capps (1989).

Comparing table 3 to table 4, one can see that own-price arc elasticities are more inelastic for a price increase (for higher prices) than they are for a price decrease (for lower prices). For example, the own-price elasticity of demand for ground beef for low income consumers is -1.96 for a price increase and -2.51 for a price decrease. Moreover, the magnitude of the cross-price elasticities is generally higher for price decreases than price increases. Stated differently, there is less substitutability at higher prices than lower prices. This result, while somewhat

[4] Note, however, the insignificant own-price elasticity estimated by Capps (1989) of 0.36 is inconsistent with curvature expectations. Moreover, the Coffey, Schroeder, and Marsh (2010) study actually provides a 'Roast/Ham' estimate of -0.17 which is also not statistically different from zero.

counterintuitive at first blush, seems to be consistent with outcomes in the current market environment. This finding may be related to shifts in the relative purchasing of higher-income vs. lower-income households in the presence of higher prices. That is, if higher-income households are less price sensitive, they would comprise a larger share of total purchases in a higher meat price environment.

Indeed, within either table 3 or 4, the results show that higher-income consumers tend to have more inelastic own-price elasticities and smaller cross-price elasticities than lower-income consumers, again with middle-income consumers falling somewhere in between. As figure 4 revealed, the cross-price elasticities for ground beef and steak with respect to chicken breast are larger than the cross-price elasticities for chicken breast with respect to ground beef and steak. The results in table 3 show that for low income consumers, a 1% increase in the price in chicken breast results in a 0.54% increase in the market share for ground beef; however, a 1% increase in the price of ground beef only results in a 0.34% increase in the market share for chicken breast.

Discussion and Conclusion

Banks, Blundell, and Lewbel (1997) argue that (pg. 527) "… for many commodities, standard empirical demand models do not provide an accurate picture of observed behavior." This study sought to help resolve a similar disconnect between the current meat demand environment and analyst expectations. Utilizing a novel data set generated by an on-going series of nationally-distributed choice experiments, we reveal non-linear demands for meat products, with demand being more inelastic at higher prices. We also identify a series of insights into how cross-price relationships vary across meat prices, meat products, and consumers with different incomes.

A number of implications result from this analysis. The often-imposed assumption of linearity in empirical work and policy analyses using constant elasticities warrants further scrutiny. It is common to use econometrically estimated elasticities of demand in general or partial equilibrium models investigating various policy or market shocks (e.g., Balagtas and Kim, 2007; Pendell et al, 2010; Weaber and Lusk, 2010; Okrent and Alston, 2012). Similarly, elasticities published in the literature (typically based on econometric models utilizing time series data spanning multiple decades) are frequently inputs for models providing forecasts of longer-term prices, net farm incomes, government expenditures, and other statistics of key interest to stakeholders throughout the entire U.S. agricultural system (FAPRI, 2014; Rosegrant, Tokgoz, and Bhandary, 2013; USDA ERS, 2014). In many applications, analysts assume constant elasticities over all price ranges, and as a result may over- or under-estimate economic impacts if elasticities are actually non-linear. Our findings reinforce the assertion that equilibrium displacement models should be limited to situations characterized by small changes (Wohlgenant, 2011). Research that seeks to project effects of larger shocks might do well to utilize approaches with widely varying prices or market environments, perhaps by applying split sample survey or experiment designs (Tonsor, 2011). Furthermore, our finding of demand patterns differing by income not only adds to the large body of research on Engel curves but suggests that such effects need to further consideration in the discrete choice demand literature. These differential consumption patterns across income categories buttress Gustavsen's (2014, p. 15) conclusion that "consumption patterns are usually different in different cohorts." This highlights the potential importance of conducting research separately for consumer segments distinguished by income group.

The empirical demand estimates might also be useful in helping forecast future developments in the meat market. As the old adage goes, "the cure for high prices is high prices." High beef and pork prices are incentivizing producers to hold back breeding stock. If expansion occurs as expected in the coming years, then real retail prices will decline, assuming no countervailing demand or supply shocks. The estimates presented here suggest that the currently observed "limited substitution" may not hold as beef and pork prices fall. Moreover, because the hog cycle is shorter than the cattle cycle, we are likely to witness falling pork prices before beef, which is likely to have implications for substitution patterns within and across species categories.

One of the advantages of the on-going choice experiment is that we may ultimately be able to more cleanly determine whether and why structural change has occurred than is feasible using more conventional approaches. While the present study focused on the effects of relative price changes, future research utilizing this sort of data can study how consumers' choices vary over time to the same set of unchanging questions. The advantage of the survey-based approach used here is that more clearly delineates consumer demand from supply-side effects, and the experimental design ensures there are no confounds with unmeasured characteristics. As previously indicated, prior research provides a mixed bag of demand elasticities for disaggregate meat products, and it is difficult to ascertain whether differences arise because of differences in assumed functional forms, data sets, or time periods. Another future benefit worthy of additional attention is the potential ability to forecast future demand patterns utilizing less aggregated product-level elasticities derived from on-going choice experiments. While there currently are limited bases of comparison, either in the form of product-level quantity data or previously published elasticities, that constraint may ease over time making out-of-sample forecasting assessments feasible.

Of course, survey-based methods like choice experiments are not a panacea. One major concern is that people may answer survey questions differently than they actually shop. The potential for this sort of hypothetical bias appears less problematic for choice experiments than other methods, and are a variety of studies that have found choice experiments yield preference consistent with that from actual market transactions, but the concern exists nonetheless. Moreover, choice experiments require a number of design choices be made such as the experimental design, the way option are presented, and the choice of attributes and levels, and of which may influence the ultimate results in a way that limit external validity. For example, we chose to present pictures for each option. Would a different set of pictures yielded a different pattern of results? There is no way to know except to conduct a different study with different pictures. There is a long literature on conjoint analysis which provides guidance when making such design choices, but potentially consequential design decisions must ultimately be made by the researcher.

While all empirical analyses have their limitations, the possible demand insights offered by consistently conducting the same set of choice experiments with a large set of consumers over time are illustrated by this study. It wasn't too long ago that scanner data analysis of meat demand was in its infancy (e.g. Capps, 1989). Given the ongoing challenge of analyzing fresh meat demand with this sort of data, given the inability to identify unit weights, new approaches will be needed. There have emerged efforts to use stated preference surveys, sometimes merged with revealed preferences (e.g. Brooks and Lusk, 2010), to extend our understanding of demand patterns. The next development – larger and longer-running choice experiments – may yield further insights and help researchers better disentangle demand determinants.

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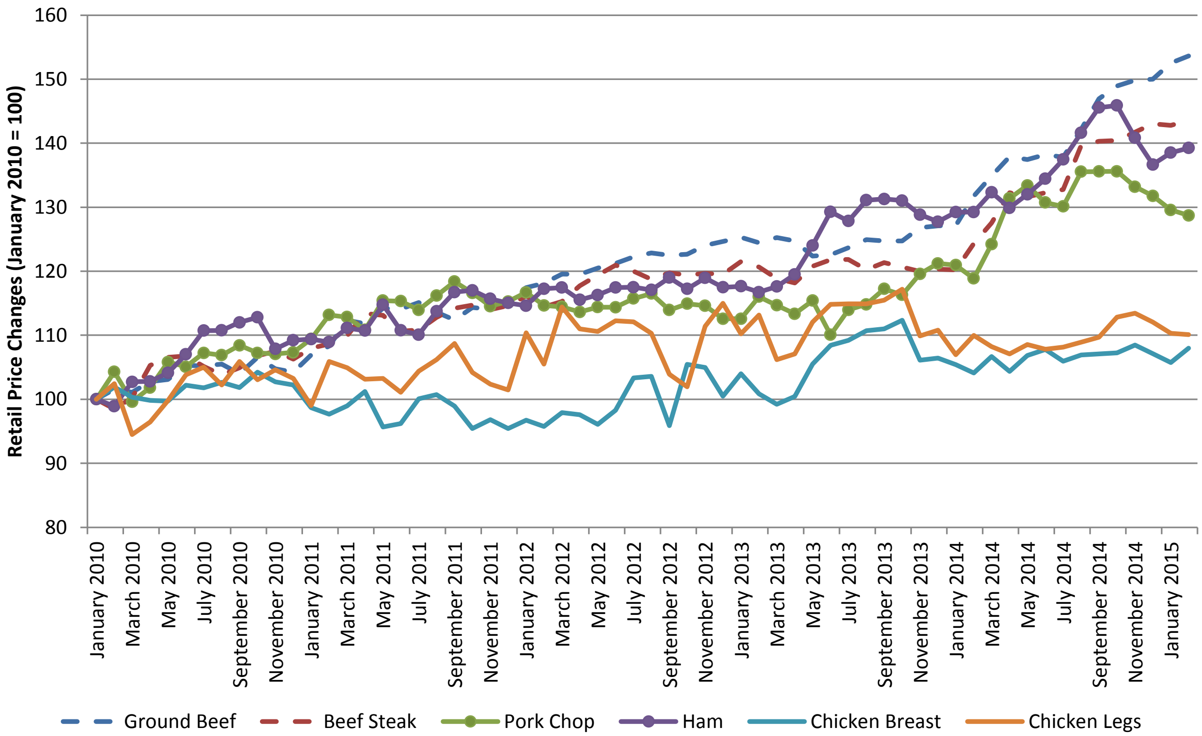

Figure 1. Change in Retail Prices for Six Meat Products from January 2010 to January 2015 (source: Bureau of Labor Statistics)

Figure 2. Example Choice Experiment Question

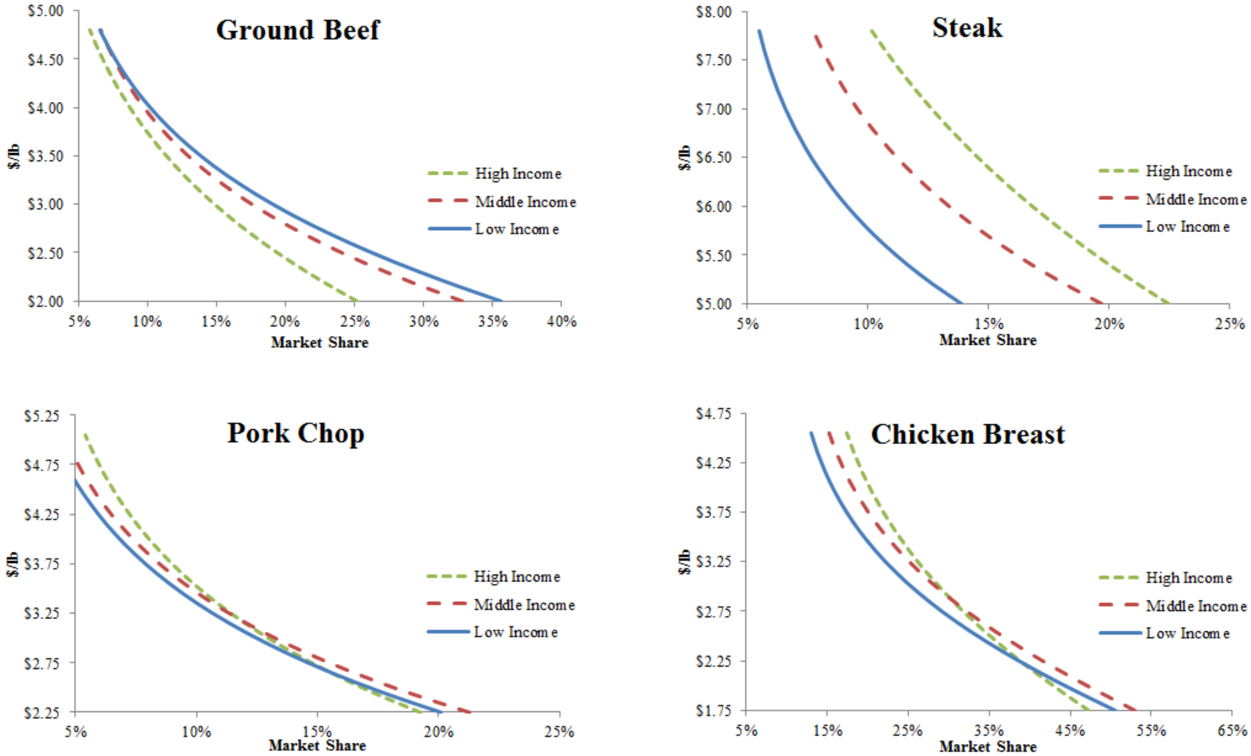

Figure 3. Implied Demand Curves for Four Meat Products, by Income

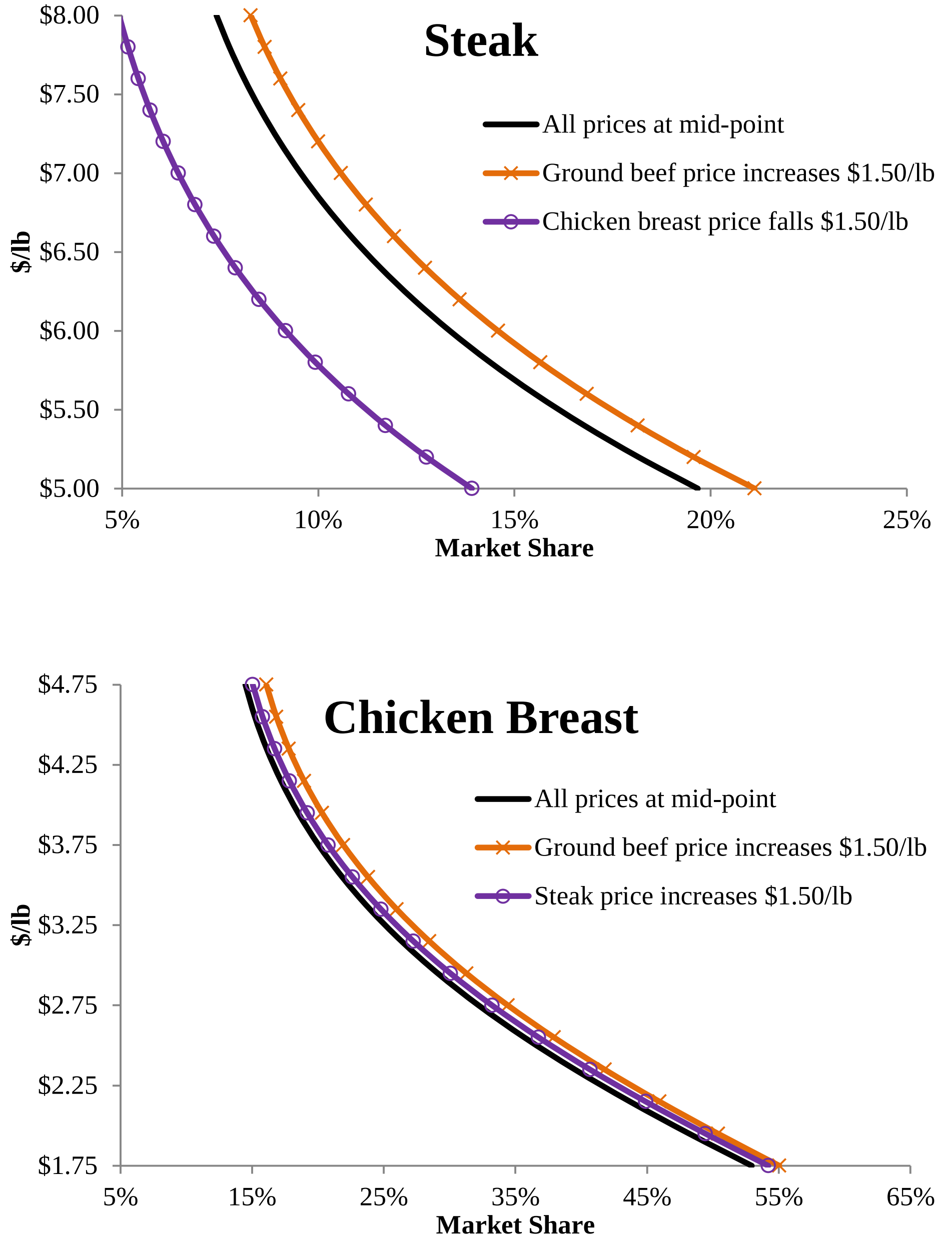

Figure 4. Change in Demand for Steak and Chicken Breast as Prices of Other Meats Change, Middle Income Consumers

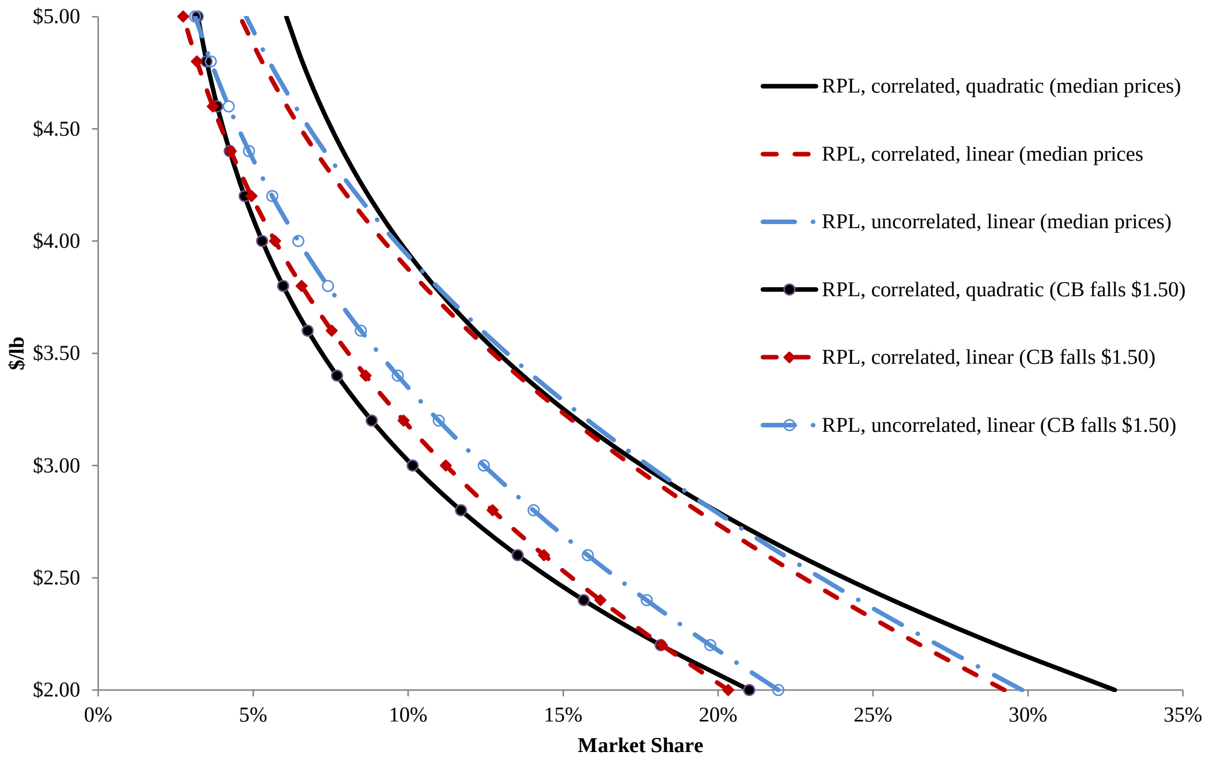

Figure 5. Ground Beef Demand Implied by Alternative Model Specifications, Middle Income Consumers (note: the RPL, correlated, quadratic model is the preferred specification)

Table 1. Estimates of Random Parameter Models by Income

Variables	Pooled		Low income <$40,000		Middle income $40,000 to $99,999		High income >$100,000	
Means of Alternative-Specific constants								
Ground beef (GB)	6.295*[a]	(0.120)[b]	6.379*	(0.190)	6.353*	(0.179)	5.730*	(0.291)
Steak (SK)	7.534*	(0.496)	7.446*	(0.883)	8.107*	(0.737)	6.874*	(1.045)
Pork chop (PC)	5.537*	(0.158)	5.239*	(0.260)	5.654*	(0.235)	5.626*	(0.354)
Deli ham (DH)	3.943*	(0.091)	4.051*	(0.141)	3.781*	(0.136)	3.752*	(0.231)
Chicken breast (CB)	7.612*	(0.097)	7.555*	(0.155)	7.627*	(0.142)	7.534*	(0.227)
Chicken wing (CW)	3.478*	(0.081)	3.444*	(0.123)	3.419*	(0.120)	3.440*	(0.198)
Rice and beans (RB)	2.847*	(0.069)	2.903*	(0.106)	2.695*	(0.101)	2.957*	(0.171)
Pasta (PA)	5.898*	(0.209)	6.012*	(0.340)	5.856*	(0.315)	5.674*	(0.481)
Linear Price Effects								
Ground beef (GB)	-1.437*	(0.070)	-1.531*	(0.113)	-1.512*	(0.105)	-1.040*	(0.169)
Steak (SK)	-1.394*	(0.158)	-1.534*	(0.283)	-1.555*	(0.236)	-0.958*	(0.332)
Pork chop (PC)	-1.271*	(0.090)	-1.203*	(0.150)	-1.324*	(0.135)	-1.165*	(0.197)
Deli ham (DH)	-1.115*	(0.068)	-1.256*	(0.109)	-1.062*	(0.104)	-1.049*	(0.169)
Chicken breast (CB)	-2.021*	(0.054)	-2.172*	(0.090)	-2.039*	(0.080)	-1.683*	(0.122)
Chicken wing (CW)	-1.131*	(0.068)	-1.073*	(0.105)	-1.256*	(0.106)	-0.994*	(0.166)
Rice and beans (RB)	-0.907*	(0.048)	-0.960*	(0.076)	-0.865*	(0.073)	-0.916*	(0.118)
Pasta (PA)	-1.894*	(0.113)	-2.008*	(0.185)	-1.894*	(0.171)	-1.640*	(0.258)
Quadratic Price Effects								
Ground beef (GB)	0.094*	(0.001)	0.098*	(0.017)	0.107*	(0.016)	0.050*	(0.025)
Steak (SK)	0.069*	(0.012)	0.084*	(0.022)	0.079*	(0.018)	0.034	(0.026)
Pork chop (PC)	0.083*	(0.012)	0.071*	(0.021)	0.088*	(0.019)	0.079*	(0.027)
Deli ham (DH)	0.098*	(0.013)	0.112*	(0.022)	0.086*	(0.021)	0.108*	(0.033)
Chicken breast (CB)	0.177*	(0.008)	0.196*	(0.014)	0.180*	(0.013)	0.133*	(0.019)
Chicken wing (CW)	0.086*	(0.017)	0.054*	(0.027)	0.121*	(0.027)	0.075	(0.042)
Rice and beans (RB)	0.089*	(0.012)	0.092*	(0.020)	0.082*	(0.019)	0.105*	(0.030)
Pasta (PA)	0.177*	(0.014)	0.192*	(0.024)	0.178*	(0.022)	0.144*	(0.033)
Variances of Alternative-Specific Constants								
Ground beef (GB)	11.122*	(0.351)	11.183*	(0.562)	9.892*	(0.484)	10.769*	(0.780)
Steak (SK)	15.117*	(0.491)	14.277*	(0.719)	15.257*	(0.671)	18.081*	(1.105)
Pork chop (PC)	11.614*	(0.378)	12.563*	(0.622)	9.909*	(0.500)	10.693*	(0.793)
Deli ham (DH)	10.556*	(0.355)	9.810*	(0.528)	9.235*	(0.482)	13.173*	(0.876)
Chicken breast (CB)	11.338*	(0.351)	11.912*	(0.612)	10.021*	(0.506)	12.453*	(0.831)
Chicken wing (CW)	12.784*	(0.424)	12.702*	(0.585)	11.015*	(0.535)	12.919*	(0.907)
Rice and beans (RB)	9.108*	(0.603)	9.732*	(0.492)	8.086*	(0.408)	10.490*	(0.787)
Pasta (PA)	8.220*	(0.398)	9.174*	(0.526)	7.310*	(0.417)	9.058*	(0.656)

Table 1 continued on next page . . .

Table 1 continued

Covariances of Alternative-Specific Constants								
SK, GB	11.619*	(0.383)	11.430*	(0.597)	11.118*	(0.528)	12.493*	(0.828)
PC, GB	10.790*	(0.351)	11.548*	(0.569)	9.327*	(0.467)	9.895*	(0.700)
PC, SK	10.359*	(0.395)	12.798*	(0.625)	11.201*	(0.529)	12.567*	(0.855)
DH, GB	10.292*	(0.337)	9.743*	(0.520)	8.981*	(0.453)	11.107*	(0.731)
DH, SK	11.071*	(0.382)	10.116*	(0.580)	9.813*	(0.521)	12.243*	(0.864)
DH, PC	10.498*	(0.343)	10.613*	(0.544)	8.988*	(0.456)	11.029*	(0.759)
CB, GB	10.130*	(0.337)	10.528*	(0.540)	8.968*	(0.437)	10.100*	(0.672)
CB, SK	10.677*	(0.376)	11.007*	(0.590)	9.602*	(0.504)	11.620*	(0.811)
CB, PC	10.435*	(0.347)	11.325*	(0.567)	9.002*	(0.441)	10.035*	(0.706)
CB, DH	9.334*	(0.329)	9.242*	(0.518)	7.984*	(0.438)	10.619*	(0.726)
CW, GB	10.048*	(0.364)	10.093*	(0.547)	8.641*	(0.456)	9.722*	(0.676)
CW, SK	9.830*	(0.405)	10.848*	(0.598)	10.213*	(0.524)	11.431*	(0.824)
CW, PC	10.275*	(0.375)	10.869*	(0.569)	8.670*	(0.458)	9.414*	(0.707)
CW, DH	10.479*	(0.361)	9.725*	(0.527)	8.944*	(0.457)	11.399*	(0.757)
CW, CB	9.816*	(0.355)	10.162*	(0.546)	8.318*	(0.441)	9.552*	(0.694)
RB, GB	7.373*	(0.305)	7.783*	(0.484)	5.898*	(0.394)	7.415*	(0.574)
RB, SK	8.047*	(0.346)	8.484*	(0.541)	6.239*	(0.466)	8.219*	(0.719)
RB, PC	7.445*	(0.304)	8.645*	(0.506)	6.055*	(0.390)	6.661*	(0.589)
RB, DH	7.558*	(0.301)	7.662*	(0.482)	5.896*	(0.389)	9.385*	(0.652)
RB, CB	7.197*	(0.300)	8.002*	(0.494)	6.041*	(0.387)	7.845*	(0.587)
RB, CW	8.369*	(0.337)	8.667*	(0.497)	6.739*	(0.405)	9.950*	(0.707)
PA, GB	7.887*	(0.302)	8.608*	(0.499)	6.795*	(0.412)	7.172*	(0.578)
PA, SK	7.962*	(0.341)	9.797*	(0.567)	7.517*	(0.486)	9.067*	(0.703)
PA, PC	7.943*	(0.303)	9.392*	(0.523)	6.651*	(0.413)	6.708*	(0.588)
PA, DH	7.345*	(0.301)	7.672*	(0.494)	6.094*	(0.400)	8.280*	(0.634)
PA, CB	7.523*	(0.298)	8.557*	(0.519)	6.634*	(0.402)	7.798*	(0.591)
PA, CW	7.588*	(0.331)	8.347*	(0.505)	6.347*	(0.413)	9.921*	(0.654)
PA, RB	5.305*	(0.366)	8.691*	(0.493)	6.923*	(0.385)	9.105*	(0.620)
N choices (people)	110295 (12255)		41913 (4657)		47952 (5328)		20430 (2270)	
Log Likelihood	-180574.4		-68654.4		-78669.7		-32621.8	

[a]One asterisk represents statistical significance at the 0.01 level or lower
[b]Numbers in parentheses are standard errors

Table 2. Estimated Market Shares by Income

Product	Aggregate[a]	Low income	Middle income	High income
Ground beef (GB)	12.97%	13.83%	12.91%	11.33%
Steak (SK)	10.47%	7.64%	11.20%	14.55%
Pork chop (PC)	8.34%	7.89%	8.46%	8.99%
Deli ham (DH)	7.11%	7.68%	7.07%	6.03%
Chicken breast (CB)	24.57%	22.17%	25.11%	28.22%
Chicken wing (CW)	11.19%	13.35%	10.22%	9.04%
Rice and beans (RB)	10.35%	10.82%	10.61%	8.75%
Pasta (PA)	5.85%	5.83%	6.02%	5.49%
No Purchase	9.16%	10.79%	8.39%	7.61%

Note: Market shares estimated using mid-points of prices employed in the experimental design; shares for each income category are calculated by averaging over 25,000 draws from the respective estimated parameter distributions.

[a]Aggregate market share is the weighted average share across income category (the sample has 38% low income, 43.5% middle income, and 18.5% high income).

Table 3. Arc Elasticities for a Price Increase by Income

	Change in price							
Change in quantity	GB	SK	PC	DH	CB	CW	RB	PA
Low income								
Ground beef (GB)	-1.959	0.184	0.224	0.141	0.544	0.152	0.071	0.075
Steak (SK)	0.375	-1.738	0.269	0.097	0.425	0.141	0.065	0.091
Pork chop (PC)	0.470	0.277	-1.927	0.157	0.566	0.151	0.078	0.076
Deli ham (DH)	0.421	0.141	0.225	-1.306	0.422	0.194	0.103	0.064
Chicken breast (CB)	0.339	0.131	0.169	0.089	-1.503	0.145	0.075	0.064
Chicken wing (CW)	0.276	0.126	0.132	0.119	0.419	-0.939	0.099	0.054
Rice and beans (RB)	0.211	0.096	0.111	0.103	0.355	0.162	-0.744	0.152
Pasta (PA)	0.310	0.188	0.151	0.089	0.425	0.123	0.212	-1.252
No Purchase	0.186	0.069	0.065	0.083	0.272	0.091	0.087	0.065
Middle Income								
Ground beef (GB)	-1.834	0.373	0.197	0.135	0.603	0.107	0.060	0.078
Steak (SK)	0.344	-1.836	0.221	0.075	0.365	0.108	0.039	0.056
Pork chop (PC)	0.325	0.398	-1.844	0.136	0.623	0.109	0.068	0.070
Deli ham (DH)	0.398	0.239	0.243	-1.224	0.449	0.172	0.077	0.064
Chicken breast (CB)	0.286	0.189	0.179	0.073	-1.394	0.101	0.067	0.071
Chicken wing (CW)	0.231	0.253	0.142	0.127	0.457	-0.949	0.094	0.057
Rice and beans (RB)	0.168	0.117	0.116	0.074	0.394	0.121	-0.658	0.171
Pasta (PA)	0.258	0.199	0.141	0.072	0.492	0.087	0.202	-1.253
No Purchase	0.166	0.109	0.101	0.068	0.341	0.073	0.093	0.083
High Income								
Ground beef (GB)	-1.703	0.459	0.185	0.094	0.580	0.090	0.051	0.053
Steak (SK)	0.253	-1.674	0.187	0.041	0.378	0.066	0.028	0.052
Pork chop (PC)	0.271	0.496	-1.524	0.097	0.599	0.086	0.036	0.045
Deli ham (DH)	0.342	0.265	0.242	-0.940	0.479	0.128	0.086	0.050
Chicken breast (CB)	0.207	0.244	0.147	0.048	-1.151	0.063	0.047	0.058
Chicken wing (CW)	0.203	0.268	0.133	0.080	0.392	-0.869	0.101	0.144
Rice and beans (RB)	0.157	0.152	0.076	0.072	0.401	0.137	-0.632	0.191
Pasta (PA)	0.148	0.262	0.087	0.039	0.454	0.180	0.176	-1.327
No Purchase	0.163	0.132	0.122	0.028	0.339	0.050	0.063	0.082

Note: Arc elasticities are calculated by determining the proportionate change in market shares resulting from a 10% increase in the price of each respective food divided by 0.1; shares for each income category are calculated by averaging over 25,000 draws from the respective estimated parameter distributions.

Table 4. Arc Elasticities for a Price Decrease by Income

	Change in price							
Change in quantity	GB	SK	PC	DH	CB	CW	RB	PA
Low income								
Ground beef (GB)	-2.511	0.280	0.292	0.173	0.681	0.167	0.081	0.119
Steak (SK)	0.478	-2.652	0.347	0.120	0.546	0.155	0.075	0.145
Pork chop (PC)	0.587	0.408	-2.526	0.192	0.705	0.166	0.088	0.121
Deli ham (DH)	0.530	0.217	0.292	-1.614	0.542	0.211	0.116	0.102
Chicken breast (CB)	0.435	0.202	0.223	0.111	-1.916	0.159	0.085	0.103
Chicken wing (CW)	0.358	0.195	0.175	0.146	0.537	-1.031	0.112	0.087
Rice and beans (RB)	0.278	0.149	0.148	0.128	0.460	0.177	-0.839	0.238
Pasta (PA)	0.398	0.282	0.199	0.111	0.544	0.136	0.234	-1.995
No Purchase	0.244	0.108	0.088	0.103	0.357	0.101	0.098	0.104
Middle Income								
Ground beef (GB)	-2.377	0.514	0.260	0.161	0.735	0.122	0.068	0.121
Steak (SK)	0.441	-2.606	0.290	0.092	0.467	0.123	0.045	0.087
Pork chop (PC)	0.420	0.545	-2.437	0.163	0.758	0.124	0.077	0.109
Deli ham (DH)	0.504	0.343	0.316	-1.480	0.566	0.193	0.087	0.099
Chicken breast (CB)	0.370	0.274	0.236	0.089	-1.737	0.115	0.076	0.110
Chicken wing (CW)	0.304	0.358	0.190	0.152	0.572	-1.079	0.104	0.089
Rice and beans (RB)	0.224	0.175	0.155	0.090	0.499	0.137	-0.735	0.259
Pasta (PA)	0.336	0.286	0.188	0.087	0.611	0.099	0.221	-1.935
No Purchase	0.220	0.163	0.136	0.083	0.435	0.084	0.104	0.129
High Income								
Ground beef (GB)	-2.075	0.548	0.236	0.114	0.673	0.100	0.059	0.078
Steak (SK)	0.307	-2.061	0.238	0.051	0.455	0.074	0.033	0.076
Pork chop (PC)	0.328	0.588	-1.947	0.118	0.693	0.095	0.042	0.067
Deli ham (DH)	0.406	0.332	0.303	-1.157	0.568	0.141	0.098	0.074
Chicken breast (CB)	0.254	0.307	0.188	0.059	-1.360	0.070	0.055	0.085
Chicken wing (CW)	0.249	0.333	0.171	0.098	0.471	-0.967	0.115	0.207
Rice and beans (RB)	0.194	0.196	0.100	0.089	0.479	0.151	-0.724	0.272
Pasta (PA)	0.184	0.325	0.114	0.049	0.535	0.196	0.198	-1.931
No Purchase	0.200	0.171	0.157	0.035	0.409	0.057	0.072	0.119

Note: Arc elasticities are calculated by determining the proportionate change in market shares resulting from a 10% decrease in the price of each respective food divided by -0.1; shares for each income category are calculated by averaging over 25,000 draws from the respective estimated parameter distributions.

Appendix

Calculating Market Shares and Elasticities

Most of the results are based off the RPL with correlated random parameters. The deterministic portion of the utility function is given the estimated parameters (indicated by the ^) is:

(A1) $\hat{V}_{ij} = \left(\hat{\beta}_j + \sum_{t=1}^{8} \widehat{\omega}_{jt} d_{it}\right) + \hat{\alpha}_j p_j + \hat{\delta}_j p_j^2$,

Plugging (A1) into the multinomial logit formula yields:

(A2) $S_{ij}|\boldsymbol{d_i} = \frac{e^{\hat{V}_{ij}}}{\sum_{k=1}^{9} e^{\hat{V}_{ik}}}$,

where S_{ij} is the probability of purchase (or market share) for individual *i* and food option *j* and $\boldsymbol{d_i}$ is a vector containing the terms d_{it}. Equation (A2) cannot be directly evaluated because it contains the random terms d_{it} which are each distributed according to a standard Normal distribution. Following Train (2009), the mean share can be approximated through simulation. In particular, for a set of *N* draws for d_{it}, the unconditional share can be written as:

(A3) $S_j = \frac{1}{N} \sum_{i=1}^{N} \frac{e^{\hat{V}_{ij}}}{\sum_{k=1}^{9} e^{\hat{V}_{ik}}}$.

In all our calculations, we use N=25,000.

The demand curves reported in figures (3)-(5) are created simply by evaluating (A3) at successively higher price levels. For example, to construct the steak demand curve, prices of all other products would be set at their mid-points (see table A2), and equation A3 would be calculated for $p_{steak} = 5$, $p_{steak} = 5.1$, $p_{steak} = 5.2$, . . . , $p_{steak} = 7.9$, $p_{steak} = 8$. The resulting share values are then plotted against the corresponding prices.

The arc elasticities in tables 3 and 5 are calculated as follows. First, equation (A3) is used to calculate the shares for each of the *j* = 9 options at the midpoint of the price levels (see table A3). Call these values $\bar{S}_j$. Then, to determine arc elasticities associated with a change in the price of good *k*, the price of good *k* is increased (or decreased) from its midpoint by 10%

(i.e., $p'_k = 0.1\bar{p}_k$, where $\bar{p}_k$ is the midpoint price level for good *k*) while all other prices are kept at their midpoints. Then, (A3) is recalculated for each *j*=1 to 9. Let S'_j be the new share values given the new price p'_k. Now, the elasticity, or percentage change in the share of good *j* that results from a 1% increase in the price of good *k* is:

(A4) $\gamma_{jk} = \frac{S'_j - \bar{S}_j}{\bar{S}_j} \frac{1}{0.1}$.

Table A1. Characteristics of Survey Respondents

Variable	Sample (N=12,257)	Population/ Census
Income < $40K	38.0%	34.4%
$40K < Income < $99K	44.5%	43.1%
Income > $100K	18.5%	22.5%
Age < 24	11.0%	12.9%
25 < Age < 34	20.9%	18.0%
35 < Age < 44	20.6%	17.2%
45 < Age < 54	17.2%	19.0%
55 < Age < 64	12.4%	16.0%
Age > 65	17.9%	17.0%
HS degree or less	19.0%	43.2%[a]
Some college	35.7%	28.6%[a]
College degree	45.3%	28.2%[a]
Female	49.6%	51.1%
White	72.4%	77.7%
Black	15.0%	13.2%
Hispanic	12.4%	17.1%
Northeast US	19.1%	18.3%
Midwest	22.3%	21.7%
South US	36.2%	36.8%
West	22.2%	23.2%
Household size	2.63	2.61
Food stamp participation	15.1%	15.0%

[a] Education attainment statistics are for individuals 18 years and older; for 25 years and older census data indicate, 39% have a HS degree or less, 31% have some college, and 30% have a BS degree or higher.

Table A2. Prices Used in Choice Experiment ($/lb)

Product	**Low**	**Mid**	**High**
Ground beef (GB)	$2.00	$3.50	$5.00
Steak (SK)	$5.00	$6.50	$8.00
Pork chop (PC)	$2.25	$3.75	$5.25
Deli ham (DH)	$1.15	$2.65	$4.15
Chicken breast (CB)	$1.75	$3.25	$4.75
Chicken wing (CW)	$0.75	$1.75	$3.25
Rice and beans (RB)	$0.50	$2.00	$3.50
Pasta (PA)	$2.50	$4.00	$5.50

Table A3. Bureau of Labor Statistics (BLS) Retail Prices for Products Associated with Products used in the Choice Experiment (2013 average)

BLS product descriptor	**Price ($/lb)**
Ground beef, 100% beef	$3.40
Steak, sirloin, USDA Choice, boneless	$6.83
All Pork Chops	$3.55
All Ham (Excluding Canned Ham and Luncheon Slices)	$3.79
Chicken breast, boneless	$3.45
Chicken legs, bone-in	$1.61
Beans, dried, any type, all sizes	$1.42
Rice, white, long grain, uncooked	$0.72
Spaghetti and macaroni	$1.30
Tomatoes, field grown	$1.53

Table A4. Main Effects Orthogonal Design Used in Choice Experiment Survey

Question	Ground beef (GB)	Steak (SK)	Pork chop (PC)	Deli ham (DH)	Chicken breast (CB)	Chicken wing (CW)	Rice and beans (RB)	Pasta (PA)	Block
1	$2.00	$6.50	$3.75	$2.65	$3.25	$1.75	$0.50	$2.50	1
2	$5.00	$5.00	$2.25	$2.65	$4.75	$0.75	$2.00	$5.50	1
3	$3.50	$5.00	$2.25	$4.15	$3.25	$0.75	$3.50	$4.00	1
4	$2.00	$8.00	$5.25	$4.15	$4.75	$3.25	$0.50	$2.50	1
5	$5.00	$8.00	$5.25	$1.15	$3.25	$3.25	$2.00	$5.50	1
6	$3.50	$8.00	$5.25	$2.65	$1.75	$3.25	$3.50	$4.00	1
7	$5.00	$6.50	$3.75	$4.15	$1.75	$1.75	$2.00	$5.50	1
8	$2.00	$5.00	$2.25	$1.15	$1.75	$0.75	$0.50	$2.50	1
9	$3.50	$6.50	$3.75	$1.15	$4.75	$1.75	$3.50	$4.00	1
10	$2.00	$8.00	$3.75	$1.15	$1.75	$0.75	$2.00	$4.00	2
11	$3.50	$6.50	$2.25	$2.65	$1.75	$3.25	$0.50	$5.50	2
12	$5.00	$8.00	$3.75	$2.65	$4.75	$0.75	$3.50	$2.50	2
13	$5.00	$6.50	$2.25	$1.15	$3.25	$3.25	$3.50	$2.50	2
14	$3.50	$8.00	$3.75	$4.15	$3.25	$0.75	$0.50	$5.50	2
15	$2.00	$6.50	$2.25	$4.15	$4.75	$3.25	$2.00	$4.00	2
16	$3.50	$5.00	$5.25	$1.15	$4.75	$1.75	$0.50	$5.50	2
17	$5.00	$5.00	$5.25	$4.15	$1.75	$1.75	$3.50	$2.50	2
18	$2.00	$5.00	$5.25	$2.65	$3.25	$1.75	$2.00	$4.00	2
19	$5.00	$6.50	$5.25	$2.65	$4.75	$0.75	$0.50	$4.00	3
20	$5.00	$5.00	$3.75	$1.15	$3.25	$3.25	$0.50	$4.00	3
21	$2.00	$6.50	$5.25	$1.15	$1.75	$0.75	$3.50	$5.50	3
22	$5.00	$8.00	$2.25	$4.15	$1.75	$1.75	$0.50	$4.00	3
23	$3.50	$6.50	$5.25	$4.15	$3.25	$0.75	$2.00	$2.50	3
24	$3.50	$8.00	$2.25	$1.15	$4.75	$1.75	$2.00	$2.50	3
25	$2.00	$5.00	$3.75	$4.15	$4.75	$3.25	$3.50	$5.50	3
26	$2.00	$8.00	$2.25	$2.65	$3.25	$1.75	$3.50	$5.50	3
27	$3.50	$5.00	$3.75	$2.65	$1.75	$3.25	$2.00	$2.50	3

Table A5. Alternative Model Specifications fit to the Choice Data

Model	Description	Utility Specification
1	MNL with single price effect	$U_{ij} = \beta_j + \alpha p_j + \varepsilon_{ij}$
2	MNL with alternative-specific price effects	$U_{ij} = \beta_j + \alpha_j p_j + \varepsilon_{ij}$
3	MNL with alternative-specific & quadratic price effects	$U_{ij} = \beta_j + \alpha_j p_j + \delta_j p_j^2 + \varepsilon_{ij}$
4	Mother logit with linear price effects	$U_{ij} = \beta_j + \sum_{k=1}^{8} \alpha_{jk} p_k + \varepsilon_{ij}$
5	Mother logit with symmetric & quadratic price effects	$U_{ij} = \beta_j + \sum_{k=1}^{8} \alpha_{jk} p_k + \delta_j p_j^2 + \varepsilon_{ij}, \alpha_{jk} = \alpha_{kj}$
6	Mother logit with quadratic price effects	$U_{ij} = \beta_j + \sum_{k=1}^{8} \alpha_{jk} p_k + \delta_j p_j^2 + \varepsilon_{ij}$
7	Error component model with linear price effects	$U_{ij} = \beta_j + \alpha_j p_j + \epsilon_{ij} + \varepsilon_{ij}$ [a]
8	Error component model with quadratic price effects	$U_{ij} = \beta_j + \alpha_j p_j + \delta_j p_j^2 + \epsilon_{ij} + \varepsilon_{ij}$ [a]
9	RPL with linear price effects, uncorrelated alternative-specific constants	$U_{ij} = (\beta_j + \sigma_j d_{ij}) + \alpha_j p_j + \varepsilon_{ij}, d_{ij} \sim N(0,1)$
10	RPL with linear price effects, correlated alternative-specific constants	$U_{ij} = (\beta_j + \sum_{k=1}^{8} \omega_{jk} d_{ik}) + \alpha_j p_j + \varepsilon_{ij}, d_{ik} \sim N(0,1)$ [b]
11	RPL with quadratic price effects, correlated alternative-specific constants	$U_{ij} = (\beta_j + \sum_{k=1}^{8} \omega_{jk} d_{ik}) + \alpha_j p_j + \delta_j p_j^2 + \varepsilon_{ij}, d_{ik} \sim N(0,1)$ [b]

[a] Our specification included 7 mean-zero Normally distributed error components that we parsimoniously summarize in this equation with a single term, ϵ_{ij}. In particular, over-lapping error components were included for: 1) all food products vs. the "none" alternative, 2) all meat products vs. non meat, 3) beef products, 4) pork products, 5) chicken products, 6) higher value meat products (steak, pork chop, chicken breast), and 7) lower value meat products (ground beef, deli ham, chicken wing).

[b] The terms, ω_{jk}, are the elements of the lower-triangle of the Cholesky decomposition associated with the covariance matrix of the random parameters.

Table A6. Eleven Competing Models fit to Choice Data (N=110,295 choices made by 12,255 people)

Model	Description	# Parms	LLF	AIC
1	MNL with single price effect	9	-210542	421102
2	MNL with alternative-specific price effects	16	-209847	419726
3	MNL with alternative-specific & quadratic price effects	24	-209543	419134
4	Mother logit with linear price effects	72	-209458	419059
5	Mother logit with symmetric & quadratic price effects	52	-209278	418659
6	Mother logit with quadratic price effects	80	-209170	418499
7	Error component model with linear price effects	23	-185449	370944
8	Error component model with quadratic price effects	31	-185057	370175
9	RPL with linear price effects, uncorrelated alternative-specific constants	24	-188511	377070
10	RPL with linear price effects, correlated alternative-specific constants	52	-181162	362428
11	RPL with quadratic price effects, correlated alternative-specific constants	60	-180574	361269

Table A7. Likelihood Ratio Tests associated with models in Table A6.

Test	χ^2	df	p-value	Explanation
Model 2 vs. 1	1389	7	<0.001	common price specification rejected in favor of alternative-specific price effects
Model 3 vs. 1	1997	15	<0.001	common price & linear specification effect rejected in favor of quadratic & alternative-specific effects
Model 3 vs. 2	608	8	<0.001	linear price specification rejected in favor of quadratic
Model 6 vs. 4	576	8	<0.001	linear price specification rejected in favor of quadratic
Model 6 vs. 5	216	28	<0.001	linear price specification rejected; symmetry rejected
Model 6 vs. 3	747	56	<0.001	MNL rejected in favor of mother logit
Model 8 vs. 7	784	8	<0.001	linear price specification rejected in favor of quadratic
Model 8 vs. 3	48973	7	<0.001	MNL rejected in favor of ECM
Model 10 vs. 9	14698	28	<0.001	uncorrelated ascs rejected in favor of correlated ascs
Model 11 vs. 9	15874	36	<0.001	linear price specification rejected in favor of quadratic; uncorrelated ascs rejected in favor of correlated ascs
Model 11 vs. 10	1176	8	<0.001	linear price specification rejected in favor of quadratic
Model 11 vs. 3	57938	36	<0.001	MNL rejected in favor of RPL

Table A8. Correlation Matrices for Random Parameters Implied by the Variance-Covariance Matrix Reported in Table 1 of the Main Text

Pooled Model

GB|	1.00000	.89604	.94934	.94986	.90205	.84265	.73259	.82490
SK|	.89604	1.00000	.78181	.87644	.81557	.70713	.68577	.71424
PC|	.94934	.78181	1.00000	.94812	.90936	.84320	.72387	.81291
DH|	.94986	.87644	.94812	1.00000	.85318	.90208	.77086	.78847
CB|	.90205	.81557	.90936	.85318	1.00000	.81537	.70825	.77927
CW|	.84265	.70713	.84320	.90208	.81537	1.00000	.77554	.74024
RB|	.73259	.68577	.72387	.77086	.70825	.77554	1.00000	.61305
PA|	.82490	.71424	.81291	.78847	.77927	.74024	.61305	1.00000

Low Income

GB|	1.00000	.90460	.97424	.93016	.91213	.84683	.74603	.84980
SK|	.90460	1.00000	.95565	.85482	.84400	.80553	.71976	.85608
PC|	.97424	.95565	1.00000	.95601	.92573	.86040	.78184	.87486
DH|	.93016	.85482	.95601	1.00000	.85496	.87121	.78419	.80874
CB|	.91213	.84400	.92573	.85496	1.00000	.82613	.74324	.81853
CW|	.84683	.80553	.86040	.87121	.82613	1.00000	.77957	.77322
ARB	.74603	.71976	.78184	.78419	.74324	.77957	1.00000	.91983
PA|	.84980	.85608	.87486	.80874	.81853	.77322	.91983	1.00000

Middle Income

GB|	1.00000	.90499	.94212	.93963	.90076	.82777	.65946	.79907
SK|	.90499	1.00000	.91099	.82669	.77654	.78780	.56171	.71179
PC|	.94212	.91099	1.00000	.93962	.90344	.82987	.67645	.78150
DH|	.93963	.82669	.93962	1.00000	.82993	.88683	.68228	.74167
CB|	.90076	.77654	.90344	.82993	1.00000	.79174	.67110	.77510
CW|	.82777	.78780	.82987	.88683	.79174	1.00000	.71409	.70726
RB|	.65946	.56171	.67645	.68228	.67110	.71409	1.00000	.90046
PA|	.79907	.71179	.78150	.74167	.77510	.70726	.90046	1.00000

High Income

GB|	1.00000	.89529	.92203	.93254	.87216	.82419	.69761	.72619
SK|	.89529	1.00000	.90379	.79332	.77438	.74790	.59680	.70848
PC|	.92203	.90379	1.00000	.92925	.86956	.80092	.62891	.68162
DH|	.93254	.79332	.92925	1.00000	.82913	.87381	.79834	.75802
CB|	.87216	.77438	.86956	.82913	1.00000	.75307	.68637	.73419
CW|	.82419	.74790	.80092	.87381	.75307	1.00000	.85472	.91710
RB|	.69761	.59680	.62891	.79834	.68637	.85472	1.00000	.93406
PA|	.72619	.70848	.68162	.75802	.73419	.91710	.93406	1.00000

Table A9. Arc Elasticities for a $1.50/lb Price Increase by Income

	Change in price							
Change in quantity	GB	SK	PC	DH	CB	CW	RB	PA
Low income								
Ground beef (GB)	-1.337	0.140	0.157	0.091	0.352	0.108	0.048	0.033
Steak (SK)	0.257	-1.322	0.190	0.061	0.269	0.100	0.044	0.041
Pork chop (PC)	0.329	0.213	-1.342	0.102	0.367	0.107	0.052	0.034
Deli ham (DH)	0.292	0.107	0.158	-0.834	0.266	0.141	0.070	0.028
Chicken breast (CB)	0.231	0.099	0.118	0.057	-0.957	0.102	0.050	0.028
Chicken wing (CW)	0.186	0.096	0.091	0.076	0.266	-0.665	0.068	0.024
Rice and beans (RB)	0.140	0.072	0.077	0.066	0.222	0.116	-0.508	0.068
Pasta (PA)	0.210	0.143	0.105	0.056	0.270	0.085	0.153	-0.555
No Purchase	0.124	0.052	0.044	0.053	0.169	0.063	0.059	0.029
Middle Income								
Ground beef (GB)	-1.237	0.302	0.135	0.091	0.404	0.068	0.041	0.038
Steak (SK)	0.234	-1.468	0.153	0.050	0.234	0.069	0.027	0.027
Pork chop (PC)	0.220	0.323	-1.268	0.092	0.420	0.069	0.047	0.034
Deli ham (DH)	0.275	0.190	0.169	-0.818	0.291	0.114	0.054	0.031
Chicken breast (CB)	0.193	0.149	0.123	0.048	-0.916	0.064	0.047	0.034
Chicken wing (CW)	0.154	0.202	0.097	0.085	0.299	-0.604	0.066	0.027
Rice and beans (RB)	0.111	0.092	0.079	0.049	0.255	0.078	-0.461	0.084
Pasta (PA)	0.174	0.158	0.096	0.047	0.324	0.054	0.148	-0.612
No Purchase	0.110	0.086	0.069	0.045	0.220	0.046	0.065	0.041
High Income								
Ground beef (GB)	-1.251	0.407	0.132	0.059	0.429	0.061	0.032	0.030
Steak (SK)	0.187	-1.463	0.134	0.025	0.268	0.044	0.017	0.030
Pork chop (PC)	0.200	0.442	-1.085	0.061	0.445	0.058	0.023	0.026
Deli ham (DH)	0.258	0.230	0.175	-0.583	0.346	0.089	0.055	0.028
Chicken breast (CB)	0.152	0.211	0.104	0.029	-0.833	0.042	0.030	0.033
Chicken wing (CW)	0.148	0.233	0.094	0.050	0.279	-0.594	0.065	0.084
Rice and beans (RB)	0.113	0.130	0.053	0.045	0.288	0.095	-0.404	0.112
Pasta (PA)	0.106	0.228	0.061	0.024	0.329	0.128	0.117	-0.767
No Purchase	0.119	0.112	0.087	0.017	0.240	0.033	0.040	0.047

Note: Arc elasticities are calculated by determining the percentage change in market shares divided by the percentage change in prices, when moving from the mid-points to the high points of prices employed in the experimental design; shares for each income category are calculated by averaging over 25,000 draws from the respective estimated parameter distributions.

Table A10. Arc Elasticities for a $1.50/lb Price Decrease by Income

	Change in price							
Change in quantity	GB	SK	PC	DH	CB	CW	RB	PA
Low income								
Ground beef (GB)	-3.673	0.369	0.438	0.284	0.931	0.231	0.125	0.228
Steak (SK)	0.685	-3.526	0.507	0.209	0.802	0.217	0.117	0.271
Pork chop (PC)	0.796	0.521	-3.870	0.309	0.952	0.231	0.135	0.231
Deli ham (DH)	0.737	0.291	0.435	-2.722	0.798	0.278	0.171	0.201
Chicken breast (CB)	0.634	0.272	0.343	0.194	-2.771	0.221	0.131	0.200
Chicken wing (CW)	0.542	0.262	0.277	0.245	0.786	-1.431	0.165	0.173
Rice and beans (RB)	0.439	0.204	0.236	0.216	0.698	0.242	-1.247	0.426
Pasta (PA)	0.589	0.370	0.311	0.193	0.792	0.196	0.310	-3.791
No Purchase	0.385	0.149	0.145	0.176	0.567	0.150	0.147	0.200
Middle Income								
Ground beef (GB)	-3.594	0.628	0.402	0.249	0.956	0.202	0.102	0.221
Steak (SK)	0.644	-3.280	0.438	0.153	0.695	0.201	0.069	0.162
Pork chop (PC)	0.624	0.661	-3.782	0.251	0.974	0.204	0.113	0.203
Deli ham (DH)	0.712	0.435	0.471	-2.370	0.803	0.290	0.126	0.187
Chicken breast (CB)	0.559	0.353	0.366	0.148	-2.402	0.191	0.112	0.204
Chicken wing (CW)	0.478	0.451	0.304	0.237	0.801	-1.761	0.148	0.169
Rice and beans (RB)	0.366	0.231	0.249	0.147	0.720	0.219	-1.060	0.443
Pasta (PA)	0.513	0.366	0.298	0.144	0.837	0.170	0.287	-3.529
No Purchase	0.355	0.216	0.220	0.136	0.645	0.145	0.149	0.237
High Income								
Ground beef (GB)	-2.850	0.609	0.342	0.185	0.822	0.151	0.095	0.139
Steak (SK)	0.416	-2.353	0.343	0.089	0.610	0.116	0.055	0.133
Pork chop (PC)	0.443	0.651	-2.854	0.191	0.840	0.145	0.070	0.120
Deli ham (DH)	0.526	0.385	0.424	-1.928	0.729	0.204	0.147	0.134
Chicken breast (CB)	0.352	0.356	0.277	0.101	-1.746	0.111	0.088	0.149
Chicken wing (CW)	0.346	0.383	0.254	0.161	0.626	-1.456	0.175	0.340
Rice and beans (RB)	0.276	0.233	0.156	0.146	0.629	0.219	-1.124	0.436
Pasta (PA)	0.265	0.374	0.176	0.085	0.685	0.268	0.276	-3.289
No Purchase	0.281	0.205	0.232	0.063	0.555	0.093	0.113	0.204

Note: Arc elasticities are calculated by determining the percentage change in market shares divided by the percentage change in prices, when moving from the mid-points to the low points of prices employed in the experimental design; shares for each income category are calculated by averaging over 25,000 draws from the respective estimated parameter distributions.

Table A11. Estimates from Competing Models for Middle Income Respondents used to Construct Figure 4 in the Main Text

Variables	**RPL with correlated ASCs and quadratic prices**	**RPL with correlated ASCs and linear prices**	**RPL with uncorrelated ASCs and linear prices**	**MNL with quadratic prices**	**MNL with linear prices**
Means of Alternative-Specific constants					
Ground beef (GB)	6.353* (0.179)	5.323* (0.097)	3.182* (0.048)	3.831* (0.148)	3.024* (0.042)
Steak (SK)	8.107* (0.737)	5.015* (0.136)	2.873* (0.104)	4.829* (0.621)	2.844* (0.084)
Pork chop (PC)	5.654* (0.235)	4.670* (0.102)	2.419* (0.059)	3.223* (0.211)	2.443* (0.053)
Deli ham (DH)	3.781* (0.136)	3.411* (0.096)	1.263* (0.048)	1.759* (0.100)	1.454* (0.041)
Chicken breast (CB)	7.627* (0.142)	6.117* (0.095)	3.926* (0.044)	4.488* (0.097)	3.440* (0.034)
Chicken wing (CW)	3.419* (0.120)	3.115* (0.098)	0.937* (0.049)	1.575* (0.072)	1.388* (0.035)
Rice and beans (RB)	2.695* (0.101)	2.531* (0.094)	0.443* (0.049)	1.156* (0.045)	1.054* (0.031)
Pasta (PA)	5.856* (0.315)	3.456* (0.110)	1.343* (0.073)	3.597* (0.028)	1.613* (0.064)
Linear Price Effects					
Ground beef (GB)	-1.512* (0.105)	-0.800* (0.014)	-0.829* (0.015)	-1.277* (0.010)	-0.718* (0.013)
Steak (SK)	-1.555* (0.236)	-0.550* (0.016)	-0.549* (0.016)	-1.037* (0.200)	-0.392* (0.013)
Pork chop (PC)	-1.324* (0.135)	-0.698* (0.017)	-0.715* (0.017)	-1.133* (0.130)	-0.638* (0.016)
Deli ham (DH)	-1.062* (0.104)	-0.647* (0.018)	-0.665* (0.018)	-0.934* (0.099)	-0.597* (0.017)
Chicken breast (CB)	-2.039* (0.080)	-0.908* (0.012)	-0.913* (0.012)	-1.462* (0.069)	-0.677* (0.010)
Chicken wing (CW)	-1.256* (0.106)	-0.799* (0.022)	-0.818* (0.022)	-0.915* (0.093)	-0.636* (0.019)
Rice and beans (RB)	-0.865* (0.073)	-0.555* (0.017)	-0.557* (0.017)	-0.604* (0.063)	-0.415* (0.014)
Pasta (PA)	-1.894* (0.171)	-0.515* (0.019)	-0.513* (0.018)	-1.592* (0.160)	-0.452* (0.017)
Quadratic Price Effects					
Ground beef (GB)	0.107* (0.016)	0	0	0.084* (0.015)	0
Steak (SK)	0.079* (0.018)	0	0	0.051* (0.016)	0
Pork chop (PC)	0.088* (0.019)	0	0	0.070* (0.018)	0
Deli ham (DH)	0.086* (0.021)	0	0	0.070* (0.020)	0
Chicken breast (CB)	0.180* (0.013)	0	0	0.126* (0.011)	0
Chicken wing (CW)	0.121* (0.027)	0	0	0.074* (0.024)	0
Rice and beans (RB)	0.082* (0.019)	0	0	0.051* (0.016)	0
Pasta (PA)	0.178* (0.022)	0	0	0.147* (0.020)	0
Variances of Alternative-Specific Constants					
Ground beef (GB)	9.892* (0.484)	9.854* (0.484)	0.952* (0.057)	0	0
Steak (SK)	15.257* (0.671)	15.237* (0.671)	3.660* (0.162)	0	0
Pork chop (PC)	9.909* (0.500)	9.888* (0.501)	0.956* (0.069)	0	0
Deli ham (DH)	9.235* (0.482)	9.252* (0.484)	1.080* (0.078)	0	0
Chicken breast (CB)	10.021* (0.506)	9.990* (0.508)	1.931* (0.073)	0	0
Chicken wing (CW)	11.015* (0.535)	10.989* (0.535)	2.712* (0.132)	0	0
Rice and beans (RB)	8.086* (0.408)	8.091* (0.410)	3.213* (0.151)	0	0
Pasta (PA)	7.310* (0.417)	7.317* (0.419)	1.614* (0.105)	0	0

Table 1 continued on next page . . .

Table 1 continued

Covariances of Alternative-Specific Constants					
SK, GB	11.118* (0.528)	11.095* (0.528)	0	0	0
PC, GB	9.327* (0.467)	9.304* (0.467)	0	0	0
PC, SK	11.201* (0.529)	11.186* (0.530)	0	0	0
DH, GB	8.981* (0.453)	8.976* (0.454)	0	0	0
DH, SK	9.813* (0.521)	9.819* (0.522)	0	0	0
DH, PC	8.988* (0.456)	8.989* (0.457)	0	0	0
CB, GB	8.968* (0.437)	8.951* (0.438)	0	0	0
CB, SK	9.602* (0.504)	9.597* (0.506)	0	0	0
CB, PC	9.002* (0.441)	8.987* (0.442)	0	0	0
CB, DH	7.984* (0.438)	8.007* (0.440)	0	0	0
CW, GB	8.641* (0.456)	8.628* (0.456)	0	0	0
CW, SK	10.213* (0.524)	10.207* (0.525)	0	0	0
CW, PC	8.670* (0.458)	8.668* (0.459)	0	0	0
CW, DH	8.944* (0.457)	8.967* (0.459)	0	0	0
CW, CB	8.318* (0.441)	8.318* (0.442)	0	0	0
RB, GB	5.898* (0.394)	5.907* (0.395)	0	0	0
RB, SK	6.239* (0.466)	6.250* (0.469)	0	0	0
RB, PC	6.055* (0.390)	6.070* (0.392)	0	0	0
RB, DH	5.896* (0.389)	5.926* (0.391)	0	0	0
RB, CB	6.041* (0.387)	6.065* (0.389)	0	0	0
RB, CW	6.739* (0.405)	6.736* (0.407)	0	0	0
PA, GB	6.795* (0.412)	6.805* (0.413)	0	0	0
PA, SK	7.517* (0.486)	7.540* (0.489)	0	0	0
PA, PC	6.651* (0.413)	6.675* (0.415)	0	0	0
PA, DH	6.094* (0.400)	6.131* (0.401)	0	0	0
PA, CB	6.634* (0.402)	6.656* (0.405)	0	0	0
PA, CW	6.347* (0.413)	6.365* (0.414)	0	0	0
PA, RB	6.923* (0.385)	6.937* (0.388)	0	0	0
N choices (people)	47952 (5328)	47952 (5328)	47952 (5328)	47952 (5328)	47952 (5328)
Log Likelihood	-78669.7	-78885.5	-82049.7	-90518.4	-90661.1

[a]One asterisk represents statistical significance at the 0.01 level or lower
[b]Numbers in parentheses are standard errors