Firm-level Pass-through of Supply Chain Disruptions: Insights from the US Beef Market*

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Abstract

The pass-through of supply-chain disruptions to consumers depends on how firms along the chain react and interact with each other. We study firm-level responses to disruptions in a unique setting where a temporary and substantial capacity loss hit the US beef processing sector. In August 2019, a fire caused the shutdown of the largest beef plant owned by Tyson, the largest beef packer in the US, and the plant processed 5-6% cattle in the nation. We document increases in marginal costs of processing after the fire. Interestingly, higher marginal costs did not pass through to retail prices of Tyson's products, while retail prices of products owned by other packers went up. We rationalize such patterns with a model of bilateral bargaining between beef packers and retailers, incorporating increased uncertainty in the delivery of products by the packer who loses capacity. We argue that higher uncertainty with delivery presses markups for the packer, which reduces the pass-through of marginal costs to retail prices. Counterfactual simulations reveal heterogeneous price effects of production disruptions across packers, and hence differential welfare impacts on consumers and farmers.

JEL Codes: Q13, Q18, L13, D81

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1 Introduction

Disruptions in the supply of goods and services have been recurring in recent years. The widespread outsourcing of domestic production to overseas suppliers (House, 2012; Baldwin and Freeman, 2022), the advent of climate and other natural disasters (Stern, 2008; Carvalho et al., 2021), the threat of pandemics (Hadachek et al., 2024), geo-political conflicts (Caldara and Iacoviello, 2022), and cyber-security attacks (Grossman et al., 2023) have made unexpected supply shocks much more prominent. Disruptions can have important and long-lasting effects on production and welfare. For example, supply chain disruptions resulting from the COVID-19 pandemic strangled production capacities worldwide and were a major contributor to the higher inflation observed in subsequent years (LaBelle and Santacreu, 2022).

Concerns about supply shocks have led policymakers to consider various policy options that improve chain resilience.[1] However, being able to predict the costs and benefits of such measures depends critically on understanding how the individual firms that make up the chain respond to disruptions. Firm-specific factors can be the key to the final pass-through of cost shocks to consumers: the pricing rule, the vertical relationships between firms within the chain, the magnitude of the shock relative to marginal costs, reputation effects, and changes in expectations after a shock (Magnolfi et al., 2022a; Glover et al., 2023; Cajal-Grossi et al., 2023; Grossman et al., 2023). Although an important topic, the literature still lacks a depth of empirical evidence on the importance of those factors, hindering policymakers' ability to effectively aid firms facing disruptions. This is partly due to data availability and identification issues when dealing with large shocks that potentially have demand effects like COVID-19.

This paper uses product-level information on prices and quantity to explore firm-level responses to a major negative shock in production capacity in the US beef industry. The temporary capacity reduction was caused by a fire at a large beef processing plant in early August 2019, which poses an unexpected and exogenous

[1] See language on bills passed by the US congress related to the CHIPS and Science Act of 2022, the Inflation Reduction Act of 2022, and the Executive Order 14017 of America's Supply Chains of 2021.

variation in the supply conditions of packing firms. After the fire, we document an increase in marginal costs across the industry. These higher costs lead to higher retail prices for beef products from all processors but, surprisingly, for products owned by the packer directly affected by the fire. We show that traditional models of cost pass-through cannot rationalize these price movements. To explain the price changes after fire, we propose a new pricing mechanism that incorporates uncertainty in product delivery in a model of bilateral bargaining between beef processors and retailers.

The US beef supply chain consists of three main stages: ranchers that sell cattle to beef packers, and packers sell processed beef to retailers. Products are sold to consumers under either private labels owned by retailers or processor-owned brands. In the processing stage, sales are highly concentrated among four firms: Cargill, JBS, National Beef, and Tyson. Together, the big-four firms process 80% to 85% of US beef. The fire forced Tyson's largest plant in Holcomb, Kansas, which represented 15-20% of Tyson's capacity and 5- 6% of the US capacity to shut down from mid-August to December 2019. Unlike other recent economic-wide disruptions (e.g., COVID-19), the fire can be interpreted as a rather isolated shock exclusive to the production capacity of the beef industry and with minimal effects on demand. Therefore, this setting offers an ideal natural experiment to examine the effects of a temporary and significant supply-chain shock on firms' responses under oligopolistic competition and heterogeneous products.

We start with reduced-form evidence showing the evolution of market outcomes around the time of the fire. From August to September, uncertainty about future slaughter capacity of Tyson led to lower future cattle prices, but with only a short-lived decline in spot cattle prices, as processors relocated production to other plants.[2] This adjustments in production significantly increased Saturday

[2]Notice that most cattle procurement uses formula contracts. Formula contracts are contracts that guarantee the supply of cattle at a future date to processors. Prices are determined a few

slaughter and, sequentially, average wages of animal slaughter. The increase in the cost of beef processing led to an increase in the average wholesale price of beef. However, in the retail stage, while branded products owned by other packers enjoyed price increases, we document a negative pass-through to the retail prices of Tyson's products. These findings are counterintuitive, as traditional models of cost pass-through under imperfect competition and realistic demand elasticities would predict either an increase in prices for all firms or decreases or no change in prices for non-Tyson products (Magnolfi et al., 2022b), none of which are observed in our data.

We rationalize the observed price movements by arguing that the fire increased the probability that Tyson fails to deliver products as scheduled with retailers and hence increased the chances of stockouts in retail stores. Stockouts of beef are costly to a retailer, particularly near peak periods of beef demand, because disappointed consumers tend to leave the retailer with a basket of potential goods to purchase for the current shopping trip as well as future trips (Campo et al., 2003; Ailawadi et al., 2008; Briesch et al., 2009; Matsa, 2011). As the uncertainty increases, the payoff from selling the packer's products falls for a retailer. In our model, the reduction in expected retailer payoff affects retail prices through a bilateral bargaining process between the retailer and the processor, which creates a downward pressure on wholesale prices for Tyson's products, but not for its competitors. This helps reconcile the increased marginal processing costs with the differential pass-through rates for Tyson and its competitors.

Fires are common in food processing plants (Verzoni, 2022), and it is of policy interest to know *ex ante* how disruptive similar fires would be in other processing plants. Hence, we develop a structural model of the industry that allows us to translate the observed shock into changes in marginal costs and delivery uncer-

weeks before delivery using a formula that uses realized cash prices in a region. The final prices that processors pay for cattle are an average of all prices paid at different plants.

tainty. We then impose counterfactual shocks on plants not owned by Tyson. We do so by leveraging exclusive information about plant capacity for all major processors in the US and accounting for potential partial absorption of shock impacts by packers through the negotiation between processors and retailers. Counterfactual simulations show that shocks of similar magnitudes to other beef processors lead to heterogeneous price effects: retail prices may fall or increase in various degrees across manufacturers.

We follow previous work on differentiated products and model demand for beef products using a discrete-choice approach (e.g., Nevo, 2001; Villas-Boas, 2007; Bonnet and Dubois, 2010; Conlon and Gortmaker, 2020). We bridge these demand models with a model of expected sales that mimics key aspects of the beef industry, namely, the negotiation of processor-retailer prices and scheduled delivery of beef ahead of demand realization. On the supply side, we show that price negotiations between processors and retailers describe well the pricing conduct in the US beef market, similarly to other industries and as described in Grennan (2013). We use a model selection approach as in Duarte et al. (2023) to provide evidence that the supply side we propose better explains the price movements observed relative to traditional supply models.

We contribute to the literature as one of the first empirical studies on the impact of supply chain disruptions in successive oligopolistic markets where prices are negotiated to settle and where delivery uncertainty is taken into account in the negotiation. By proposing a novel pricing mechanism and using detailed scanner data, our structural model rationalizes the impacts on market outcomes that conventional frameworks of pass-through tend to overlook. This finding has critical implications for policy design that aims to improve supply chain resilience and firm adaptation to shocks.

2 The US Beef Industry

The US beef supply chain comprises roughly three stages: cattle raising, meat processing, and retailing. The entire cycle of a single calve, from offspring to maturity, takes about three years. The cycle starts in cow-calve operations, where weaning calves start to gain weight. After reaching the desired weaning weight, the calves are sold to stockers and backgrounders and follow feedlots to reach maturity. After achieving a proper weight, the cattle are sold to the packing plants through spot market auctions or future contracts(Cowley, 2022). Packing plants harvest mature cattle and pack them into primal cuts. Today, most plants also process primal cuts into case-ready beef products that consumers buy at grocery stores. In the US, more than two thirds of beef is fresh and is purchased in grocery stores (Hahn, 2001).

At least since the early 2000s, concentration in beef processing has been increasing. Today, the four large beef packers slaughter and pack some 85% of cattle in the nation (Crespi et al., 2012; Crespi and Saitone, 2018). The bulk of cattle slaughter is carried out in the US Great Plains, where the majority of cattle are also raised (Crespi and Saitone, 2018). Plants with a processing capacity of more than 1 million head per year account for 1.8% of all plants in 2019, but 52.4% of the total beef production. In recent years, the concentration of beef retail has increased, following a broader trend of higher concentration in food retailing (Hamilton et al., 2020).

Beef industry has the highest retail value in the US agricultural sector: 106 billion USD in 2018 and 111 billion USD in 2019 (USDA, 2022). The domestic processing and distribution are almost self-sufficient, and net imports have accounted for less than 0.5% of the US consumption in recent years. Retail stores offer a diverse beef product line that includes different beef cuts. The different cuts of beef are normally grouped according to similar characteristics. For example, rib-eye steak, tenderloins, and top rounds are popular cuts.

Beef products are sold under both processor and retailer brands. The brands owned and managed by retail chains (e.g., Great Value of Walmart) are called private labels, while brands owned by manufacturers are often referred to as national brands. In the whole US fresh beef market, around 150 national brands occupy about 30% of sales, while the rest are taken up by about 80 private labels. There is considerable variation in the market share of national brands at the local market level. Specifically, across the Designated Market Areas (DMA) defined by Nielsen, the average jointly market share of national brands is 43.7% of the volume sold, with a standard deviation of 31.40%. Although different types of cuts are more popular within the sales of each brand (e.g., patty represents 38% of JBS's sales, but only 3% of National Beef), ground beef is always the most popular cut, accounting for more than 60% of the sales for all brands, as can be seen in Table A3 in the Appendix.

Retailers mainly purchase beef cuts by negotiating directly with processors, with price offers on the spot market as a complementary channel in case of unexpectedly high demand. Most retailers receive case-ready fresh beef from processors that are negotiated and scheduled for delivery weeks in advance. This is because beef is a product that tends to attract consumers to stores, particularly around celebratory dates. This calendar dictates the advertisement and availability of some cuts by specific processors. For example, the holiday of Fourth of July and the Labor Day represent annual peaks of beef demand. A retailer needs to order more beef from specific processors weeks ahead to meet the demand surges around a coming holiday.

2.1 Data sources

We collect information on the US beef supply chain from multiple sources. Information on retail prices and sales comes from the NielsenIQ Scanner Dataset. NielsenIQ Scanner data are organized by Universal Product Codes (UPCs) in weekly reports for thousands of retail stores. There are 961 beef Universal Product Codes (UPCs) in our dataset of interest. The dataset also contains information on the characteristics of beef products, including the cuts. The finalized NielsenIQ Retail dataset consists of more than 21,000 fresh-beef-selling stores from some 130 retail chains and 49 US states.

Information on cattle prices, wholesale beef prices, and cattle slaughter is obtained from the United States Department of Agriculture's Agricultural Market Service (AMS). We use AMS's historical cattle and wholesale prices at the national level. We also collect national information on wages for beef processing from the Bureau of Labor Statistics (BLS).

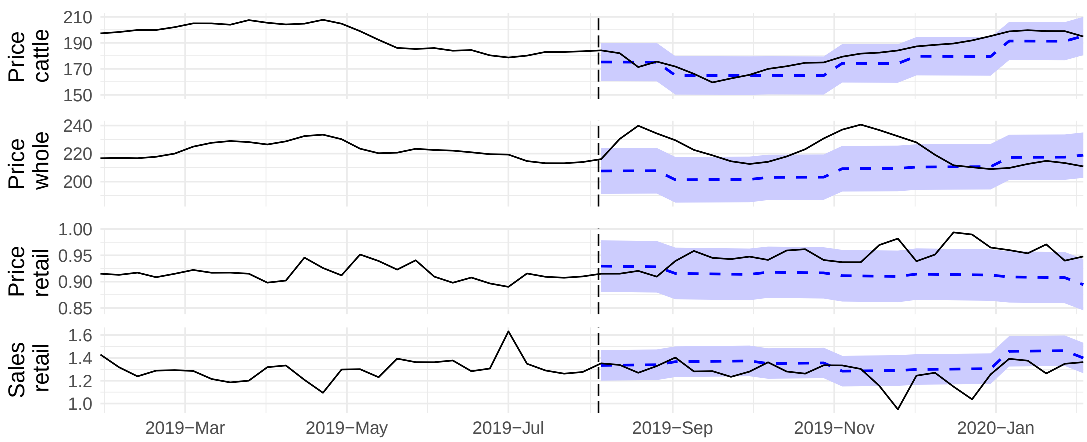
3 The Holcomb Fire

Tyson's largest plant in Holcomb, Kansas, suffered a fire incident on August 9, 2019. The plant accounted for 15-20% of Tyson's slaughter capacity and 5-6% of the US capacity. The fire caused great damage, and the Holcomb plant was closed until December 2019.

The impact of the fire on Tyson's costs is well documented in agricultural news outlets at the time. The Holcomb plant purchased cattle from a large geographical radius, mainly from the High Plains of Texas to Nebraska. Tyson had to divert the cattle to its other plants that are smaller (Gabel, 2019; Ishmael, 2019). In conversations with industry experts and regulators, we learned that the divergence of cattle to plants with smaller capacity was costly due to additional freight costs and overtime pay for workers. Tyson's own estimate of additional costs due to the fire was \$31 million, which is close to 10% of its contemporaneous quarterly earnings (Maidenberg, 2019).

Uncertainty over when and if any Tyson would reopen the plant, maintained for most of the second semester of 2019. Only in the first week of December was part of the operations restarted and the plant became fully active in the first week of January. (Foods, 2019).

Figure 1: Fire Effects on Aggregate Sales and Prices across the Beef Supply Chain



Note: Price cattle: Average price for national weekly direct slaughter cattle, for steers and heifers' purchases that are negotiated and domestic (USDA's AMS Datamart); *Price whole*: Average price for national weekly Boxed Beef Cutout for negotiated sales and weight 600-900 (USDA's AMS Datamart); *Price retail*: Price index for a bundle of all beef retail cuts survey by NielsenIQ using Marshall–Edgeworth's index calculation; *Sales retail*: Quantity index for a bundle of all beef retail cuts survey by NielsenIQ using the Marshall–Edgeworth's index calculation. Dashed line and shaded region are respectively the prediction's average and the 90% confidence interval based on a trend and seasonality regression for the Jan/2016-Jul/2019 period.

In figure 1, we show the evolution of nationwide average prices at different stages of the beef supply chain around the time of the fire, as well as the aggregate retail sales of beef. We contrast the actual price and quantity series observed after the fire (solid line) with what would have been expected based on the trend and seasonality of these average market outcomes during the three years before the shock (dashed line).[3] Though we do not observe a significant change in the negotiated spot prices for cattle after the fire, we see an increase in the average wholesale price during the second semester of 2019. We also observe a positive transfer from the higher wholesale prices to the average retail price of beef in supermarkets. As expected, there is a parallel reduction in aggregate beef sales in the fourth quarter of 2019. In the next section, we discuss the reaction of agents at each level of the supply chain in more detail.

3.1 Fire impacts in detail

The fire triggered different reactions from the cattle, wholesale, and retail markets.

Cattle market Uncertainty about the capacity of processing cattle after the fire put downward pressure on cattle futures prices.[4] Lower processing capacity post-fire implied short-term oversupply of already-finished cattle and, consequently, short-term futures price decreases followed. Cattle markets were unsure whether the Holcomb plant would be back to fully operational until November 2019, when Tyson announced the plant would be restored by the end of 2019. Table 1 shows that average future prices for feeder and live cattle decreased until September to then rebound for the remainder of 2019, when downside risk to processing was considered lower by ranchers.

Lower cattle prices likely had a small effect on processors' marginal costs, since

[3] Although we observe data after January 2020, we do not include them in our investigation because of the closeness to the COVID-19 shock.

[4] For example, the Texas Cattle Feeder Association informed their members that "*beginning Saturday morning (August 10, 2019), TCFA [the Texas Cattle Feeders Association] staff and leadership reached out to the big-four packers to assess the impacts of the Holcomb plant fire and determine what accommodations would help allow for increased processing capacity at other plants, minimize uncertainties, and help stabilize the markets.*" (Ishmael, 2019). The National Cattleman's Beef Association requested the regulatory arm of the USDA for the "*flexibility needed to move to other plants and work expanded shift hours, including weekends, in order to help the packing segment of our industry process the cattle headed to harvest*" (Ishmael, 2019).

Table 1: Evolution of Cattle Futures Prices After the Fire

	log(Feed Cattle Futures)	log(Live Cattle Futures)
	(1)	(2)
Fire mid Aug	−0.093 (0.008)	−0.089 (0.008)
Fire Sep	−0.073 (0.008)	−0.102 (0.008)
Fire Oct	−0.017 (0.007)	−0.009 (0.008)
Fire Nov	0.010 (0.008)	0.024 (0.007)
Fire Dec	0.027 (0.010)	0.033 (0.009)
R^2	0.910	0.865
Adj. R^2	0.908	0.863
Num. obs.	1263	1293

Note: Standard errors in parenthesis. Data on first expiring futures contract for live cattle and cattle on feed from 2015 to 2019. All specifications account for month seasonality and a quadratic time trend with a trend break on January 2017.

the prevalence of formula contracts in cattle procurement limited the benefits of short-lived swings on future prices. Under formula contracts, feedlots contract cattle to processors for future delivery, and prices are pegged to a formula that uses cash prices across regions close to delivery dates (MacDonald, 2006; Garrido et al., 2022). It also probably did not create any major differences in costs between processors, as the fast drop and recovery of prices were uniform across the different regions where cattle transactions are negotiated. See Dennis (2020) who discusses how cash prices recovered uniformly in different regions.

One reason for the fast recovery of the cattle price was the fact that the increase in cattle slaughter on weekends at other plants helped maintain beef processing levels during the second semester of 2019. In Table 2 we show an increase in Saturday slaughters after the fire at the same time as the weekly slaughter numbers fell. The substitution of weekend slaughter for weekday slaughter is consistent with the large decrease in the capacity of the Holcomb plant. There are also news reports of an increase in weekday shifts at non Tyson plants, but that we cannot capture using aggregate data.

Table 2: Evolution of Weekday and Saturday Slaughter After the Fire

	log(Daily Slaughter)
Fire Aug-Sep	−0.137 (0.099)
Fire Oct-Dec	−0.087 (0.095)
Fire Aug-Sep×Saturday	0.529 (0.124)
Fire Oct-Dec×Saturday	0.554 (0.105)
Adj. R^2	0.283
Num. obs.	1250

Note: Daily observations on cattle and calf slaughter from 2016 to 2019. All specifications account for seasonality (day of the week and month of the year) and a linear time trend. Data extracted by authors from https://lmic.info/

As a result of the increase in weekend slaughter, there is a slight increase in wage rates for slaughter workers after the fire. Based on data from the BLS, in Table 3 we estimate a 2% nationwide average wage increase received by employees in the animal slaughter industry after the fire. There is also a increase in the total overtime hours post-fire for production workers in the animal slaughtering industry, parallel with a small decrease in the total time hours post-fire for all employees in the industry. The decrease in total average work hours is likely driven by workers at the Holcomb plant who, after the fire, were unable to work. To compensate for lost hours, a smaller group of active workers worked overtime more.

Table 3: Evolution of Wages and Working Hours After the Fire

	log(Hourly wages)	log(Prod. Work Hours)	log(Overtime)
	(1)	(2)	(3)
Fire Aug-Sep	0.020 (0.004)	−0.015 (0.011)	0.111 (0.056)
Fire Oct-Dec	0.023 (0.004)	0.007 (0.012)	0.113 (0.051)
Adj. R^2	0.977	0.789	0.457
Num. obs.	60	60	60

Note: Bureau of Labor Statistics national data for NAICS code 311611 from 2016 to 2019 on a monthly frequency. *Prod. Work Hours* : total hours of work in slaughtering, excluding administrative staff. *Overtime*: total hours of Saturday slaughtering. All specifications control for a quadratic time trend and specification (2) to (4) for seasonality.

Wholesale market Boxed beef cutout values have been following a positive trend since 2016, and seasonality would have implied lower prices during the second half of a year compared to the first half, reflecting the fact that, in the US, most calves are spring-born and fall-weaned. However, in the second half of August 2019, we observed significantly higher wholesale prices for the boxed beef cutout.

As discussed in Dennis (2020), the initial wholesale price increase at the end of August was driven not only by the reduction in beef processing but also by retailers that rushed to guarantee the supply of beef that would be consistent with their promotional schedules for the coming Labor Day holiday. However, higher wholesale prices persisted for most of the second semester of 2019, most probably reflecting higher processing costs. In Table 4, we show that the average price for boxed beef cutout was around 9% higher than the price implied by trend and seasonality during September and October 2019. Moreover, in Table 4 we also show evidence that this increase in wholesale prices occurred in different cuts of beef, suggesting that costs were uniformly higher even after accounting for differences in product composition between firms.

Table 4: Evolution of National Wholesale Beef Prices After the Fire

	(1) log(Price Boxed Beef)	(2) log(Price Select)	(3) log(Price Choice)	(4) log(Price Ground Beef)
mid Aug	**0.119** (0.014)	**0.054** (0.014)	**0.114** (0.013)	**0.223** (0.020)
Sep	**0.086** (0.017)	0.019 (0.019)	**0.097** (0.017)	**0.129** (0.049)
Oct	**0.087** (0.020)	0.007 (0.019)	**0.077** (0.017)	**0.083** (0.021)
Nov	**0.123** (0.017)	**0.095** (0.019)	**0.118** (0.017)	**0.176** (0.027)
Dec	0.030 (0.020)	**0.061** (0.017)	0.039 (0.020)	−0.008 (0.039)
Adj. R^2	0.599	0.574	0.615	0.448
Num. obs.	208	208	208	208

Note: Weekly observations on wholesale beef prices for selected, choice, and ground beef (81% fat, the most traded quality of ground beef) collected by the USDA from 2016 to 2019. All specifications control for month of the year and time trend.

Retail market: We leverage the product-level scanner data to investigate effects of the Holcomb fire on retail prices. Table 5 shows that beef retail prices increased around 4% after the fire compared to August of the same year. Surprisingly, if we breakdown prices by packer, Tyson's products declined on average by more than 2% in the months following the Holcomb fire, suggesting a differential effect on Tyson's pricing behavior relative to other beef processors.[5]

Table 5: Percentage Changes in Beef Retail Prices in Relation to August 2019

	Month				Semester
	Sep.	Oct.	Nov.	Dec.	Avg.
Tyson	-2.45	-4.41	-0.98	-0.71	
Others	3.95	4.67	3.74	5.93	
Regional Brands	0.56	1.70	2.42	3.33	
Cargill	2.71	2.90	1.65	2.95	
JBS	7.28	9.15	-4.13	10.16	
National Beef	2.55	3.50	3.45	4.43	
Private label	4.76	5.43	4.61	6.81	

Note: The table calculates monthly average percentage change in the price of Tyson's beef products after the fire in relation to August of 2019 using product level data from NielsenIQ. We weight each product by its volume sold in August of 2019 to calculate a weighted month prices.

Tyson's lower retail prices after the fire could have resulted from a strong negative trend in Tyson prices before the fire, which could have more than offset price increases stemming from higher marginal costs. We test this possibility by examining price deviations from the trend using a two-step regression model as in Bhattacharya et al. (2023). In the first step, we regress prices for beef products on processor-specific flexible trends as depicted in equation 1, while controlling for seasonality, retailer and DMA fixed effects, and product-specific controls using data from January 2017 to mid August 2019. We then find trend-implied retail

[5] Appendix B shows that products from both large and small processors experienced increases in retail beef prices after the fire. However, Tyson beef prices consistently fall from September to December compared to August 2019.

beef prices by projecting equation 1 on the data after the fire. Specifically, for product j owned by processor b during time t:

$$log(p_{jbt}) = \sum_b \beta_b\big(f(trend) \cdot \mathbf{1}_b\big) + \alpha_{season} + \alpha_{retail} + \alpha_{DMA} + Controls_j + \epsilon_{ijt}. \quad (1)$$

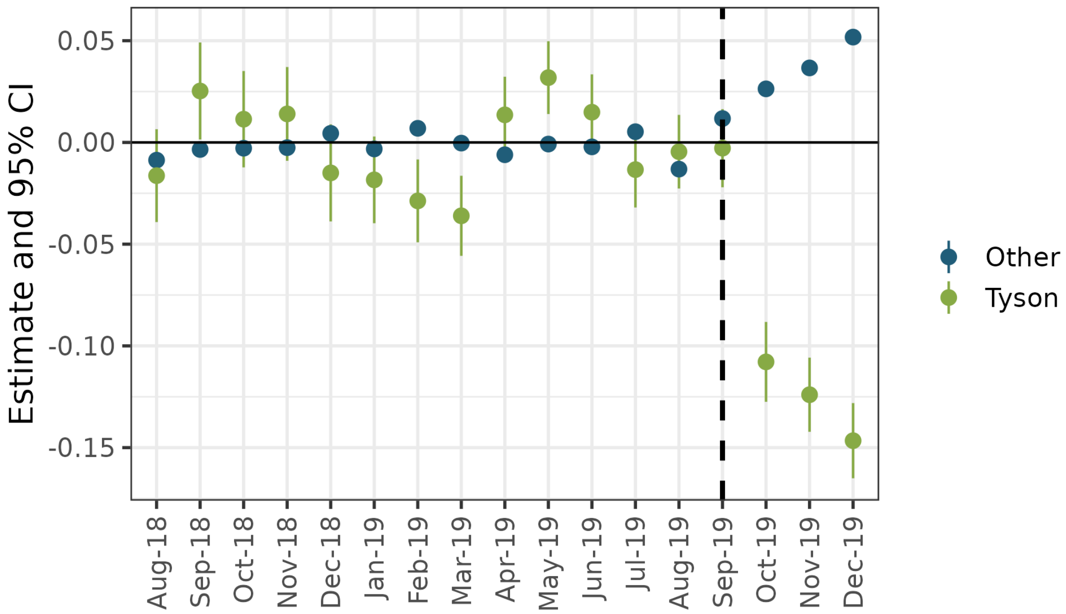
The second step consists of assessing the differential effect of the fire on Tyson and other processors. We do so by using equation 2, which comprises of an event-study around the Holcomb fire. We estimate the average deviation from trend-implied beef prices (i.e., $log(p_{jbt}) - \widehat{log(p_{jbt})}$), where trend-implied prices come from equation 1, considering a time window around the fire of 12 months before and 4 months after for processors.

$$log(p_{jbt}) - \widehat{log(p_{jbt})} = \sum_{\tau=-12}^{\tau=4} (\beta_{tyson,\tau}(\mathbf{1}[t=\tau] \cdot \mathbf{1}[b = Tyson] + \beta_{other,\tau}(\mathbf{1}[t=\tau] \cdot \mathbf{1}[b \neq Tyson]) + \nu_{ijt} \quad (2)$$

We show the results of the two-step approach in Figure 2. The fire has imposed differential effects across packers. The fire led to a downward shift from trend-implied prices of 10 percentage points for Tyson products and an upward shift from trend-implied prices of 5 percentage points for products owned by other processors. As expected, there appear to be no major deviations from trend prices before the fire.[6] Altogether, Table 5 and Figure 2 suggest a price effect of the Holcomb fire on Tyson's products that is different from price effects on other packers, and the patterns cannot be explained by pre-fire trends.

[6] Appendix B shows a more detailed decomposition of equation 2 where we plot deviations for different groups of processors. The results are qualitatively similar to figure 2.

Figure 2: Effect of Fire on Deviation from Trend-Implied Retail Prices by Processor



Note: This figure shows the coefficients of the event study as depicted in equation 2. Upward shifts from 0 indicate observed prices increasing in relation to trend-implied prices estimated as in equation 1. Downward shifts from 0 indicate observed prices decreasing from trend-implied prices.

4 Rationalizing the impacts of the fire

As Weyl and Fabinger (2013) have shown, given the elasticity and curvature of the demand, different oligopoly models predict different aggregate pass-through rates. Magnolfi et al. (2022b) provides an intuitive and simple setting to illustrate the implied pass-through of a few classic assumptions about firm conduct in vertical models. Consider a differentiated-product environment of a discrete choice logit demand model with many retailers and manufacturers.[7] For a given demand elasticity, the pass-through from an increase in marginal cost of one manufacturer to

[7]Inference on pass-through is drawn from a discrete choice logit demand model, but the sign of the pass-through is the same for a more general family of demand models, as discussed in Magnolfi et al. (2022b).

the vector of retail prices will depend on the conduct assumption made for each level of the supply chain. As an example, the vertical models of price setting discussed in Villas-Boas (2007) and Bonnet and Dubois (2010), plus a model of competition in quantity choice. All these models share the prediction that prices of Tyson products would raise prices due to an increase in Tyson's marginal cost, which contradicts the data patterns shown before.

In the case of perfect competition on both levels of the chain, an increase in Tyson's marginal cost would only pass-through fully to Tyson retail prices and would not affect retail prices of other manufacturers. In a Bertrand-Nash competition among retailers and no wholesale markup, products are strategic complements. This would imply positive pass-through of Tyson's marginal cost on all products offered, including products not owned by Tyson. The same rationale applies to a model with zero retail markup and Bertrand-Nash competition among manufacturers. In a Cournot competition among manufacturers and no or constant retail markup, the pass-through of an increase in Tyson's marginal cost would be positive for Tyson products and zero for other products. In the case where manufacturer and retailer perfectly collude, and retail prices are set to maximize the joint profits, the pass-through of an increase in Tyson's marginal cost would be positive for retail prices of Tyson products, but negative for products by other manufacturers.

To rationalize the effect of the fire, we model two key elements of the beef market after the closure of the Holcomb plant. First, the uncertainty regarding the ability of Tyson to deliver beef products to retailers as described by Dennis (2020). Second, the ability to negotiate price of beef that stem from long-term relationship of processors and retailers in this market.

ARGUMENTATION FOR DELIVERY UNCERTAINTY + NEGOTIATION -> LOWER WHOLESALE PRICES

1) Retailers have some bargaining power over wholesale price determination (not a take-it-or-leave-it offer).

a) Industry insiders point out that during calls for negotiating supply it is normal that retailers make counteroffers.

b) Concentration is also high among retailers during this period.

c) Salesman from processors have some freedom when setting prices and quantity discounts 2) Unreliable suppliers must charge less.

a) Based on marketing literature, stockouts can be very costly for retailers. This make retailers willing to pay more for reliable suppliers.

b) Brand loyalty is not as strong in beef as in other grocery goods, which makes the disagreement not so costly for retailers.

3) Tyson became an unreliable supplier after the fire.

a) Slack in capacity utilization give processors freedom to adjust supply in case of unexpected demand shocks. Tyson was operating at capacity for most of the semester after the fire.

b) Uncertainty over how long would have taken to reopen the plant was only solved in mid November. Hence, for most of the semester, retailers were unsure on how many clients Tyson could actually serve.

equilibrium post-fire consists of Tyson reducing its markup to compensate for its unanticipated, reduced reliability of delivery. If the reduced delivery reliability is large enough to offset the effects of higher marginal costs for Tyson, there can be a negative effect on Tyson's retail prices.

5 Structural Model

We present the structural model of demand and supply for the US beef supply chain. We focus on the processing and retail stages of the chain and take the price of cattle as exogenous to processors.[8] We first characterize the demand for fresh beef products by extending the discrete choice model of Berry et al. (1995) to incorporate the possibility of stock shortages in retail stores. On the supply side, we construct a model of negotiated beef pricing that accounts for bargaining between retailers and processors and incorporate the uncertainty of delivery in an empirically tractable way.

Our framework describes the relationship between processors and retailers in two stages. In the first stage, beef processors and retailers negotiate wholesale prices for deliveries of beef products. We assume that retail markups are zero. This assumption translates the common characterization of beef products as loss-leaders by retailers and is justified by a goodness-of-fit test.[9] In the second stage, delivery and sales are realized, while retail and wholesale prices remain fixed. As a novel feature of our model, a processor-specific randomness in the amount of beef actually delivered is incorporated. Before first-stage negotiations are done, retailers form expectations about the probability of delivery of each processor based on their information set.

5.1 A demand model with random stockouts

In what follows, we construct the sales expectation that processors and retailers rely on when negotiating prices in the first stage. Let $\mathcal{J}$ be the set of possible

[8]Processors and cattle ranchers have a small degree of vertical coordination. Unlike egg and broiler production, where processors often control quality and inputs farmers use (Crespi and Saitone, 2018).

[9]Our pricing model is also consistent to the case when retailers set a constant markup for beef products. In our empirical exercise, it would only imply a reinterpretation of the recovered marginal cost.

products that can be supplied to a given store in a given market (quarter-retailer-DMA), t. For easier exposition, we suppress the market subscript. In the second stage, a product $j \in \mathcal{J}$ is delivered or not. Consumer $i \in I$ maximizes utility by choosing between beef products from a set of *available* products $J \subset \mathcal{J}$ and an outside option of not buying beef.

The indirect utility of consumer i from choosing product j with brand b is

$$u_{ij} = X_j' \beta_i - \alpha_i p_j + \xi_j + \epsilon_{ij}, \tag{3}$$

where, in reference to the researcher, X_j and ξ_j are the observed and unobserved characteristics for product j, respectively, p_j is the retail price, and ϵ is the residual random term assumed to be distributed according to the standard Type I extreme-value (T1EV) distribution. The deterministic part of the utility of the outside option is normalized to zero.

The average choice probability, ρ^C, for product j takes the form

$$\rho^C(j|j \in J_t) = \int \frac{\exp\left[X_j' \beta_i - \alpha_i p_j + \xi_j\right]}{1 + \sum_{k \in J_t} \exp\left[X_j' \beta_i - \alpha_i p_j + \xi_j\right]} f(\mu_i) d\mu_i, \tag{4}$$

where $f(\mu_i)$ is the distribution of consumers' idiosyncratic terms. We assume that the choice probability for a product that is not delivered is zero.

Let $\mathcal{S}$ be the set of subsets of $\mathcal{J}$ that has the outside option as an element. We model the delivery uncertainty by imposing a probability distribution ρ^D over the elements of $\mathcal{S}$. Assume that the event of a firm's product delivery is independent from the delivery from other firms and what happened in previous periods. Assume also that products from the same brand are delivered in batch, i.e., we only need to focus on the probability of delivering the batch and not on individual products.[10]

[10]This implies that the probability of any given subset of $\mathcal{S}$ is the product of each brand's delivery probability. For example, the probability of observing the assortment set {0,1,2} in a given week from a contracted supply of {0,1,2,3} from three independent brands is $\rho_1^D \times \rho_2^D \times (1 - \rho_3^D)$, where ρ_j^D is the probability of delivery of product j.

If every period there is a mass of M consumers, then we can calculate the expected aggregate volume sales during the second stage for the product j, $\mathbb{E}[q_j]$, as part of the batch J_f that is owned by the processor f,

$$\mathbb{E}[q_j] = M \sum_{\{J \in \mathcal{S} | J_f \subset J\}} \rho_f^D \times \rho^C \left(j | J_f \subset J\right). \tag{5}$$

Note that equation 5 represents a lottery over lotteries. Without data on delivery realizations and without knowledge of exogenous delivery shocks to a firm, we cannot separately identify delivery probabilities from the unobserved component $\tilde{\xi}_j$ using variation in the available data. We, therefore, assume that in "business-as-usual" periods, such as the months before the fire, deliveries are made with probability normalized to one and we deal with deviations from this normalization for individual processors.[11] To ease notation, we denote a deviation over the "business-as-usual" probability by processor f as $\tilde{\rho}_f^D \leq 1$.

The expected sales share for any product j owned by f in the case of a delivery shock $\tilde{\rho}_f^D$ is

$$\mathbb{E}[s_j] = \frac{\mathbb{E}[q_j]}{M} = \tilde{\rho}_f^D \rho^C(j|\mathcal{J}),$$

while the expected sales share for any product k that is not owned by f is

$$\mathbb{E}[s_k] = \frac{\mathbb{E}[q_k]}{M} = \tilde{\rho}_f^D \rho^C(k|\mathcal{J}) + (1 - \tilde{\rho}_f^D)\rho^C(k|\mathcal{J}_{-f})$$

where $\mathcal{J}_{-f}$ refers to the retail shelf if f's products are absent.

Finally, the T1EV distribution assumption for the error term implies that the *ex ante* expected utility that the consumer i derives from the assortment $\mathcal{J}$, given

[11] In our empirical application, if there were differences in expectations before the fire, it would be incorporated into our $\tilde{\xi}$ estimates. Impacts of the fire are calculated relative to those expectations during the period before the fire. See appendix C for more discussion.

the price vector p, is

$$\mathbb{E}[V_i(p,\mathcal{J})] = \tilde{\rho}_f^D \frac{1}{\alpha_i} \log\left[\sum_{j\in\mathcal{J}} \exp(X_j'\beta_i - \alpha_i p_j + \xi_j)\right] + (1-\tilde{\rho}_f^D)\frac{1}{\alpha_i}\log\left[\sum_{j\in\mathcal{J}_{-f}} \exp(X_j'\beta_i - \alpha_i p_j + \xi_j)\right].$$

The expected average inclusive value $\mathbb{E}[V(p,\mathcal{J})]$ is the weighted sum of the individual values, the weights reflecting the mass of consumers of type i.

5.2 Bargaining game

After expectations for delivery and sales are formed, retailers and processors bargain on wholesale prices in the first stage. Based on conversations with industry insiders, some beef cuts are used as a loss leader to attract consumers to shop at the store, a practice that finds theoretical justification for larger retailers (Chen and Rey, 2012).

To take into account the character of the loss leader, we model the negotiation between retailers and beef processors assuming that the retail margins are zero and that the parties have opposing incentives when bargaining over the wholesale price.[12] While processors want to set prices to maximize profits in the supply chain, retailers want to maximize the consumer experience over the assortment of beef products by reducing prices. Specifically, for a given retailer-processor pair (r,f), the Nash-Bargain objective takes the form

$$\max_{[p_j]_{j\in\mathcal{J}_f^r}} \left(\mathbb{E}\left[\sum_{j\in\tilde{\mathcal{J}}_f^r} q_j(p,\tilde{\mathcal{J}}_f^r)(p_j - c_j)\right]\right)^a \left(\mathbb{E}\left[W(p,\tilde{\mathcal{J}}^r)\right] - \mathbb{E}\left[W(p,\tilde{\mathcal{J}}_{-f}^r)\right]\right)^b \quad (6)$$

[12]The results would be the same if we assume that retailers set a fixed uniform margin across products and that the margin does not change after a shock in delivery expectations. If that were the case, then our marginal cost estimates should be interpreted as incorporating both marginal cost and any retail margin.

where $(a, b) \in \mathbb{R}_+^2$ is a bargaining weight pair, c_j is a constant marginal cost for product j, W is a measure of consumer experience from facing the actual assortment $\tilde{\mathcal{J}}^r \subseteq \mathcal{J}^r$ and the price vector p during the shopping trip, and expectation is taken over the assortment delivery.

The negotiation between retailers and processors depends on the importance of the processors' products for the expected consumer experience, $W(\cdot, \cdot)$. For consistency with our logit assumption on demand and for empirical tractability, we use the inclusive value of the consumers as a measure of the expected consumer shopping experience. Moreover, we assume that any missed delivery has a negative retailer-specific impact, F_r, on retailer's payoffs that is beyond the effect on current period consumer experience. For example, there could be a reputation or goodwill effect that hits the retailer, when consumers face stockouts (Matsa, 2011).[13]

Formally, the expected consumer experience in the scenario where only firm f has a shock on delivery probability, $\tilde{\rho}_f^D < 1$, is

$$\mathbb{E}[W(p, \tilde{\mathcal{J}})] = \mathbb{E}[V(p, \tilde{\mathcal{J}})] = \tilde{\rho}_f^D V(p, \mathcal{J}) + (1 - \tilde{\rho}_f^D) \left(V(p, \mathcal{J}_{-f}) - F_r\right).$$

In problem 6, we also make the standard assumption that parties take the negotiation of others as given and that there is no replacement threat from retailers or processors.[14] In this case, the disagreement payoff for retailers is just the inclusive value from the vector of prices and assortment absent the negotiating processor's products, while the disagreement payoff for processors is zero.

[13]Without F_r, delivery probabilities have a proportional impact on processors' and retailers' negotiation payoffs, which in turn results in Tyson's prices not being directly affected by shocks in Tyson's delivery expectation. A proportional change in payoffs for both Tyson and retailers would only affect prices through the effect on the expected share of Tyson opponents, which has a small impact on Tyson equilibrium prices due to the low cross-price elasticities. We are able to avoid this unrealistic feature by introducing F_r to the model.

[14]This might not be a strong assumption in the case of beef, as negotiations are for the most part not done frequently. The processor-retailer pairs tend to stay for long periods. The canonical upstream-downstream bargain model in the Nash-Bargain environment is discussed in Lee et al. (2021).

The solution of the pricing game for any product j that is part of the batch $\mathcal{J}_f$ owned by processor f takes the form:

$$a\frac{\mathbb{E}[s_j] + \sum_{k\in\mathcal{J}_f}\mathbb{E}\left[\frac{\partial s_k}{\partial p_j}\right](p_k - c_k)}{\sum_{k\in\mathcal{J}_f}\mathbb{E}[s_k](p_k - c_k)} = b\frac{\mathbb{E}[s_j]}{\mathbb{E}[(V(p,\tilde{\mathcal{J}}) - V(p,\tilde{\mathcal{J}}_{-f})]} \tag{7}$$

where s_j is the market share of product j, and expectations are taken over the randomness of the realized assortment. Note that if retailers have zero bargain weight ($b = 0$), then equation 7 is the standard Bertrand-Nash pricing equation. In contrast, as the bargain weight of retailers increases in relation to the processors' ($a \to 0$), prices are set lower to increase the expected shopping experience of consumers.

By rearranging terms and stacking the solution from each product, we can write an expression for the equilibrium price vectors

$$\mathbf{p} = \mathbf{c} - (\boldsymbol{\Omega} - \boldsymbol{\Lambda})^{-1}\mathbf{s}$$

where $\boldsymbol{\Omega}$ with an element (j,k) equal to $\mathbb{E}\left[\frac{\partial s_k}{\partial p_j}\right]$ if the products are owned by the same firm and zero otherwise, and $\boldsymbol{\Lambda}$ has element $(j,k) = \frac{b}{a}\frac{\mathbb{E}[s_k]\mathbb{E}[s_j]}{\mathbb{E}\left[(V(p,\tilde{\mathcal{J}}) - V(p,\tilde{\mathcal{J}}_{-f})\right]}$ if the products are owned by the same firm, and zero otherwise.

Most of the terms in equation 7, i.e., the expected shares pre-fire and inclusive values, stem directly from the demand system. We can also simulate inclusive values if product j drops for the market. What is left out are the measure of F_r and an estimate of the bargaining weights a and b.

6 Empirical Implementation

In what follows, we discuss the assumptions of functional form that we make to estimate the structural model. We also present the set of instruments that we use to construct moments for estimation.

Demand: We decompose the individual-specific taste parameter β_i into a population mean taste and a vector of observed demographic shifters: $\beta_i = \beta + d_i\Pi$. For the latter, we use information from Nielsen Panel Survey Data about market-level consumers characteristics such as income, age, and the presence of children in a household, and use the matrix of parameters Π to govern the allowed interaction between observed product characteristics. We also decompose the unobserved taste component into a brand b fixed effect, market t fixed effect, and product-market unobservables: $\xi_{jt} = \xi_b + \xi_t + \Delta\xi_{jt}$.

As in Conlon and Gortmaker (2025), we use two types of moment conditions in our estimation of demand: aggregate and micro-moments. Given a set of instruments Z_{jt}, we construct the aggregate moment conditions based on the assumption $\mathbb{E}[\Delta\xi_{jt}Z_{jt}] = 0$. The presence of market shares in equation 5 requires excluded instruments to identify the parameters that enter demand non-linearly or interacted with price. We use the local version of the differentiation instruments (Gandhi and Houde, 2019), its intersection with median income, the share of products in a retailer to capture shelf space, prices predicted by product characteristics (see Backus et al., 2021), and several costs shifters (prices of cattle, hay, corn, and soybeans, electricity price, fuel price, and hourly wages in meatpacking). Although the differentiation instruments and shelf space allow for variation within and between markets, the costs shifters allows variation across time.[15]

Moreover, we supplement market-level moments with micro-moments derived out of consumer-level decision data from Nielsen Panel Survey. Specifically, for a given parameter, we use the previously derived choice probabilities to construct

[15]Price of cattle, hay, soybeans, and corn are obtained from the United States Department of Agriculture (USDA), the price of energy is obtained from the Energy Information Administration (EIA) at the regional level, and the Bureau of Labor and Statistics (BLS) provides hourly wage for meatpacking workers

the analogous moment from the model, $g(\theta)$. The estimation condition is the difference between the sample and model moments: $\hat{g} - g(\theta)$.

Supply: The estimation of different supply models requires researchers to identify the products offered by each processor in different retail stores. Estimating the beef demand in a differentiated product setting, for example, requires observing products marketed by Tyson in a certain retail store. In the US markets, however, beef labeled by brands owned by retail chains (i.e., private labels) are often processed by several packers. This makes identification of the processor-retailer pair impossible for private labels.

Therefore, we treat national brands and private labels as different types of processors. We abstract away from trying to interpret the effect of the Holcomb fire on private labels because the mix of beef from different processors can endogenously change after the fire. A detailed account of the packer for private-label products would suffice for a more formal treatment of private labels, but this information is not available to researchers.

We lack information about F_r, the parameter that captures the loss in sales in the chain after the stockout of beef. There is some evidence that stockouts have a heterogeneous effect on sales. Approximately 30% to 50% of consumers delay purchases or leave stores when facing a stockout (Zinn and Liu, 2001). We take these estimates to feed the supply side of our model and assume that F_r is 40% of the total sales. We also conduct a few robustness checks in which we vary the magnitude of the stockout cost.

For our empirical exercise, we also need values for b/a. In principle, we could estimate the ratio of bargaining weights for processors and retailers. Since markups are determined in equilibrium, we would need instruments that exogenously shift markups. Similar to other empirical papers on vertical contract inference, in our setting, there is no clear, valid source of variation that implies strong instruments. Instead, we assume that the bargaining weights for retailers and processors are equal on average. This leads the ratio b/a to equal 1.0. It could be a strong assumption, and we test the lack of fit of this assumption against other possible conducts using the process described in Duarte et al. (2023).[16]

Supply models comparison We also test the strength of our bargaining model against competing pricing models that, to our institutional knowledge, could potentially characterize the behavior of retailers and beef processors.We use Rivers and Vuong (2002)'s model selection approach, characterized in our context by (Duarte et al., 2023), to check which model better fits the pricing pattern before the fire.

We hypothesize four different conducts on the supply side of the beef industry: (1) a two-part tariff in which the retailer sets prices for beef products, and wholesale margins are zero, (2) a two-part tariff in which the processor sets prices for beef products with zero retail margins, (3) a model of linear pricing across the supply chain, and (4) the bargaining model described in the previous section.

The two-part tariff with zero retail margins is a common way to model grocery goods price decisions (e.g., Miller and Weinberg, 2014). Under this mode of conduct, first-order conditions take the matrix form of $p = \Delta^w + c$, where, again, p represents the prices, Δ refers to markup, w refers to the processors, and c refers to marginal costs. If retailers set prices, the first-order conditions take the matrix form of $p = \Delta^r + c$, where r refers to retailers. Linear pricing assumes that processors decide their margins at the wholesale level and then sell their products to retailers who set their margins by choosing retail prices of beef

[16]While conduct testing also involves instruments that shift markups, a pairwise model selection test is much less demanding over instruments' strength than fully estimating bargaining weights.

products. We further assume that private labels are vertically integrated. The pricing behavior of national brands, therefore, generates a double marginalization model similar to Villas-Boas (2007) where the first-order condition takes the form of $p = \Delta^r + \Delta^w + c$.

Sample construction: Our estimation uses NielsenIQ Retail Scanner data, covering 2018 and 2019. Fresh beef products involve little processing other than cutting and packaging, and the only ingredient is the flesh itself. Thus, beef varieties are easy to define based on package sizes and cuts. Specifically, beef cuts include rib-eye steak, fillet steak, ground, patties, and so on. In terms of package sizes, the majority of beef UPCs weigh less than three pounds. Given the cuts and package sizes, we can divide the NielsenIQ beef UPCs into 21 varieties. There is considerable heterogeneity in price and market shares across varieties. In particular, ground beef and beef patties occupy some 80% of the market by volume and are sold at relatively low prices (see appendix table A1).

We aggregate the original Universal Product Code (UPC) level data by grouped cut (i.e., ground, steak, and others), package size, and brand for each market. Here, *brand* refers to the parent brand or the packer. Large beef processors typically own multiple sub-brands. For instance, Tyson owns Tyson, Jimmy Dean, Hillshire Farm, and others. Appendix table A2 displays the market shares by volume for the major processors. Private-label products dominate our sample, but the market shares of Cargill, JBS, National Beef, and Tyson are not small.

We define the size of market at the month-retailer-DMA level. We infer the size of the market from egg and milk sales, an approach similar to Backus et al. (2021). We also select DMAs with high coverage by NielsenIQ.

The summary statistics of the sample are presented in table 6. The number of cut-size-brand products by market ranges from 10 to 204, with an average of

77. The average share of products offered by a big-four packer is 1%, up to 9% in a market. Private-label products take on average of 11% of a market, and the outside option reaches an average of 85% and no more than 95% across markets. Average real-dollar price per pound is $5.82.

Table 6: Sample Summary Statistics

	Mean	Std. Dev.	Min	Q1	Median	Q3	Max
Products per market	77	33	10	54	73	99	204
Products per retailer-market	11	5	1	7	11	14	33
Products per wholesaler-market	3	3	1	1	2	4	34
Retailers per market	7	3	2	5	7	9	17
Wholesalers per market	24	8	5	18	25	30	46
Cuts per market	5	0	2	5	5	5	5
Outside option share	0.85	0.05	0.66	0.81	0.85	0.89	0.95
Big 4 shares	0.01	0.01	0	0	0	0.01	0.09
Private label shares	0.11	0.06	0	0.06	0.1	0.14	0.31
Prices ($/lb.)	5.82	2.88	1.93	3.95	5.43	6.86	24.143
Size tier	1.48	1.00	0.25	1.00	1.00	2.00	5.00

Note: Authors' creation based on 2018-2019 NielsenIQ Retail Scanner Data.

7 Results

Next, we present and discuss the results of the demand and supply estimate.

7.1 Demand results

We start with the demand results in table 7. All specifications include dummies for quarter-year, DMAs, retailers, and products. Column 1 presents parameters from a simple logit demand specification. Column 2 shows the results from a nested logit model. We find that nesting by grouped cut in the demand system leads to demand elasticities more in line with the literature.[17] Column 3 displays results from a random coefficient nested logit model (RCNLM) that uses micro-moments to aid the identification of parameters. The first form of micro-moments matches average income markets for those who consume beef across markets. The second form of micro-moments matches the covariance of prices and income for those who buy beef across markets.

All models estimate a downward-slopping demand system with own-price elasticities varying between -1.2 and -4.4. The RCNLM in column 3 allows for an interaction between income and prices and income and a constant. The results suggest that higher income households are less sensitive to beef prices.

Table 7: Demand Estimates

	Logit-OLS		Nested Logit-2SLS		RCNL-GMM	
Prices	-0.201	(0.004)	-0.197	(0.086)	-0.267	(0.088)
Summer (indicator)	0.026	(0.02)	0.044	(0.013)	0.046	(0.013)
Package size	0.123	(0.009)	-0.075	(0.094)	-0.115	(0.095)
log(Shelf space)	0.207	(0.016)	1.066	(0.038)	1.067	(0.04)
σ			0.769	(0.033)	0.773	(0.034)
Income $\times$ Const					-7.332	(0.406)
Income $\times$ Prices					0.488	(0.076)
Own price elasticity-mean	-1.167		-3.746		-4.417	
Own price elasticity-median	-1.083		-3.464		-4.108	
Diversion outside option-mean	0.80		0.29		0.29	
Diversion outside option-median	0.84		0.23		0.23	
Observations	66829		66829		66829	

Note: In all regressions, we include dummies for quarter-year, big-four product, retailer, and DMA. *Summer* controls for summer seasonality, *shelf space* computes the share of product j among all other products in a retail store, and σ refers to the nest parameter.

Our demand model also generates reasonable substitution patterns. Table 8 shows average diversion ratios across grouped cuts. Primarily, price shocks in a particular cut (represented by the rows in the table) lead consumers to deviate to

[17] We instrument the nest with the number of products per nest, a common practice in the literature (Conlon and Gortmaker, 2020).

the outside good, but a significant share of consumers deviate to the most popular cut, namely, ground beef with relatively fat content. Consumers buying ground beef tend to stick with ground beef or substitute away to the outside good when prices increase.

Table 8: Average Diversion Ratios across Cuts

	1.	2.	3.	4.	5.	Out
1. Others	11.4	2.6	0.8	0.6	0.4	46.5
2. Ground Beef, fat	0.1	70.1	1.2	0.7	0.4	24.9
3. Ground Beef, lean	0.1	4.6	46.9	0.9	0.4	31.4
4. Patty	0.1	5.0	1.5	49.6	0.5	28.6
5. Steak	0.1	5.1	1.4	0.9	33.3	30.9

Note: Diversion ratios measures the ratio of changes in the share of products c and j from a price shock in j, $\frac{ds_k}{dp_j}/\frac{ds_j}{dp_j}$. In this table, rows show where we shock prices. The higher the value of the diversion ratio, the closer substitute products are.

7.2 Supply results

On the supply side, we closely follow the RV tests as specified in Duarte et al. (2023) to decide between competing pricing models. Each model of conduct implies a markup, and instruments that shift marginal revenue can identify markups (Bresnahan, 1982). Given a set of instruments, we can estimate markups for two competing models and compare how well they fit the data because orthogonality conditions between instruments and the marginal revenue imply sample moments and a GMM objective function. Differentiation instruments (Gandhi and Houde, 2019) are used to form the GMM function and are found to be strong in our context.

Markups for models of two-part tariff and linear pricing across the supply chain can be readily calculated from demand elasticities and different configurations of the ownership matrix (Villas-Boas, 2007). As discussed, we assume equal bargain-

Table 9: RV Test Results

	Test Stat.			F-stat			MCS
	2.	3.	4.	2.	3.	4.	
1. Retail Markup	3.89	9.76	8.76	3.13	423.63	2.48	0.00
2. Processor Markup		-2.59	43.59		2.93	71.56	0.01
3. Double Marginalization			7.59			2.38	0.00
4. Bargaining							1.00

Note: Retail Markup refers to a two-part tariff model with retailers making price decisions. Processor Markup is a two-part tariff with processors making price decisions. Double marginalization refers to a model of double marginalization with vertical integration for private labels, and Bargaining refers to the model of bargaining defined before.

ing ratios to generate markups for the bargaining model to conduct the RV test. Table 9 shows that the RV tests favor the bargaining model over other models.

Table 10 shows the marginal costs and markups implied by the bargaining model. Not surprisingly, steak has considerably higher marginal costs than all other cuts, reflecting its costly processing method. Lean ground beef shows up with higher marginal cost, most probably due to its more expensive cut composition. The Learner index is similar for all packers except for National Beef which enjoys a higher average markup. As a sanity check, we compare the implied markup with gross margins from the accounting data of the two public companies in our sample. Our model generate reasonable margins that are not far from the actual margins set by firms in this industry.[18]

7.3 Fitting post-fire price movements

With the demand parameters and marginal cost estimates in hand, we calibrate wedges at the marginal cost and the probability of delivery to match the observed price dynamics after the fire. The reduced-form evidence suggests that Tyson's

[18]As discussed in Nevo (2001), this exercise should be taken with cautious since measures of cost-of-good-sold that are used to compute gross margin might not fully capture all elements that constitute marginal cost.

Table 10: Supply Model Results

(a) Marginal Cost Estimates by Cut

	Median	Mean	SD	MC< 0
Others	3.69	4.00	2.69	0.00
Ground Beef, fat	3.00	3.29	2.06	0.02
Ground Beef, lean	4.24	4.43	1.63	0.00
Patty	4.07	4.28	1.86	0.00
Steak	7.15	8.08	4.02	0.00

(b) Lerner Index by Processor

	Median	Mean	SD	Gross Margin
Cargill	0.26	0.34	0.20	-
JBS	0.12	0.17	0.12	0.15
National Beef	0.59	0.53	0.28	-
Tyson	0.16	0.21	0.14	0.15
Private label	0.19	0.27	0.22	-

prices moved down around 2%, while its largest competitors – the other big-four processors – experienced an average price increase of around 3%. In our calibration, only the probability of delivery of Tyson products is reduced after fire ($0 < \tilde{\rho}^D_{Tyson} \leq 1$), while the probabilities of delivery of other processors remain at 1.0.

Conditional on a cost of stockout, F_r, of 40% of realized sales, we show in column 1 of Table 11 that we can get close to an average increase in prices for all products by increasing marginal costs of all processors by 2% in relation to the pre-fire levels. However, an industry-wide increase in marginal costs without considering delivery uncertain also increases Tyson's prices, which contradicts the reduced-form evidence. The third column of table 11 shows that only increasing the post-fire marginal cost for Tyson by 2% barely changes prices for products of other processors, which is also misaligned with observed data patterns.

The third column fully rationalizes the price dynamic immediately post fire. By increasing marginal costs for all firms by 2% and adjusting the delivery uncertainty parameter for Tyson to $\tilde{\rho}^D_{Tyson} = 0.4$, we estimate a decline in Tyson's prices after the shock and a positive change in price of other processors, matching price changes after the Holcomb fire.

Table 11: Percentage Changes in Prices Post Fire

	(1)	(2)	(3)
	↑ Industry MC	↑ Industry MC ↓ Tyson's Delivery Probability	↑ Tyson's MC
Tyson	1.49	1.18	-2.72
Others			
Cargill	1.64	-0.00	1.64
JBS	1.58	0.00	1.74
NB	1.37	0.00	1.85
PL	1.22	0.01	1.36
Regional	1.75	0.00	1.89

Note: The calibration exercise assume a cost of stockout of 40% of the sales share for the processor products, $\tilde{\rho}^D_{Tyson} = 0.4$, and a 6% increase in marginal costs for all processors (first and third columns), or just for Tyson (second column).

8 Counterfactual Analysis

Food processing plants are particularly prone to fire because food is combustible, and food processing often involves factors that increase the likelihood of a fire, such as heat, high pressure, and combustible dusts (e.g., flour, spices). The fire outbreak we examine here is only one, albeit a consequential one, of thousands of fires that occur in US agricultural plants every year. Specifically, more than 11,000 (10,000) fires occurred in some of the 41,080 food and beverage processing plants (Bureau of the Census's County Business Patterns, 2022) in 2022 (2021) (Verzoni, 2022).

From a policy perspective, it is important to evaluate the resiliency of the supply chain to unexpected disruption and to identify potential weak links. A fire in the proportion of the Holcomb's, which can close a plant for a long period of time, could generate heterogeneous changes in market equilibrium depending on which plant is hit. The effect depends on a number of factors, such as the plant size, capacity utilization, how much lower expected delivery reliability becomes, the market shares of each processor and retailer, the cross-price elasticities of demand in each market, etc. Therefore, to compare short-term price effects of major fire outbreaks across different plants, we leverage the estimate from our structural model and information about the Holcomb fire to run counterfactual simulations where other plants are shut-down.

Since the implications of a plant shutting-down are complex, and we estimate our model for only one fire event, we need to further assumptions for the tractability. In our simulations we focus only on the largest plant of the top 4 packers. Plant size data comes from the Agricultural Marketing and Service (AMS). The data specifies the capacity of each plant under Federal Inspection, that is, 95% of all the cattle processing capacity in the nation. All plants owned by the four big packers are included in the dataset.

Once the fire is imposed on a plant, we reduce the probability of delivery, $\tilde{\rho}^D$, for the packer in a way that is proportional to what is observed for Tyson's plant. Specifically, we assume a power function, $\tilde{\rho}_i^D = X_i^a$, where $X \in [0, 1]$ is the portion of the active capacity of packer i. The delivery certainty equals 1 if $X = 1$ and equals 0 if $X = 0$. We have a third point on this function, $X_{Tyson} = x^*$ and $\tilde{\rho}_{Tyson}^D = 0.4$ to help back out the value of a, which is assumed to be equal between packers. Once we have a, we can impose different $\tilde{\rho}_i^D$ for different packers after the fire. The increase in the marginal cost of processing is set at 2% because the scale of the largest plants among packers is similar, implying comparable needs for the industry to expand the Saturday slaughter to make up lost capacity.

The results in table 12 highlight the heterogeneous price impacts induced by similar shocks on processing capacity across packers. Cargill, for instance, presses markups of its products significantly due to its higher delivery uncertainty, whereas JBS would only absorb the increased marginal costs in processing to a much less extent. National Beef, in contrast, even more than pass-through increased marginal costs to the downstream.

Table 12: Percentage Changes in Prices Post Counterfactual Shocks

Manufacturer	Shock on Cargill	Shock on JBS	Shock on National Beef
Cargill	-4.06	1.74	2.46
JBS	1.77	-0.97	2.37
National Beef	1.86	2.33	2.06
PL	1.70	1.25	1.84
Small	1.98	1.92	2.63
Tyson	1.49	2.00	2.24

Note: We simulate price changes by packer, assuming a industry-wide increase in marginal cost of 2%.

9 Concluding Remarks

The 2019 fire at Tyson's Holcomb plant was a major disruption in the US beef supply chain, temporarily removing 5-6% of processing capacity from the industry. Using data on cattle production, meat packing, and beef retailing, we show that the fire increased the marginal costs of beef processing for all packers by increasing weekend slaughter and overtime wages for workers after the fire. Despite higher marginal costs of processing, Tyson's products did not experience any significant increase in retail prices. However, products for other processors experienced significant increases in retail prices. We argue that traditional supply models on pass-through are unable to rationalize these price dynamics. We hence build a model of bargaining with processor-specific delivery uncertainty that fully rationalizes the observed changes in beef prices.

Delivery uncertainty harms consumers' experience and retailers payoffs due to the increased likelihood of stockouts in retail stores. This potential decline in retailers' payoff is partly absorbed by Tyson, which suffers a lower probability of delivery due to the shutdown of its largest plant. Tyson ends up absorbing part of reduced retailer payoffs through bargaining pricing, resulting in significant declines in the markup and lower retail prices for Tyson. Other packers who maintain the normal-time certainty of delivery, in contrast, see near complete pass-through of marginal costs to their retail prices.

Counterfactual simulations show that shocks of similar magnitudes on other beef processors lead to heterogeneous market outcomes. Price changes can be positive or negative depending on which processor is directly affected by the shock, the structure of the market, and the local demand.

We highlight that supply chain disruptions can lead to a variety of market outcomes, sometimes surprising outcomes, in industries in which price dynamics are characterized by bargaining games. Any policy or regulation that distorts the bargaining process incurs the risk of harming consumers by inducing higher retail prices.

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A Additional Summary Statistics

The table below summarizes definition, the average price, market share, for the 21 beef varieties in our 2018-2019 dataset. A variety is determined by a particular cut and the package size. Specifically, we separate family sizes (i.e., greater than 3 pounds per UPC) from small sizes. It is clear that ground beef UPCs are the dominant products and are sold at relatively low prices.

Table A1: List of Beef Varieties and Summary Statistics 2018-19

Typ	Variety	Size (lb.)	Avg Price	UPC%	Revenue%	Volume%	Notes
1	Beef rools	≤ 3	2.99	0.2	0.1	0.1	
2	Beef rools	>3	3.14	0.2	0.002	0.002	
3	Ground, fat	>3	3.33	34.7	53.2	61.3	Fat $\geq$ 15%
4	Ground, fat	>3	2.22	3.1	5.4	9.4	Fat $\geq$ 15%
5	Ground, lean	>3	5.32	14.5	21.4	15.4	Fat < 15%
6	Ground, lean	>3	3.54	0.2	0.4	0.4	Fat < 15%
7	Others	>3	2.53	0.4	0.05	0.1	Sliced sirloin, tripe, etc.
8	Others	>3	2.38	0.4	0.02	0.03	Sliced sirloin, tripe, etc.
9	Patty, fat	>3	4.87	21.3	11.0	8.7	Fat $\geq$ 15%
10	Patty, fat	>3	3.46	0.5	0.1	0.1	Fat $\geq$ 15%
11	Patty, lean	>3	5.84	3.4	2.1	1.4	Fat < 15%
12	Roast	≤ 3	5.71	0.3	0.03	0.02	Bulk, round, etc.
13	Roast, other	≤ 3	5.24	1.3	0.1	0.1	
14	Roast, tenderloin	≤ 3	5.14	1.1	0.4	0.3	
15	Steak, fillet	≤ 3	16.13	3.1	0.4	0.1	Flank, round, chuck, etc.
16	Steak, other	≤ 3	5.86	2.3	2.0	1.3	Flank, round, chuck, etc.
17	Steak, other	>3	2.65	0.1	0.0002	0.0002	
18	Steak, ribeye	≤ 3	11.28	3.1	0.6	0.2	
19	Steak, sirloin	≤ 3	9.04	4.2	1.5	0.6	Top sirloin steak etc.
20	Steak, shaved	≤ 3	4.04	1.9	0.2	0.2	Shaved steak etc.
21	Steak, strip	≤ 3	12.09	3.6	0.8	0.3	Shortloin steak etc.

Note: The table summarizes all beef varieties recorded in the Nielsen database 2018-2019. The prices are measured in the unit of real 2015 USD per pound. The number of UPCs is 961.

The volume shares of the "big four" meatpacking firms in the retail market are listed in the table below. Tyson has been the leader among the "big four" from 2018 to 2019.

Table A2: List of Brand Volume Shares 2018-19

	Cargill	JBS	NBF	Tyson	Big Four
Brand volume shares (%)					
2018	1.5	1.7	1.0	4.9	9.1
2019	1.3	2.1	0.8	5.1	9.3
Brand average price ($/lb.)					
2018	3.6	3.8	3.5	2.8	
2019	3.7	3.9	3.3	2.7	

Note: The volume shares are measured in percentage. *NBF* refers to National Beef.

Table A3: Share of Cut on Total Volume Sold by Firm (2018-19)

firm	Ground Beef, fat	Ground Beef, lean	Patty	Other Cut	Steak
Cargill	82.2	17.6	0.2	0.0	0.0
JBS	57.2	3.6	37.7	0.0	1.5
National Beef	71.6	2.3	2.9	23.2	0.1
Other	47.8	26.5	18.0	1.4	6.3
PL	69.8	19.0	9.1	0.3	1.8
Tyson	77.9	1.1	14.1	0.1	6.7

Note: The volume shares are measured in percentage.

B Impacts of the Fire

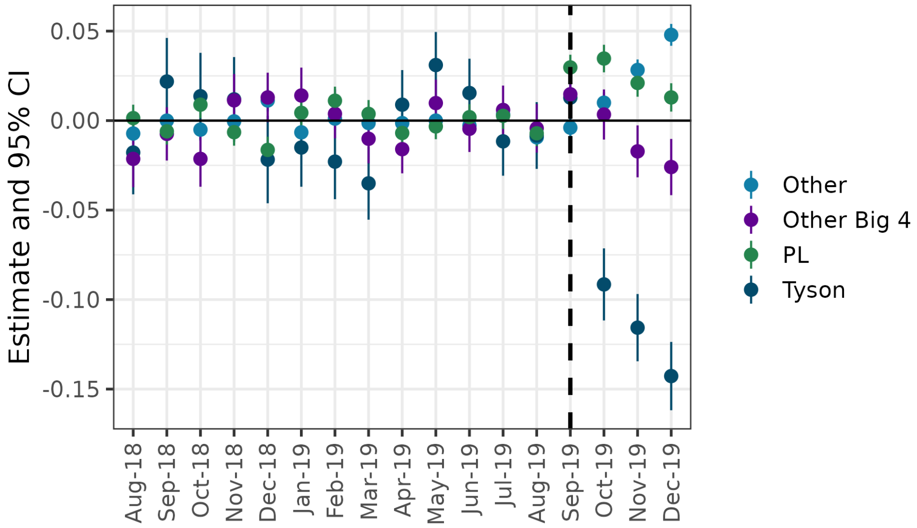
We show the differential impact of the fire on beef prices by processor.

Table B1: Percentage change in Beef Price Level After the Fire in relation to August

		Sep.	Oct.	Nov.	Dec.
1	Regional	0.56	1.70	2.42	3.33
2	Tyson	-2.45	-4.41	-0.98	-0.71
3	Cargill	2.71	2.90	1.65	2.95
4	JBS	7.28	9.15	-4.13	10.16
5	Nat. Beef	2.55	3.50	3.45	4.43
6	PL	4.76	5.43	4.61	6.81

Note: The table calculates monthly average percentage change in the price of Tyson's beef products after the fire in relation to August of 2019 using product level data from NielsenIQ. We weight each product by its volume sold in August of 2019 to calculate a weighted month prices.

Figure B1: Effect of Fire on Deviation from Trend-Implied Retail Prices by Processor



Note: This figure shows the coefficients of the event study where we show price deviations from trend-implied prices by processor. Upward shifts from 0 indicate observed prices increasing in relation to trend-implied prices estimated as in equation 1. Downward shifts from 0 indicate observed prices decreasing from trend-implied prices.

The table below displays regional differences in term of the fire impact on retail beef prices. The average price effect is positive, while the effect is weaker in the New England and Rocky Mountains states.

Table B2: Fire Effects on Retail Prices across US Regions

	log(Price)
Fire	**0.013** (0.003)
x Great Lakes	−0.006 (0.003)
x Mideast	−0.001 (0.003)
x New England	−**0.013** (0.004)
x Plains	0.002 (0.003)
x Rocky Mountains	−**0.016** (0.004)
x Southeast	**0.008** (0.003)
x Southwest	**0.009** (0.003)
Cut quality	All
Adj. R^2	0.872
Num. obs.	322662

Note: Computed using the Nielsen IQ data.

This table reports the fire impacts on beef volume sales, sales shares, and number of products offered for the big-four manufacturers and private labels.

Table B3: Fire Effects on Retail Beef Prices

	log(Price)			
	(1)	(2)	(3)	(4)
Fire	**0.014** (0.002)	**−0.011** (0.002)	**0.007** (0.002)	**−0.018** (0.002)
x Tyson		**−0.015** (0.004)		−0.005 (0.005)
x Cargill		**0.083** (0.005)		**0.090** (0.006)
x JBS		**0.043** (0.005)		**0.057** (0.006)
x NBF		**0.034** (0.005)		**0.031** (0.006)
x Private label		**0.047** (0.002)		**0.044** (0.002)
Fire (Nov-Dec)			**0.030** (0.002)	**0.030** (0.002)
x Tyson				**−0.027** (0.007)
x Cargill				−0.017 (0.009)
x JBS				**−0.035** (0.009)
x NBF				0.012 (0.010)
x Private label				**0.009** (0.003)
Adj. R^2	0.870	0.870	0.870	0.870
Num. obs.	408585	408585	408585	408585

Note: Data from Nielsen IQ from 2016 to 2019. One observation refers to a product (cut type, size, brand) in a market (retail chain, DMA, month). In all regressions, we control for product size, cut type, seasonality, and fixed effects for DMA, brand, year, and retailer.

Table B4: Fire Effects on Beef Sales and Assortment

	log(Volume)				Rev. Share	N. Prod
	(1)	(2)	(3)	(4)	(5)	(6)
Fire	**0.032**	**0.100**	0.021	**0.100**	0.024	**−0.118**
	(0.013)	(0.015)	(0.014)	(0.016)	(0.014)	(0.041)
x Tyson		**0.153**		**0.134**	**0.200**	**−0.221**
		(0.035)		(0.043)	(0.036)	(0.063)
x Cargill		**−0.117**		**−0.132**	**0.123**	**−1.005**
		(0.043)		(0.054)	(0.052)	(0.112)
x JBS		−0.046		0.046	**0.131**	**−0.729**
		(0.038)		(0.047)	(0.041)	(0.076)
x NBF		**−0.182**		**−0.209**	**−0.184**	**−2.153**
		(0.064)		(0.073)	(0.066)	(0.129)
x Private label		**−0.147**		**−0.174**	**−0.047**	**−0.445**
		(0.014)		(0.017)	(0.014)	(0.040)
Fire (Nov-Dec)			**0.044**	0.017	**0.076**	**−0.517**
			(0.015)	(0.020)	(0.017)	(0.052)
x Tyson				0.049	0.036	**0.392**
				(0.061)	(0.049)	(0.090)
x Cargill				0.036	−0.048	**0.477**
				(0.082)	(0.079)	(0.169)
x JBS				**−0.237**	**−0.229**	**0.304**
				(0.069)	(0.061)	(0.114)
x NBF				0.077	0.089	**1.056**
				(0.129)	(0.119)	(0.185)
x Private label				**0.071**	0.007	**−0.928**
				(0.025)	(0.021)	(0.060)
Adj. R^2	0.548	0.548	0.548	0.548	0.470	0.743
Num. obs.	408585	408585	408585	408585	408542	408585

Note: Computed using the Nielsen IQ data.

C Pass-through under Classic Firm Conducts

Magnolfi et al. (2022b) provides a general framework for characterizing the pass-through of marginal costs (MCs) under different firm conducts. We adopt this framework to illustrate the price effects of increased Tyson MC relative to its competitors in a simplified setup.

Consider two single-product beef packers, Tyson and another packer ($i = 1, 2$), one retailer, and a logit demand. The demand is realized, after prices are posted. Like Villas-Boas (2007) and Miller and Weinberg (2014), we evaluate pricing models with the first-order conditions for the price p_j of given product j and firm conduct κ. For a given market t (e.g., a retailer-DMA-quarter combination), the equilibrium price takes the form $p_{jt} = \Delta_{\kappa t}(s(p)) + c_{jt}$, with c being the MC and $\Delta = p_{jt} - c_{jt}$ the markup.

The simple logit demand implies market shares in the form below

$$s_{jt} = \exp(\delta_{jt})/(1 + \exp(\delta_{1t}) + \exp(\delta_{2t}), \tag{8}$$

with $\delta_{jt} \equiv x_{jt}\beta - \alpha p_{jt}$ and x represents the vector of product characteristics.

Stacking all the products from the market and using the Implicit Function Theorem, the pass-through of a vector of marginal changes in cost on prices can be written as $\rho_\kappa \equiv dp/dc = (I - d\Delta_\kappa/dp)^{-1}$ where I is the identity matrix. The diagonal elements in ρ_κ predict the sign of price effect for own MC changes, while the off-diagonal elements predict the sign of price effect for rival's MC changes.

If the conduct is perfect competition, $p_{jt} = c_{jt}$, and the markup is zero. A change in Tyson MC fully passes through to the retail price of Tyson product and does not affect the price of product made by the other packer, namely, $\rho_{perf} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$.

For Bertrand competition among retailers and zero wholesale markup, the pass-through matrix takes a different form. Suppress the subscript for market, t, the pass-through matrix is expressed as

$$\rho_{bert} = \frac{(1-s_1)^2(1-s_2)^2}{1 - s_1 - s_2} \begin{bmatrix} \frac{1}{1-s_2} & \frac{s_1 s_2}{(1-s_1)^2} \\ \frac{s_1 s_2}{(1-s_2)^2} & \frac{1}{1-s_1} \end{bmatrix}. \tag{9}$$

Elements in the matrix are all positive, implying positive price effects of Tyson MC on both products.

If there is Cournot competition, retailers simultaneously choose market shares. The first-order conditions becomes $p_{jt} - c_{jt} + s_{jt}\frac{\partial p_{jt}}{\partial s_{jt}}$. Suppress the subscript for market, t, the pass-through matrix is

$$\rho_{cour} = \begin{bmatrix} \frac{1-s_1-s_2}{1-s_2} & 0 \\ 0 & \frac{1-s_1-s_2}{1-s_1} \end{bmatrix}. \tag{10}$$

A zero pass-through of Tyson MC to the other packer's product is implied.

Finally, the manufacturers and the retailer may adopt a two-part tariff and jointly maximize the profits. Suppress the subscript for market, t, the corresponding pass-through matrix is

$$\rho_{tpt} = \begin{bmatrix} 1 - s_1 & -s_2 \\ -s_1 & 1 - s_2 \end{bmatrix}. \tag{11}$$

The diagonal elements are positive, while the off-diagonal elements are negative.

D Post-Fire Marginal Costs of Processing

Empirical evidence suggests significant economies of scale in the US beef processing sector. The total cost function for a processing plant can be expressed approximately as $C(q) = mq^g$ where m is a multiplier, q is the output of the plant, marginal cost is $c(q) = gmq^{g-1}$, and $g = \frac{ln(TC)}{ln(q)} = \frac{MC}{AC}$ with $0 < g < 1$ denoting the size economies. Morrison Paul (2001a) and Morrison Paul (2001b) report estimates of g in the range of $[0.90, 0.98]$ for US beef processing based on industry-level and plant-level data, respectively.

LMIC data indicate that a weekday before the fire processes cattle 200% as much as the Saturday on average. After the fire, a weekday output becomes only 149% as much as the Saturday slaughter. Given that plants already run at capacity during weekdays, it must be that Saturday slaughter increases substantially in order to process the cattle which would have been processed at the Holcomb plant if the fire did not take place.[19]

Confidential USDA-AMS (Agricultural Marketing Service) data provide us the total Tyson capacity on a weekday (Q_{Tys} in the number of head slaughtered) and the total weekday beef packing capacity of all plants under Federal inspection (Q in the number of head slaughtered). The data also tell us the share of Holcomb plant out of Tyson's capacity (s_{Hol}). After the fire, weekday capacity of Tyson falls by s_{Hol}.[20]

Thus, the total post-fire Saturday slaughter grows from $\frac{Q}{2}$ to $\frac{Q - Q_{Tys} \times (1 - s_{Hol})}{1.49}$. The total weekly output (i.e., 5 weekdays plus Saturday) of the industry falls from $Q \times 5 + \frac{Q}{2}$ to $[Q - Q_{Tys} \times (1 - s_{Hol})] \times 5 + \frac{Q - Q_{Tys} \times (1 - s_{Hol})}{1.49}$. It implies that the industry output decreases by about 2.5%, which again echoes reduced-form findings based the LMIC data.[21]

The marginal cost comes essentially from the additional Saturday slaughter. Assuming that all plants increase the Saturday slaughter by the same portion. The plants run at about 67% of capacity. The formula of marginal costs suggests that the corresponding marginal costs relative to the marginal costs at capacity is

$$\frac{MC^{67\%}}{MC^{100\%}} = \frac{mg(0.67q)^{g-1}}{mgq^{g-1}} = 0.67^{g-1}. \tag{12}$$

[19] Reduced-form results using the LMIC data are available upon request.

[20] Due to confidentiality of the AMS data, we are not able to report specific values of processing capacity at the plant or industry levels.

[21] If we only let Tyson increase its Saturday slaughter, even increase by 100%, but all other packers' Saturday slaughter remains unchanged, the change in the total output would fall by nearly 4%, which does not align as well as the data pattern. We hence assume the same increase in marginal costs for all packers.

If $g = 0.95$, this ratio equals 1.02, meaning that MC increases by 2% relative to the normal-time level. If $g = 0.90$, the implied increase in MC becomes 4% relative to the normal-time level. Here, we are not accounting for higher wage rates due to overtime work on Saturday. This increase of 2%, thus, is likely the lower bound.