Processor-Retailer Markup and Pricing Decision:

Insights from the U.S. Beef Market 2011-16

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Insights from the U.S. Beef Market 2011-16

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Abstract

The real processor-retailer markup for beef in the United States increases by 33% from 2011 to 2016, a substantial and rare increase for a major agricultural commodity. Meanwhile, the processor-retailer markup ratio increases from 40% to 50%. We explain the increase in industry-level markup by employing a structural model and product-level data. Econometric outcomes show that the increase is not driven by price collusion; instead, it is because that the industry switches from a processor-led to a retailer-led pricing conduct, implying a significant change in the bargaining position of retailers against beef processors. Change in the bargaining position is likely to be driven by the considerable growth of private beef brands during the period. Our findings contribute new empirical evidence that private labels of retailers may collectively change the supply conduct of an industry.

Keywords: Beef market, Private labels, Processor-retailer margin, Product-level scanner data, Structural models.

JEL Codes: L11, L13, Q13.

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1. Introduction

One most remarkable development of agriculture in the United States since the 1970s is the evolving vertical and horizontal structures of supply chains, and specifically, the integration of upstream and downstream segments and the concertation within each segment. The U.S. livestock industries are usually considered to have experienced most significant increases in vertical integration (Crespi and Saitone, 2018) as well as segment concentration (Sexton, 2013; Wohlgenant, 2013). Among U.S. livestock industries, beef industry is of the highest production value with the nation being the world's largest producer and consumer of beef. Retail equivalent value of beef produced has been growing and reached $107 billion as of 2018.[1] Regarding vertical integration, contract-based transactions count for 60% of all cattle transactions by 2016, and, in terms of market concentration, the four-firm concentration ratio for beef processing has been around 80% in recent two decades.

The increasing vertical integration and market concentration have inspired a large number of studies on profit distribution along the supply chain of beef. In particular, many economists have studied changes in the farm-processor markup (aka. price spread) from 1970 to 2000, using almost exclusively industry-level data. Prior studies examine changes in buyer and seller power of meat packing firms and the corresponding impacts on economic benefits of livestock farmers or consumers (Muth and Wohlgenant, 1999; Morrison Pual, 2001; Wohlgenant, 2013).

Focusing on the same period, substantial theoretical and empirical work has been done to identify determinants of farm- and processor-retailer markups (Whohlgenant, 2001). Changes in these markups have important policy implications, especially regarding antitrust policies

[1] Data obtained from https://www.ers.usda.gov/topics/animal-products/cattle-beef/statistics-information.aspx

(Morrison Pual, 2001; Sexton, 2013), because they directly affect the welfare of cattle farmers and consumers. For instance, the four largest meat packing firms, Tyson, JBS, Gargill, and National Beef, are again requested by the Department of Justice to offer information related to potential antitrust violations over cattle farmers (McLaughlin, 2020).

Much less attention has been paid to the markups of beef in recent years, probably due to a lack of methodological progress for the analytical framework based upon industry-level data. Yet, magnitudes of the beef markups have changed considerably. In particular, USDA data show that the real-dollar processor-retailer markup for fresh beef stayed around $2.3 per pound during 2011-14 and quickly climbed up to $3.1 by the end of 2016, an increase of 33% (see figure 1). Such a large and rapid increase in the markup is rare, implying a significant increase in the markup ratio of retailers over processors (i.e., retail price minus retail marginal cost divided by price), given that retailing marginal costs stay fairly stable over the period.

Economists and policy-makers care about significant changes in the processor-retailer margin, because the change have critical efficiency and welfare implications along the supply chain (Bresnahan, 1987). According to the Lerner Index of retailers, an increase in the markup ratio implies an increase in the collective buyer power against processors, a decrease in the elasticity of supply by processors, or both. If the increase is driven mainly by a decrease in supply elasticity, there tends not to be loss of efficiency. If, instead, the markup increase is mainly driven by reduced competition and an increase in the buyer power, efficiency loss may be considerable under a highly inelastic supply.

No explanation has been offered to the striking change in the processor-retailer markup for beef, nor has any study estimated its impacts on market efficiency and welfare outcomes. To explain the substantial change, we employ product-level price and quantity information from

Nielsen Retail Data to build a nationally representative sample of major fresh beef products. Following the econometric approach developed by Nevo (2001), we estimate the product demand and then calculate the economic price-cost margins under six hypothetical supply conducts: single-product processor or retailer pricing, multi-product processor or retailer pricing, and processor or retailer price collusion. We compare different sets of estimated price-cost margins with the observed ones to find out the best-fit hypothetical conduct for a particular period.

We find that the industry-level supply conduct is multi-product processor pricing for 2011 to June 2015 and multi-product retailer pricing for July 2015 to 2016. The switch of supply conduct indicates that the dominant position in the price bargaining moves from processors to retailers, which is likely to result from the changing bargaining position of retailers against processors. The bargaining position change leads to a higher markup ratio for retailers over processors. We argue that the growing market shares of private labels change the disagreement payoffs of beef retailers collectively (Pauwels and Srinivasan, 2004; Schmitz, 2013), giving retailers a better bargaining position as a whole.

Our study makes two major contributions to the literature. First and specific to the literature of beef markets, we are the first to explain this recent increase in the processor-retailer markup of the U.S. beef market, which has crucial implications for supply-chain efficiency as well as consumer welfare of such an important agricultural industry. By linking scanner data to the market-level phenomenon, we contribute one of the first structural models that answer a classic question of agricultural economics – determinants of the industry-level marketing margin (Wohlgenant, 2013). Product-level information and a more advanced demand model allow us to characterize beef demand more precisely than prior studies using the classic Almost Ideal Demand System model and market-level data (Eales and Unnevehr, 1993). The random coefficient discrete-choice model we employ produces more realistic demand elasticities by explicitly considering product characteristics and consumer heterogeneous preferences (Nevo, 2000).

More generally, we provide new insights to the growing empirical literature on supply conduct using structural models (Villas-Boas, 2007; Draganska et al., 2010). Prior studies mostly focus on the supply conduct within a short period of time, while we explain a structural change over years, echoing to Bresnahan's classic work (1987). Following Nevo's (2001) approach, our study avoids making nontrivial assumptions on error terms and fully specifying a supply equation as Bresnahan (1987) does to perform a formal test of non-nested hypotheses. Further, our findings provide new empirical evidence of a collective impact of growing private labels, namely, changing the industry-level supply conduct, contributing to an active literature on private labeling (Pauwels and Srinivasan, 2004; Dubé et al., 2018; Ellickson et al., 2018).

2. Features of U.S. Beef Demand and Supply

In the United States, beef remains the second most consumed meat only after chicken, despite its rising retail prices in recent years. Per capital consumption in a year ranges from 75-85 pounds.[2] Most beef is consumed fresh instead of processed, and nearly two thirds of all beef is purchased at retail stores and prepared at home (Davis and Lin, 2005).

Roughly speaking, fresh beef is produced by a three-stage process. In stage one, cattle are raised on ranches most of which are located in the Great Plains. Over 70% of the cattle on feed in 2017 were concentrated in Nebraska, Texas, Kansas, Iowa, and Colorado (Crespi and Saitone, 2018). Geographic concentration remains high moving downstream to the beef processing stage.

[2] https://www.ers.usda.gov/amber-waves/2018/june/per-capita-red-meat-and-poultry-disappearance-insights-into-its-steady-growth/

USDA (2017) reports that 56% of commercial slaughter in 2016 was done in five states: Nebraska, Iowa, Kansas, Texas, and Illinois.

Regarding the volume shares, the market concentration of beef processing sector is also high. The four largest meat processors slaughter about 85% of all steer/heifer in the nation since the 1990s (Morrison Paul, 2001; McLaughlin, 2020). In the retailing stage, concentration of the market has also been increasing. As of 2016, the top four grocery chains in the United States occupied 44% of the market by sales.[3] As shown in table 1, the concentration of beef retailing is comparable to the aggregate concentration level for grocery retailing in the country.

2.1 Rising Processor-Retailer Markup

USDA Livestock and Meat Domestic Data track value of beef at the farm, processor, and retail levels since 1970. The monthly data of beef value are converted to retail-weight equivalent units. The data include beef products with limited processing to ensure that data are comparable over years. We rely on this dataset to generate our benchmark markups for beef. More details about the data are found in Hahn (2004).

In the figure below, we report real markups based on the dataset with 2015 as the baseline. Note that these markup values are exactly price spreads, but their changes directly reflect changes in price changes at farm, processor, and retail levels. From 1980-2000, the processor-retail margin of beef stays around \$2 per pound. The margin increases to \$2.3 per pound and remains at that level until 2014. As shown in the figure, the margin goes up by nearly \$0.8 in two years, a jump of 33%. The farm-processor margin, in the meanwhile, stays stable.

[3] https://www.ers.usda.gov/topics/food-markets-prices/retailing-wholesaling/retail-trends/

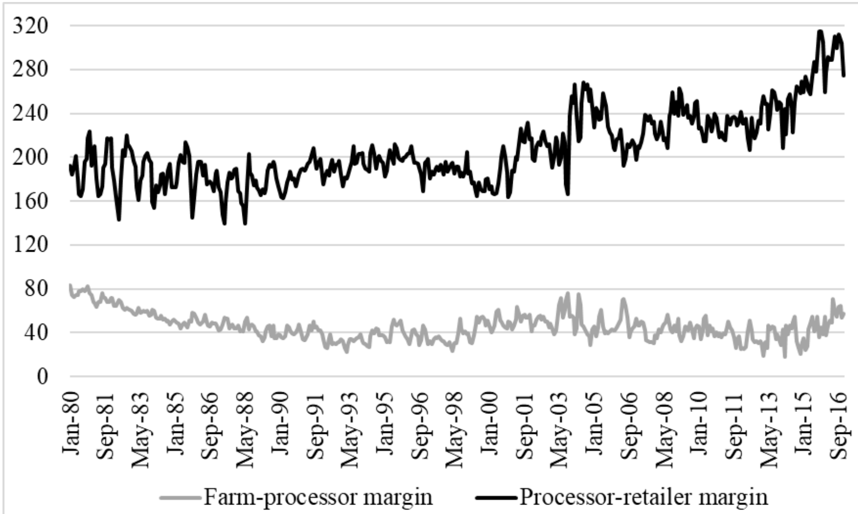

Figure 1. Real Price Margins ($cent/lb.) of U.S. Beef 1980-2016

Source: USDA Livestock and Meat Domestic Data (https://www.ers.usda.gov/data-products/livestock-meat-domestic-data/).

Notes: Real prices computed by authors based on CPI index. CPI 2015=100. The gray curve measure the price margin between processor and farm levels, and the black curve measures the margin between retail and processor levels.

Focusing on the period of 2011-16, we draw below the processor-retailer margin as well as the corresponding markup ratio. Though we do not directly observe the marginal costs for retailers, we follow (Nevo, 2001) and assume that the marginal costs mainly come from the beef bought from processors which is the dominant component of a fresh beef product. Assuming that packaging costs is included in the processor price, the retailer's markup ratio, $(p^r - mc)/p^r$, can hence be computed by substituting mc by the industry-level beef price for processors.

As the figure shows, the ratio stays around 40% until mid-2015 and gradually climbs to the level of 50% by the end of 2016. Though the markup ratio has increased largely, other variable costs for retailers, such as electricity and labor, only change mildly during the period (see appendix 1). For major agricultural commodities, such a large and rapid increase in the markup or markup ratio is rare and worth an in-depth investigation.

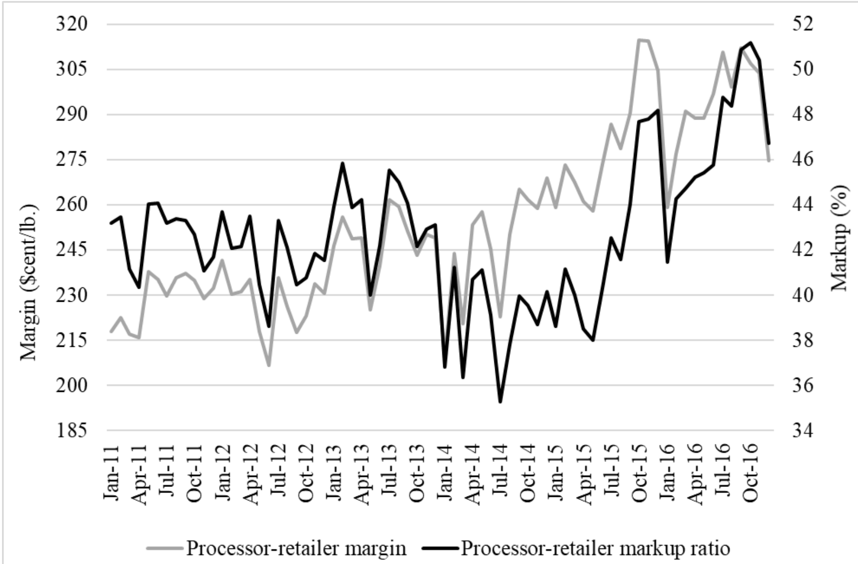

Figure 2. Processor-Retailer Margin and Markup Ratio of U.S. Beef 2011-16

Source: USDA Livestock and Meat Domestic Data (https://www.ers.usda.gov/data-products/livestock-meat-domestic-data/).

Notes: Real prices computed by authors based on CPI index. CPI 2015=100.

3. Empirical Strategy

Our empirical framework contains two parts: demand and supply. We first estimate demands for fresh beef products, which are heterogeneous and face heterogeneous consumers, by following the well-established structural model developed by Berry, Levinsohn, and Pakes (1995). Hereafter, we refer to the demand estimation strategy as BLP. For the supply side, we refer to the process introduced by Nevo (2001). The intuition of Nevo estimation is to consider alternative supply conduct models and estimate processor-retailer markups accordingly. By comparing different sets of estimated markups with the observed markup, we can find the best-fit supply model.

3.1 Demand

The goal is to consistently estimate the own- and cross-price elasticities of beef products in our sample. We follow the approach taken by the discrete-choice literature and, in particular, the estimation approach developed by BLP (1995). Because this method has been widely used and illustrated in several well-known articles, we only highlight key steps below and refer readers to Nevo (2000; 2001) for more details.

The estimation is performed by market. We define a market as the U.S. retail market for fresh beef in a particular month. Focusing on beef instead of all fresh meats allows us to use beef-specific quality characteristics in the utility function, which we illustrate more in section 4.1. Suppose there are $t = 1, \dots, T$ markets, each with $i = 1, \dots, I$ consumers. Upon one purchase, a consumer is assumed to buy one product that gives the highest utility. The conditional utility of consumer *i* choosing product *j* in market *t* is

$$u_{ijt} = \alpha_i^* p_{jt} + x_j \beta_i^* + \xi_j + \Delta\xi_{jq} + \epsilon_{ijt}, \qquad (1)$$

where $q \in \{1,2,3,4\}$ refers to quarters in a given year, x_j is a *K*-dimensional vector of observed product characteristics (e.g., ground beef dummy in table 2), p_{jt} is the price of product *j* in market *t*, ξ_j captures the unobserved product characteristics, $\Delta\xi_{jq}$ is quarter-specific deviation from this mean, and ϵ_{ijt} is the mean-zero error term.

Individual-specific coefficients can be represented by a *K*+1 by 1 vector (α_i^*, β_i^*). We assume that consumers observe and have heterogeneous tastes for all the product characteristics and take them into consideration when making decisions. We can specify the individual-specific coefficients consisting of a linear part and a nonlinear part:

$$\begin{pmatrix} \alpha_i^* \\ \beta_i^* \end{pmatrix} = \begin{pmatrix} \alpha \\ \beta \end{pmatrix} + \Pi D_i + \Sigma v_i,$$

where $\binom{\alpha}{\beta}$ represents the linear part ant the rest is the nonlinear par. In the nonlinear part, D_i is a d-dimensional vector of demographic variables, Π is a $(K+1) \times d$ matrix of coefficients that measure how the taste characteristics vary with demographics, v_i is a $(K+1)$-dimensional vector, and Σ is a scaling matrix for *unobserved* taste characteristics.

We also allow for an outside good option, so that consumers may not purchase any of the sampled products. The utility from the outside good is

$$u_{i0t} = \xi_0 + \Pi_0 D_i + \Sigma_0 v_{i0} + \epsilon_{i0t}.$$

To identify the mean utility of the outside good, we normalize $\xi_0 = 0$.

Let $\theta = (\theta_1, \theta_2)$ be a vector containing all parameters of this model. The vector $\theta_1 = (\alpha, \beta)$ contains the linear parameters, and the vector $\theta_2 = (\Pi, \Sigma)$ contains the nonlinear parameters. We can then express utility by the mean utility, denoted by δ_{jt}, and a mean-zero heteroskedastic deviation from the mean, $u_{ijt} + \epsilon_{ijt}$, which captures the effects of random coefficients.

The consumer chooses the product which gives him/her the highest utility. With the standard assumption of *i.i.d* Type I extreme-value distribution of random shocks ϵ_{ijt} following Nevo (2001), the consumer chooses product *j* with a multinomial logit model. The market share represents the average purchasing probability of consumers as:

$$s_{jt}(x, p_t, \delta_{jt} | \theta_2) = \frac{\exp\left(\delta_{jt} + [p_{jt}, x_j]'(\Pi D_i + \Sigma v_i)\right)}{1 + \sum_{m=1}^{J} \exp\left(\delta_{mt} + [p_{mt}, x_m]'(\Pi D_i + \Sigma v_i)\right)}.$$

We can then follow BLP to propose a *full model* that allows for flexible own price elasticities which are driven by the different price sensitivity of different consumers who purchase various products, and allows cross-price substitution patterns to be driven by product characteristics, not constrained by a priori segmentation of the market. We also conduct the estimation of the Simple Logit Model to serve as a baseline and make comparison with the full model. Details are discussed in section 5.3.

3.2 Supply

We consider alternative supply conducts by considering various pricing strategies of beef sellers. The pricing strategies are made at the industry level, which is an approximation of the dominant pricing strategy of the industry. The vertical relationship between the processor and the retailer is not explicated incorporated, because our goal is to figure out the industry-level supply conduct facing consumers.

First, let there be R beef retailers in the market. Each of them sells a subset of beef products, $\mathcal{R}_r$, of the $j = 1, \dots, J$ different beef products. The profits of retailer r can be expressed as:

$$\pi_r = \sum_{j \in \mathcal{R}_r} \left(p_j - mc_j\right) s_j(p) M - c_r,$$

where $s_j(p)$ is the market share of product j, M is the size of market, and c_r is the fixed cost of retailing. The market share is determined according to the demand function in section 3.1.

Assuming a pure-strategy Bertrand-Nash equilibrium in prices which are all positive, the first-order condition (FOC) with respect to p_j of product j sold at retailer r is

$$s_j(p) + \sum_{l \in \mathcal{R}_r} (p_l - mc_l) s_l(p) = 0.$$

Where $s_j(p)$ is the partial differentiation over p_j. Assuming that the marginal cost for retailers is predominately the price of beef paid to processors, this set of J equations implies the processor-retailer markup for each product.

Rewrite the equation in the matrix form:

$$s(p) - \Omega(p - mc) = 0.$$

The partial differentiation matrix is expressed by the *ownership* matrix and the *response* matrix. The ownership matrix indicates which products are under control of a given retailer.

$$\Omega_{jl} = \begin{cases} 1, if\ \exists r: \{j,l\} \subset \mathcal{R}_r, \\ 0, \qquad otherwise. \end{cases}$$

The response matrix indicates the marginal effect of changing one price on a given product's market share

$$S_{jl} = -\frac{\partial s_j}{\partial p_l}.$$

where $\Omega = \Omega_{jl} * S_{jl}$ and $s(p)$, p, and *mc* are $J \times 1$ vectors. This allows us to express the implied markup as:

$$p - mc = \Omega^{-1} s(p). \qquad (3)$$

Another supply conduct is that the processors determine retail prices to maximize profits and pay retailers commissions to rent shelf space (Tirole, 1988), which is not unusual in supermarket management (Bonnet et al., 2013). In this conduct model, a retailer effectively rents out shelf space to processors and gives them complete autonomy over retail prices (Jareth and Zhang, 2010). Accordingly, the objective function of a processor *m* is:

$$\pi_m = \sum_{n \in \mathcal{R}_m} (p_n - mc_n) s_n(p) M - c_m,$$

where $\mathcal{R}_m$ is the set of products managed by a processor. The marginal cost, mc_n, is for the processor (i.e., cost of cattle in our context), and the fixed cost includes the commission fee. Similar as equation (3), we can express the FOC. Note that the new $(p - mc)$ is the markup between the retail price and processor marginal cost. We need to back out the processor-retailer markup by subtracting the farm-processor markup from the estimated $(p - mc)$.

Using estimates from the demand side, we can specify S_{jl}. The structure of Ω_{jl} depends on our assumption of the supply conduct. In the first set of hypothetical supply conducts, we let the retailer or processor to maximize profits product by product, which captures the product differentiation effect. The second set of hypothetical supply conducts let the retailer or processor maximize profits over all the products sold, capturing the portfolio effect of multi-product retailers. Finally, we build the third set of hypothetical supply conducts where retailers or processors collude over all products to maximize the total profits, capturing the price collusion effect.

3.3 Estimation

The structural model can be estimated following the algorithm used by BLP and augmented by Nevo (2001). The key of the estimation is to exploit a population moment condition based on instrumental variables and a structural error term, forming a nonlinear GMM estimator. The GMM estimate is

$$\hat{\theta} = argmin\omega(\theta)'ZA^{-1}Z'\omega(\theta)',$$

where A is a consistent estimate of $E[Z'\omega\omega'Z]$. This weight matrix can be computed by a two-step procedure (Nevo, 2001).

We can compute unobserved product characteristics as a function of the data and parameters by figuring out the mean utility levels, δ_{jt}, that solves the implicit system of equations

$$s_{jt}\left(x, p_{jt}, \delta j_t \middle| \theta_2\right) = S_{jt},$$

where S_{jt} is the observed market share.

Thanks to the richness of our panel dataset, we are able to include brand-retailer specific dummy variables as additional and collective product characteristics in the estimation. These dummy variables capture observed and unobserved characteristics of beef products sold under a particular brand and at a particular retail chain that do not vary by market (i.e., are time-invariant) and significantly improve the fit of our model. We do not use product-retailer dummies, though, because a considerable portion of products in our sample are only observed for 1-3 times. Otherwise, we would let products that are observed for many times and experience substantial price variations over the period of interest drive our estimates of coefficients.

To identify effects of price in the population moment condition, we need a set of instrumental variables (IVs). We take advantage of variables that affect marginal costs of retailing and processing of beef, including costs of labor, energy, and cattle feed. Summary statistics and sources of these variables are discussed in section 4.3.

4. Data

For empirical analysis, we need nationally representative data to study an industry-level phenomenon. Nielsen Retail Scanner Data are employed, because they form the largest scanner dataset of the U.S. food markets. Nielsen Household Scanner Data, which contain food purchase information of thousands of U.S. households, are also employed to provide demographic information of U.S. consumers.

To construct the structural model by Nevo (2001), we need a group of variables: product market shares, product prices, product characteristics, and information on the distribution of consumer demographics. We construct two sub-samples. One sub-sample provides information of market shares, prices, and product characteristics for major beef products in a given month based on Nielsen Retail Scanner Data. We show that the Nielsen dataset well represents the U.S. beef market, and our sample well aligns with the Nielsen dataset. The other sub-sample provides information of household demographics based on randomized draws from Nielsen Household Scanner Data.

Nielsen Retail dataset consists of over 30,000 stores from approximately 90 major retail chains, covering all states of the nation. The dataset provides weekly information of products sold in every store. Weekly sales, volumes sold, product characteristics, as well as store characteristics, including the type and location. In this article, products are defined by uniform product codes (hereafter, UPCs), and we aggregate data to the month level.

Table 1. Number of Brands and Volume Market Shares in Nielsen Data

	2011	2012	2013	2014	2015	2016
# Brands	66	78	83	91	101	105
Tyson (%)	6.47	6.05	4.57	3.99	4.88	4.57
Excel (%)	5.69	6.44	4.85	2.83	0.71	0.76
Cargill (%)	4.17	4.71	3.38	2.61	0.57	0.23
Laura's (%)	1.80	2.06	2.75	3.04	3.14	2.71
National Beef (%)	0.68	0.91	0.58	0.57	1.20	2.52
CR4	48.56	49.57	55.49	57.49	56.39	56.24
CR8	64.82	65.60	69.42	69.58	68.63	67.67
Retail HHI	0.11	0.12	0.19	0.22	0.20	0.20
Private labels (%)	67.32	64.08	69.19	74.75	76.95	77.00
Top private label (%)	29.98	31.25	41.86	45.66	43.17	43.59

Source: Authors' calculation using Nielsen Retail Scanner Data.

Notes: HHI stands for Herfindahl–Hirschman Index. The index ranges from 0 to 1 with 0 indicating perfect competition and 1 indicating monopolistic market. One brand might have several sub-brands. In our sample, three out of 25 brands have 2 sub-brands. Other brands have no sub-brand.

There are 66-105 beef brands during the period of interest, with the number of brands increasing over time. The introduction of new brands is quite remarkable. As detailed in table 1, large national brands occupy one third to a quarter of the market, while private labels take the rest.

At the nation-level, concentration of the beef retail market has increased measured by the concentration ratios or the Herfindahl–Hirschman Index (HHI). Regarding the HHI, concentration of the retail market would be considered low according to the U.S. Department of Justice until 2013 and moderate afterwards.[4]

4.1 Sampling: Products

We first select a group a major beef products by selecting major national beef brands and retailers from the full Nielsen dataset. We rank monthly volume shares of brands and retailers. Top 10 retailers and top 15 national brands are selected. Because all those retailers end up selling their private brands by the end of 2016, we effectively have 25 brands throughout the sampling period.

Considering the convergence of the estimation, we drop a small number of observations that has too small volume shares in a given month. Specifically, UPCs of monthly volume shares smaller than 0.01% are excluded. In our finalized subsample, there are 267 product UPCs in total and 83-150 UPCs in each given month. The finalized sample size is 13,714.

This subsample might seem small compared to the full Nielsen dataset which contains information of 400-600 UPCs in a year. In fact, our subsample has included major UPCs which jointly account for over 70% of the market by volume. Excluded beef products are taken to represent the outside good in the structural model. We show in the figure below that the subsample represents the full sample fairly well as the subsample market price closely matches the full sample market price.

Worth noticing, by letting beef products not in our subsample as the outside good, we effectively assume away the demand substitution between beef and other meats. This is a

[4] https://www.justice.gov/atr/herfindahl-hirschman-index

reasonable assumption, given that cross-price elasticity of beef and other meats are low (Lusk and Tonsor, 2016). More importantly, by focusing on the beef market, we avoid dropping a large number of UPCs with overly small market shares (i.e., smaller than 0.01%) for preventing convergence problems in the BLP estimation. Finally, the characterization of our utility function in section 3.1 suggests that we need to consider products with a same set of characteristics. Considering different meats would be problematic, because we would not be able to use ground and steak dummies to indicate quality of other meats. Nevertheless, we estimate the Simple Logit model with excluded beef products and all other fresh meat products defined as the outside good. Outcomes are consistent with those obtained under the preferred definition of the outside good and available upon request.

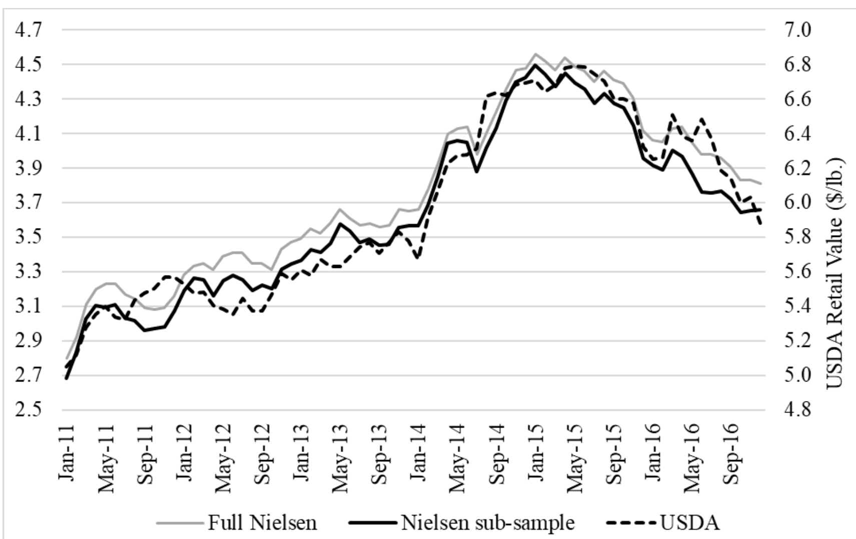

Figure 3. Sub-Sample and Full Sample Comparison

Source: Authors' calculation based on Nielsen Retail Scanner Data. USDA Livestock and Meat Domestic Data.

Notes: Real price is reported with 2015 as the base year. The unit is $ per pound. Full Nielsen refers to all data available in the Nielsen Scanner Dataset, and Nielsen sub-sample refer to our sample with 13,714 observations. USDA data measure the retail value of each pound of beef based on a unique sample discussed in section 2.1.

Summary statistics of key variables are summarized below. All variables are UPC-, retailer-, and month-specific. In Nielsen, only a few variables besides price are available to indicate the quality of fresh beef products. In particular, we are able to tell whether a UPC is organic, is private label or not, the package size, and if it is ground beef or steak. Because the predominant majority of beef products are not organic, we exclude the organic indicator variable from the structural model estimation for the purpose of convergence. The majority of UPCs are ground beef products, either ground beef or beef patty. About 6% of products are different types of beef steak. The rest are other parts for roasting, stewing, or stir frying.

Table 2. Variables in the Estimation

	Mean	SD	Min	Max
UPC volume share (%)	0.39	0.82	0.01	9.98
Outside volume share	25.36	2.71	21.10	32.02
UPC price ($/lb)	4.76	1.92	0.48	17.60
Private label dummy	0.69	0.46	0	1
UPC package size (lb)	1.86	1.52	0.31	10.0
Ground beef dummy	0.92	0.28	0	1
Steak dummy	0.06	0.24	0	1

Source: Authors' calculation using Nielsen Retail Scanner Data.

Notes: The number of observation is 13,714. The variable of *outside volume share* is weighted by numbers of observations in each market.

4.2 Sampling: Demographics

For the period studied, Nielsen Household dataset contains demographics and purchasing information of 60-63 thousand randomly selected households per year. The households are from 49 states of the United States and considered nationally representative. We extract information of household income, size, and age of the head from this dataset by randomly draw without replacement 200 households for each month and year.

Table 3. Demographic Variables of Sampled Households

	Mean	SD	Min	Max
2011-16				
Household size	2.28	1.23	1	9
Income ($1,000)	66.99	43.53	2.42	152.61
Age of the head	58.35	12.08	21	99
2011-14				
Household size	2.25	1.20	1	9
Income ($1,000)	66.67	43.41	2.47	152.61
Age of the head	58.78	11.77	23	96.5

Source: Authors' calculation using Nielsen Home Scan Data.

Notes: Income is self-reported and has a two-year lag. Because the household dataset covers 2004-17, household income observations for year *t* before 2016 are randomly drawn from observations in year *t+2*, while income observations for 2016 are randomly drawn from observations in 2017.

The age of household head is taken as the average of two ages if both the male and the female self-report as the head. Income is self-reported and measured by a categorical variable. We take the mean of each income tier as the income number used in our estimation. For example, if the income tier is $0 to $1,000, the value is converted to $500 in our sample. There are 16 tiers, and the last one is $100,000+. The last income tier is converted to $150,000.

For the 72 months of nation-level data, we have drawn 14,400 households in total. The summary statistics of the demographic variables are displayed in the table below. Income is measured by real 2015 USD with a unit of $1,000. These variables show no significant changes before and after 2014.

4.3 Instrumental Variables

To identify the population moment condition, we need a set of IVs for the retail price of beef products. Nevo (2001) explains why least squares estimations is inconsistent for the pricing decision and proposes a few IVs, when brand fixed effects are included in the estimation of linear parameters.

We include brand-retailer fixed effects in the estimation as well. However, as we are considering product prices at the nation-level, we are unable to use the Hausman (1996) approach which employs prices of a brand in other regions as IVs. Instead, we choose a set of variables that proxy for the marginal costs of retailers and processors, including the feed costs for cattle, labor rates, and energy prices as in Villas-Boas (2007). All these variables show considerable variation at the monthly basis during 2011-16 (see appendix figure A1). In addition, we interact the cost variables with the package size of a beef product to allow changes in costs to affect products differently.

To examine how plausible the IVs are, we present first-stage outcomes in appendix 2. In the Simple Logit model, all IVs except for the wage of meat packing labor have significant impact of the retail price of fresh beef. No significant concern of weak IV problems exists. Also, as shown in table 4, the coefficient of price becomes more negative after using IVs, which aligns with the economic intuition. Without an IV, an increase in price could be driven by a demand shift-out as well as a supply shift-in. Thus, the decrease in quantity demanded due to a price increase would be smaller if both demand and supply move than if only the supply moves.

5. Results

We present two sets of estimation outcomes. The Simple Logit model yields restrictive and unrealistic substitution patterns, yet still serves as a reasonable baseline. Due to its computational simplicity, we take advantage of it to demonstrate features of our data and the value of using brand-retailer fixed effects and IVs. The estimates of the random coefficient model are computed using nonlinear optimization. Comparing estimated markup ratios with the actual ones, we find the best-fit supply conduct for the early and later parts of the studied period, respectively. We interpret both sets of outcomes to explain the sharp increase in processor-retailer markup.

5.1 Simple Logit Outcomes

Table 4 displays the outcomes from regression $\ln(s_{jt}) - \ln(s_{0t})$ on UPC-level prices, product characteristics, and quarter fixed effects (ξ_t), with and without brand-retailer dummies (θ_j). Representing characteristics of a product by vector x_{jt}, we express the regression below, which resembles the estimation of linear parameters in the full model.

$$\ln(s_{jt}) - \ln(s_{0t}) = x_{jt}\beta - \alpha p_{jt} + \xi_t + \theta_j + \epsilon_{jt}.$$

In the first three columns, we report outcomes using ordinary least squares (OLS) regressions, while we apply two-stage-least-squares (2SLS) regressions to the other columns. We try a few specifications with quarter dummies always included. In column (4), we include brand-retailer fixed effects and product characteristics into the regression, but no demographic variables including household size, income, and age of the household head. In column (5), demographic variables are included. For each market, demographic variables take the mean value out of the sample of households discussed in section 4.2.

In columns (4) and (5), the nation-level monthly price of corn is the IV for price. In the last column, we try seven IVs that representing production costs of beef. Because we have price as the only endogenous variable in the Simple Logit model, the monthly price of corn, which is a major feed for cattle, is our preferred IV. Comparing columns (5) and (6) suggests that both IV strategies work, generating statistically indifferent estimated price coefficients. First stage outcomes are reported in appendix 2.

Table 4. Simple Logit Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
Variables		OLS			2SLS	
Price ($/oz)	-15.65***	-5.02***	-4.93***	-7.19***	-7.15***	-6.61***
	(0.051)	(0.121)	(0.122)	(0.562)	(0.649)	(0.534)
Log of mean HH size			-0.05		0.10	0.06
			(0.114)		(0.123)	(0.120)
Log of mean income			0.28		0.43**	0.39*
			(0.204)		(0.211)	(0.208)
Log of HH head age			1.39***		1.47***	1.45***
			(0.523)		(0.529)	(0.526)
Product characteristics	N	Y	Y	Y	Y	Y
Brand-retailer FE	N	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y
# IV	--	--	--	1	1	7
R^2	0.87	0.94	0.96	--	--	--
# observations	13,714	13,714	13,714	13,714	13,714	13,714

Source: Authors' calculation using Nielsen Retail Scanner Data.

Notes: *** p<0.01, ** p<0.05, * p<0.1. Product characteristics includes the private label dummy, package size, ground beef dummy, and steak dummy.

The estimated coefficients of price show the importance of controlling for brand-retailer fixed effects and using IVs. In particular, columns (1) and (2) show that the R^2 increases by 7 percentage points after adding the fixed effects, suggesting a considerable increase in the fit of our model. Regarding the value of using IV, the preferred specification in column (5) has an estimated coefficient of price that is of considerably larger magnitude than the estimated coefficient in column (3). Whether adding quarter dummies or adding the demographic variable do not significantly change the estimated price coefficients. Worth mentioning that the positive coefficients of household income and age of the household head in column (5) indicate that the value of beef products increases with income and age.

Further, we compute own-price elasticities based on the Simple Logit estimates. The mean own-price elasticity turns out to be -3.13, and the median is -1.94 for the 13,714 observations. The standard deviation is 0.86. Only 2.4% of the predicted elasticities have magnitudes smaller than 1, indicating a small portion of products with inelastic demand.

5.2 Full Model Outcomes

The full model estimates are reported in the table below. The price of beef has a significantly negative marginal effect, and coefficient of the price-income interaction term is large and negative. The negative interaction terms implies that the marginal utility of beef decreases more for higher-income households, when the price of beef goes up. On average, the coefficient of price is of a larger magnitude compared with the price coefficient estimated from a Simple Logit model. Own-price elasticities have a negative mean of -1.5 with a standard deviation of 1.6. With the median at -1.7, only 4% of the estimated own-price elasticities are positive.

Table 5. Full Model Outcomes

Variables	Means	SD	Interactions with demographic variables		
	(β)	(σ)	Size	Income	Age
Constant	-21.4	-0.60	-1.27	4.84	--
	(5.98)	(1.00)	(0.27)	(1.76)	
Price ($/oz)	26.90	0.29	--	-8.86	--
	(14.8)	(2.27)		(4.47)	
Private label dummy	1.94	-1.07	--	--	--
	(0.42)	(0.001)			
Package size (lb)	-0.46	--	0.14	--	--
	(0.29)		(0.08)		
Ground beef dummy	1.07	0.38	--	--	--
	(0.21)	(0.76)			
Beef steak dummy	0.91	--	--	--	--
	(0.66)				
Brand-retailer FE	N	Y	Y	N	Y
GMM objective			26.7		

Source: Authors' calculation using Nielsen Retail Scanner Data.

Notes: Based on 13,714 observations. Standard errors are reported in the parentheses. The results reported in this article are found using a grid-search optimization algorithm in Python (Conlon and Gortmaker, 2020) and the Quasi-Newton algorithm in Matlab. We verify the optimization by checking whether both the first-order conditions and second order conditions (the Hessian matrix has all positive eigenvalues) are satisfied and trying different starting values to see if estimates are consistent.

Estimated coefficients of household size and household income are statistically significant, but not for age of the household head. These coefficients suggest that the marginal valuation of a beef product decreases with the household size and increases with the household income. Only one interaction term between product characteristic and demographic variables is statistically significant. The positive coefficient means that the marginal valuation of large package size of a beef product increases with the household size, which is intuitive. Estimates of heterogeneity around the mean utilities are small and mostly insignificant (i.e., the standard deviation estimates), suggesting that heterogeneity in the coefficients is largely explained by the three demographic variables.

5.3 Price-Cost Margins

Given the estimated demand parameters, we can use equation (3) to compute price-cost margins (PCM) for retailer-led supply-conduct models. Similarly, by subtracting the farm-processor markup from equation (3), we find PCM for processor-led supply conducts. Alternative sets of PCM are computed based on estimates from column (5) of table 4 for the Simple Logit model and table 5 for the full model.

As illustrated in section 3.2, there are six conduct models that we consider: single-product processor or retailer pricing, multi-product processor or retailer pricing, and processor or retailer collusion. To examine changes in the supply conduct, we divide the period into two sub-periods: 2011 to June 2015 and July 2015 to 2016 based on what we observe from figure 2. We also vary the two periods (e.g., 2011-14 as period 1 and 2015-16 as period 2) and confirm that our findings are robust.

Our goal is to find the best-fit supply model for the two sub-periods, respectively. To determine which supply conduct fits the industry best, we compare the PCM computed assuming different models of conduct to the observed PCM shown in section 2.1. As discussed, the markup ratio stays 37-43% up till mid-2015 and climbs up to 46-51% in 2016.

The table below reports the median PCM for the Logit and the full model under different hypothetical conducts. Intuitively, the more products managed by a given seller the higher PCM can be achieved, which goes to perfect price collusion of sellers in the extreme. We hence expect to see higher PCM going from single-product to multi-product and to collusion conduct for either processors or retailers.

Table 6. Median Markup Ratios under Various Supply Conducts

	Simple Logit		Full Model	
	Period 1	Period 2	Period 1	Period 2
Single-product processor	47.34	39.27	40.30	34.17
	(5.13)	(1.52)	(5.23)	(2.68)
Multiple-product processor	52.32	43.72	43.43	36.66
	(5.04)	(1.64)	(5.65)	(2.76)
Single-product retailer	53.65	47.36	46.60	42.26
	(5.34)	(1.64)	(5.40)	(2.58)
Multiple-product retailer	59.88	53.60	50.36	45.49
	(4.70)	(1.25)	(5.81)	(2.79)
Collusion of processors	200.32	180.20	291.52	309.54
	(22.16)	(13.38)	(113.80)	(41.14)
Collusion of retailers	206.63	188.30	297.80	317.63
	(21.89)	(14.12)	(114.05)	(40.47)

Source: Authors' calculation using Nielsen Retail Scanner Data.

Notes: Markup ratios are defined as $(p^r - mc)/p^r$ where p^r is the retail price and mc is the retail marginal cost. We find median markup ratios for each market during a particular period and report the mean of the median values. Standard deviations are reported in the parentheses. Period 1 covers January 2011 to June 2015, and period 2 covers July 2015 to December 2016. There are 54 observations for period 1, and 18 observations for period 2. For the collusion conduct, estimated markup ratios are considered outliers and dropped if their magnitudes are larger than 400%.

We first check estimates from the Simple Logit model. For the first period, the conduct of single-product processor best aligns with the observed PCM. The conducts of single-product and multiple-product retailer both align with the observed PCM reasonably well for the later 18 months.

Either conduct suggests that the industry-level price making has switched from a processor-led to a retailer-led conduct from the former to the latter period. PCM under the price collusion conduct are far off the observed values.

Next, we examine the estimates from the full model. The key patterns remain the same. In particular, the conduct of single- and multi-product processor pricing best fits period 1 actual PCM, while the conduct of multi-product retailer pricing best fits period 2. This suggests that PCM in period 1 is mainly driven by product differentiation and some portfolio pricing of processors, with processors being the effective price maker at the industry-level.

In contrast, retailers are the effective price maker at the industry-level during period 2 and manifest the multi-product effect in pricing their portfolios of products. Indeed, because the median PCM under multi-product retailer pricing is still slightly lower than the actual PCM, there could be some small degree of retailer collusion in the industry.

6. Further Discussion

From 2011 to 2016, the processor-retailer markup of fresh beef in the United States increases by a third. The substantial change in such a major food commodity has not been explored, yet has critical efficiency and welfare implications. We conduct the first investigation on this change using product-level scanner data. By characterizing the demand of beef using the random coefficient discrete choice model, we infer the processor-retailer markup under various supply conducts. Our estimates suggest that the price-decision power has been reallocated from the hands of beef processors to retailers.

What drives the structural change in the supply conduct of the U.S. beef market? The Lerner Index suggests that markup ratio may change due to changes in the elasticity of beef supply or the collective power of retailers, or both. There is little evidence, though, suggesting that the supply of processed beef would be less elastic as we do not observe any major technological change of cattle production or meat packing during the period.

In recent years, product differentiation in the fresh beef market has increased through retailers' provision of more varieties in cuts, package sizes, brands, and credence attributes. In particular, there is an increasing number of private label beef products (see table 1). From 2011 to 2016, the market share by volume of private beef labels increases by 10% to reach 77%. The leading private label sees its market share increase from 30% to 43% and becomes the dominate player in the market.

Given a switch from processor-lead pricing to retailer-lead pricing, we argue that there may be a significant increase in retailer bargaining position against beef processors (Schmitz, 2013). The literature of private labeling suggests that selling private labels helps enhance bargaining position of retailers. As Pauwels and Srinivasan (2004) and Dubé et al. (2018) argue, one key incentive for a retailer to create private labels is to enhance bargaining position against national brands by changing the disagreement payoffs. Change in the bargaining position may allow retailers to become the leading price setter instead of the processors. In addition, a retailer operating private labels is most likely to own the price-decision power through vertical integration with its processors.

In regard of the U.S. beef industry, the growing collective share of private labels may have eventually led to a structural change in the supply conduct. Our next step is to search for more rigorous evidence of private-label impacts on the bargaining position of beef retailers during the period of interest. We plan to discuss welfare implications of the change in supply conduct, too.

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Appendix 1. Nation-Level Production Cost Variables

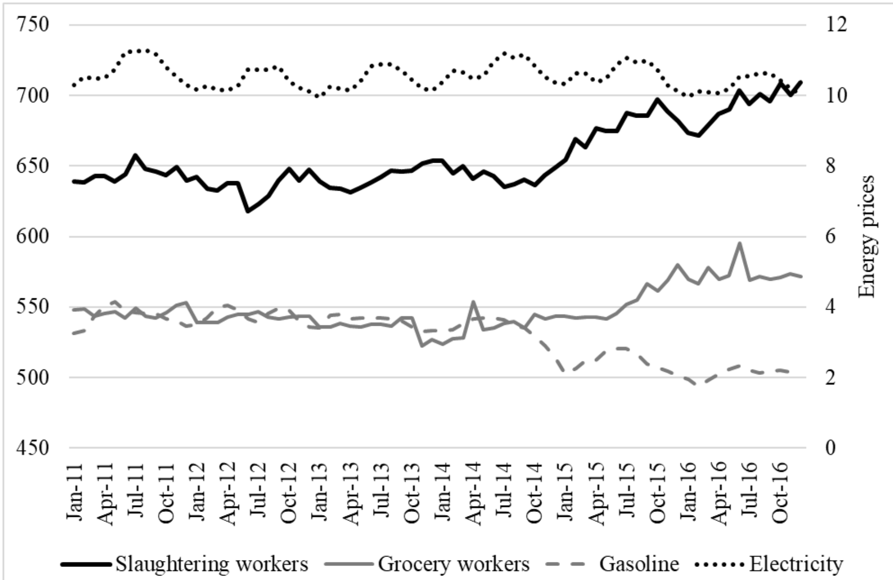

Figure A1. Production Cost Variables 2011-16

Source: Authors' calculation based on Nielsen Retail Scanner Data.

Notes: Variables are measured at the nation-level. Prices of feed are obtained from U.S. Department of Agriculture Feed Grains Data, wage rates are obtained from U.S. Bureau of Labor Statistics, and energy prices are obtained from U.S. Energy Information Administration. The black solid curve represents weekly real wage rates for workers at mean packing plants, while the gray solid curve represents weekly real wage rates for workers at grocery stores.

Appendix 2. First-Stage Outcomes for the Simple Logit Model

Table A2. First-Stage Outcomes for the Simple Logit Model

	(1)	(2)	(3)
Dep. Var.	Retail price of beef UPCs ($/oz)		
Corn price	-11.71***	-11.30***	-12.26***
	(0.451)	(0.502)	(0.917)
Hay price			0.66***
			(0.055)
Soymeal price			0.04***
			(0.012)
Wage of supermarket labor			0.33***
			(0.097)
Wage of meatpacking labor			-0.04
			(0.060)
Gasoline price			-23.31***
			(2.710)
Electricity price			15.64***
			(2.960)
Brand-retailer FE	Y	Y	Y
Demographic variables	N	Y	Y
Quarter fixed effects	Y	Y	Y
R^2	0.95	0.95	0.95
# observations	13,714	13,714	13,714

Source: Authors' calculation using Nielsen Retail Scanner Data.

Notes: *** p<0.01, ** p<0.05, * p<0.1. Demographic variables include mean of household size, mean of household income, and mean of household heads' age in the sample of households that we randomly draw from the Nielsen Home Scan Data. IVs are scaled by dividing 1000 to avoid overly small magnitudes of coefficients.