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

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Abstract

We leverage a fire outbreak that caused a large but temporary capacity loss at the largest US beef packer to study how firm conduct shapes the pass-through of supply disruptions along the supply chain. Despite evidence of industry-wide increases in processing costs, retail prices for the affected packer's products fell. To rationalize this pattern, we develop a model of bilateral retailer-packer bargaining that accounts for reliability of product delivery. The model highlights how disruptions alter bargaining leverage and shift margins between buyer and seller. Counterfactual simulations demonstrate that the sign and magnitude of pass-through are highly sensitive to the magnitude of capacity loss and perceived reliability.

JEL Codes: Q14, Q18, L13, D81

Keywords: cost pass-through, delivery reliability, supply chain disruptions

*Researcher(s) own analyses calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researcher(s) and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein. The views expressed are those of the authors and do not necessarily reflect the positions of the Federal Reserve Bank of Kansas City or the Federal Reserve System. We thank the US Department of Agriculture for providing the plant-level data on beef packing for this study.

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1 Introduction

Disruptions in the supply of goods have become increasingly frequent in recent years. Several factors contribute to the instability, including outsourcing to overseas suppliers (Baldwin and Freeman, 2022), climate and natural disasters (Stern, 2008; Carvalho et al., 2021), pandemics (Hadachek et al., 2024), geopolitical conflicts (Caldara and Iacoviello, 2022), and changes in trade policy (Grossman et al., 2024). The disruptions have had substantial effects on both corporate profits and consumer welfare, and triggered a range of strategies initiated by policymakers aimed at enhancing supply chain resilience.[1]

Previous literature has examined the effects of cost shocks under simplifying assumptions about firm behavior and industry structure, often relying on models of perfect competition and linear wholesale pricing.[2] More recent work suggests that the impact of supply disruptions depends crucially on how oligopolistic market structures, inter-firm relationships, and firm conduct interact to shape shock transmission.(Irwin, 2019; Flaaen et al., 2020; FTC, 2024; Heise, 2024; Duarte et al., 2025) Even so, empirical evidence on this interaction remains scarce, as credible identification of effects requires particularly rare data on isolated and economically meaningful shocks.

We provide new empirical evidence on the role of firm behavior in shaping the pass-through of supply chain disruptions to retail prices. We use information on product-level prices and quantities to explore firm-level reaction to a major negative shock in the production capacity of the US beef packing industry. In early August 2019, a fire forced the largest plant of Tyson — the largest beef packer in the nation — to shut down until January 2020. The plant represented around 20% of Tyson's capacity and nearly 6% of the US capacity. Our setting offers an ideal natural experiment to examine how oligopoly firm interaction drives pass-through of a temporary and significant supply-chain

[1] Gordon and Clark (2023) estimate that, from January 2020 to December 2022, supply chain disruptions were the single most important driver of inflation, relative to other factors such as demand, interest rate, and cost-push shocks. Key measures — such as the CHIPS and Science Act, Executive Order 14017, and the Meat and Poultry Processing Expansion Program — focus on expanding production capacity and incentivize reshoring initiatives in order to improve chain resilience.

[2] Gopinath and Itskhoki (2010) discuss the limitations of using constant-markup Calvo Pricing Models to study the pass-through of exchange rates. Acemoglu and Tahbaz-Salehi (2025) highlight the shortcomings of macroeconomic models of network shock transmission that assume competitive markets and exogenous network structures.

disruption. Unlike other recent economic-wide disruptions (e.g., COVID-19), the fire can be seen as an isolated and major shock to the production capacity of beef with minimal effects on end-consumer demand.

We provide evidence that the fire had a significant impact on market outcomes. In the initial weeks after the fire, uncertainty in capacity recovery of Tyson led to lower future cattle prices, but only a short-lived decline in spot cattle prices as Tyson relocated production to its other plants and other processors ramped up production.[3] The adjustments led to significant increases in Saturday slaughter and overtime payments to workers, resulting in higher average wholesale prices of beef. Surprisingly, retail prices of Tyson's products fell, while products owned by other packers enjoyed price increases. These findings can be counterintuitive at first glance because traditional models of cost pass-through would predict either increased prices for all products or increased prices in Tyson products and decreases or no change in prices for non-Tyson products (Magnolfi et al., 2022b).

We rationalize the observed price movements by arguing that the fire took away substantial slack capacity of Tyson, thus increasing the probability of Tyson failing to deliver products upon any unscheduled calls from the retailer and increasing the chances of stockouts in retail stores after the fire. Stockouts generate a direct cost to retailers due to forgone current sales and an indirect reputational cost that negatively affects future sales (Campo et al., 2003; Matsa, 2011). We argue that the fear of stockouts reduced the expected retailer profits sourcing from Tyson and, through a bilateral bargaining process, created a downward pressure on Tyson's markups. The same might not have happened to other processors not as heavily impacted by the fire. The downward pressure on Tyson's markups could have more than offset the increase in marginal costs, leading to lower retail prices of Tyson products.

We formalize our mechanism by developing a vertical pricing model for the industry based on previous work on vertical contracts in differentiated product markets (Villas-

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

Boas, 2007; Gowrisankaran et al., 2015). Firms' markups are determined by expected sales derived from a discrete-choice demand model and key features of the beef industry, namely, the bilateral negotiations of processor-retailer prices, the scheduled delivery of beef ahead of demand realization, and the possibility of costly stockouts.[4] Following Duarte et al. (2024), we provide evidence that the bargaining model we propose better fits the price movements observed relative to conventional conduct models (e.g., linear pricing and two-part tariff).

After estimating the structural supply models with data before the Holcomb fire, we recover the average marginal cost increase and the average decrease in delivery reliability for Tyson by calibrating against the observed price changes after the fire. An industry-wide increase in marginal costs of about 5% and a decline in Tyson's average delivery probability of 66% (relative to pre-fire level) matches the post-fire price dynamics.

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. Estimates from our structural models allow simulating hypothetical shocks on plants not owned by Tyson. We do so by leveraging exclusive information about plant capacity for major US beef packers. Counterfactual analysis shows that hypothetical shocks lead to heterogeneous price effects: retail prices may fall or increase by different magnitudes depending on changes in capacity and delivery reliability, local competitive landscape, and demand elasticity. For example, while the observed shock on the Holcomb plant implied a decrease in the retail price of Tyson's products, a disruption of similar magnitude in a JBS plant would imply a small increase in the retail price of JBS's products.

Our paper contributes to a fundamental issue in economics: how firms pass upstream cost shocks to downstream prices (Peltzman, 2000). Weyl and Fabinger (2013) provide a theoretical foundation, emphasizing the role of market structure and firm conduct in determining the degree of pass-through, and Hong and Li (2017) provide supporting evidence using scanner data. Miller et al. (2017) find that in the cement industry, the

[4] Effectively, certainty in delivery is modeled as an implicit quality attribute of products delivered by a packer to its retailer, which speaks to a long strand of literature on the role of non-price factors in bargaining and contracting (Akerlof, 1982; Charness and Rabin, 2002).

pass-through of fuel cost changes decreases as competition intensifies. Similarly, Genakos and Pagliero (2022) show that the pass-through of excise duties at gas stations increases substantially as the number of competitors increases in a local market. Our research instead focuses on price effects in settings where wholesale prices are negotiated, and retailers' concerns on stockouts, rather than changes in the number of competitors, affect pass-through.

We also contribute to a growing literature on the role of firm-to-firm relationships in the transmission of supply-chain shocks (Heise, 2024).[5] For example, Ksoll et al. (2023) document the adaptation efforts of flower exporters in Kenya after a production disruption triggered by post-election violence in order to preserve relationships with long-term buyers; Cajal-Grossi et al. (2023) provide evidence of higher resilience from relational sourcing relative to just-in-time sourcing in the garment industry after a sequence of disruptions. We highlight the role of markup responses in driving the pass-through of cost shocks from upstream to downstream via bargaining between wholesalers and retailers. Different from previous work, we provide a static structural approach that can simulate price responses to shocks, accounting for wholesale price negotiations, which helps inform policies aiming to improve the resilience of the supply chain.

2 The US Beef Industry

The US beef supply chain comprises roughly three stages: cattle raising, meat processing, and retailing. At the raising stage, 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, finally, feedlots to reach maturity. After achieving proper weights, the cattle are sold to the packing plants through spot-market auctions or forward contracts for processing (Cowley, 2022). At the processing stage, packing plants harvest mature cattle and pack them into primal cuts (e.g., loin,

[5]This literature studies an individual industry a time, which contrasts a parallel macroeconomics literature on the transmission of shocks along firm-to-firm networks (Carvalho et al., 2021; Acemoglu and Tahbaz-Salehi, 2025) and the implications of production reshoring (Grossman et al., 2023, 2024).

round, rib) and then into case-ready beef products that are sold to retail stores. In the United States, more than two thirds of beef is fresh and is purchased in grocery stores (Hahn, 2001).

Since the early 1980s, concentration in beef processing has been increasing. Today, the four large beef packers (JBS, National Beef, Tyson, and Cargill) slaughter and pack 80-85% of cattle in the nation (Crespi et al., 2012). The bulk of cattle slaughter is carried out in the Great Plains where the majority of cattle is 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.

The 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). Domestic processing and distribution are highly self-sufficient, and net imports have accounted for less than 0.5% of US consumption in recent years. Retail stores offer a diverse beef product line that includes ground beef, patties, and different premium beef cuts like, for example, rib-eye steak, tenderloins, and top rounds. In recent years, concentration in beef retailing has also increased, following a broader trend of higher concentration in food retailing (Hamilton et al., 2020).

Beef products are sold under 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 regional or national brands. In the US fresh beef market, regional and national brands occupy 30-35% of sales, while the rest are taken up by private labels with considerable variation across local markets and retail chains (Ma and Siebert, 2024). Although different types of cuts are more popular within the sales of each brand, ground beef is always the most popular cut, accounting for more than 60% of the sales (Peel, 2021).

Retailers typically purchase beef by negotiating directly with processors on forward contracts, and most deliveries are scheduled weeks in advance. The need to schedule deliveries from particular packers comes from the fact that beef is perishable, ruling out using stockpiles to meet demand fluctuations, and is a product that tends to attract consumers to stores, especially around holidays. Retailers hence need to ensure that they are able to meet demand surges to fulfill advertisement campaigns. For example, Fourth of July and Labor Day represent annual peaks of beef demand and advertisements staring ground beef prices are shown several weeks before the holidays. Since beef is a staple good, the alternative of buying beef at the spot market or experiencing stockouts can be extremely costly for retailers.

2.1 Data sources

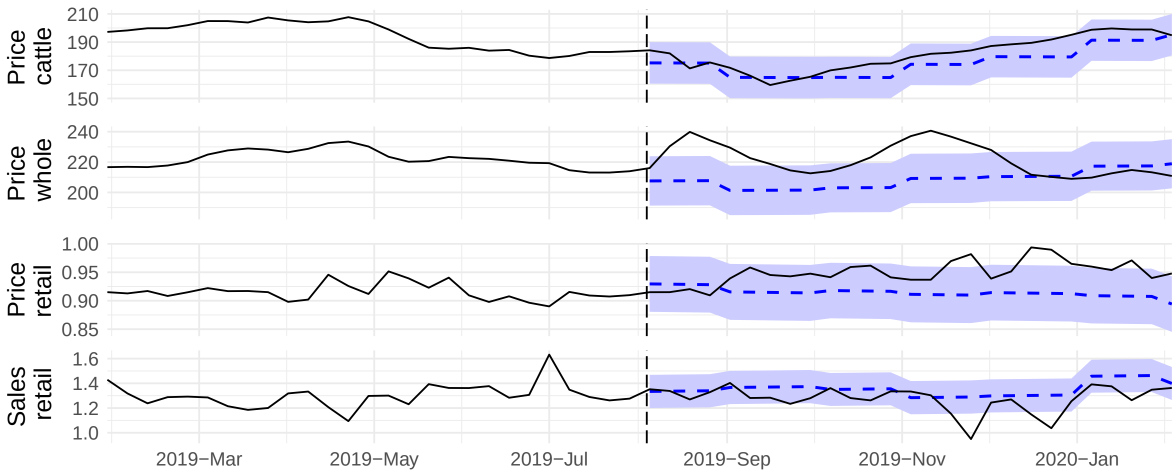
We collect information on the US beef supply chain from multiple sources. Information on retail prices and sales comes from the NielsenIQ Scanner Dataset 2016-2019. NielsenIQ Retail Scanner Data (RMS) are organized by Universal Product Codes (UPCs) in weekly reports for thousands of retail stores. The full sample consists of more than 21,000 fresh-beef-selling stores that belong to some 130 retail chains and 49 US states. There are 961 universal product codes (UPCs) for beef with information on their characteristics, such as the cut (ground beef, steak, etc.), the package size, and brand (see Appendix A for details).

Historical monthly information on cattle and wholesale beef prices is obtained from the United States Department of Agriculture's Agricultural Market Service (AMS). The data are mainly aggregated at the national level, with some information on cattle prices by region. We also collect national information on wages for beef processing from the Bureau of Labor Statistics (BLS) and information about aggregate daily slaughter from Livestock Marketing Information Center (LMIC).

3 The Holcomb Fire

Tyson's largest beef processing facility, located in Holcomb, Kansas, represented approximately 20% of the company's total slaughter capacity and approximately 6% of the national capacity. The plant sourced cattle from a broad geographic area spanning the High Plains of Texas to Nebraska. On August 9, 2019, a major fire severely damaged the facility, leading to a complete shutdown. Uncertainty surrounding the timeline and likelihood of the plant's reopening persisted throughout the rest of 2019. Partial operations resumed in early December, and full production capacity was restored by the first week of January 2020 (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 series after the fire (solid line) against what would have been expected based on the trend and seasonality of average market outcomes during the three years before the shock (dashed line). We do not observe a significant change in the negotiated spot prices for cattle after the fire, but we see an increase in the average wholesale price. We also observe higher retail price of beef in supermarkets a few months after the shock and a parallel reduction in aggregate beef sales in the fourth quarter of 2019.

3.1 Fire impacts in detail

The fire generated differential responses across the cattle, wholesale, and retail markets. In the sections that follow, we analyze price and production data to characterize the impact of the disruption at each stage of the beef supply chain.

Cattle market: Time series evidence in Figure 1 shows a muted effect of the fire on cattle spot prices relative to trend and seasonality. Appendix B provides evidence that futures cattle prices experienced a short-lived decline and the effect of the fire on spot prices was geographically homogeneous. The momentary decline in futures prices after the fire, likely had a limited effect on processors' marginal costs because the prevalence of formula contracts in cattle procurement reduced the benefits of short-lived swings on futures prices.[6]

Cattle processing: The impact of the fire on Tyson's production costs was well documented in agricultural news outlets at the time. Tyson had to divert the cattle to its other smaller plants (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 who had to work extra hours. 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).

Cattle slaughter on weekends in other plants also helped maintain beef processing levels post-fire.[7] Using daily cattle slaughter data, column (1) in Table 1 shows no significant differences in slaughter relative to trend and seasonality. In column (2), we break down the daily slaughter into weekdays and Saturdays. We observe a 70% increase in Saturday slaughters relative to the trend and seasonality after the fire. The increase in Saturday slaughter occurred at the same time as the weekly slaughter numbers slightly

[6] In formula contracts, feedlots contract cattle to processors for future delivery, and prices are pegged to a formula that uses spot prices across regions close to delivery dates (MacDonald, 2006; Garrido et al., 2022).

[7] The National Cattleman's Beef Association requested the regulatory arm of the US Department of Agriculture (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).

decreased. The signs of the weekend and weekday slaughter coefficients are consistent with the shutdown of the Holcomb plant, the loss of a significant portion of weekday capacity, and the need of other Tyson's plants to operate closer to capacity on weekdays and add shifts on weekends. According to anecdotal evidence, some non-Tyson plants may also have added weekend shifts, although we cannot capture that using the aggregate data.

Table 1: Evolution of Weekday and Saturday Slaughter After the Fire

	log(Daily Slaughter)	log(Daily Slaughter)
	(1)	(2)
Fire Aug-Sep	−0.043 (0.091)	−0.137 (0.099)
Fire Oct-Dec	0.006 (0.088)	−0.087 (0.095)
Fire Aug-Sep×Saturday		**0.529** (0.124)
Fire Oct-Dec×Saturday		**0.554** (0.105)
Adj. R^2	0.277	0.283
Num. obs.	1250	1250

Note: Daily observations on cattle and calf slaughter are 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/. Significant coefficients at the 95% confidence level are shown in bold.

As a result of the increased weekend slaughter, there is a slight increase in the wage rate for slaughter workers after the fire. Based on data from the BLS in Table 2, we identify a 2% increase in nationwide average wage received by employees in the animal slaughter industry after the fire (column 1). There is also an increase in the total overtime hours after fire for production workers in the animal slaughtering industry (column 3), parallel to a small decrease in the total time hours post-fire for all employees in the industry (column 2). The small decrease in the 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 more.

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 2019, we observed significantly higher wholesale prices for the boxed beef cutout.

Table 2: 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 (2) and (3) also control for monthly seasonality. Significant coefficients at the 95% confidence level are shown in bold.

As discussed in Dennis (2020), the initial increase in wholesale prices at the end of August 2019 was driven not only by the reduction in beef processing, but also by retailers that rushed to guarantee beef supply that would be consistent with their promotional schedules for the coming Labor Day holiday. Higher wholesale prices persisted for the rest of 2019.

In Table 3, we show that from September to October the average price for boxed beef cutout was around 9% higher than the price implied by trend and seasonality, and it move closer to the trend in December. Using USDA's beef grade taxonomy, columns (2) to (4) show that the prices of Select, Choice and Ground Beef followed similar patterns, suggesting that costs were uniformly higher across processors even after accounting for difference in their product compositions.

Table 3: Evolution of National Wholesale Beef Prices After the Fire

	(1)	(2)	(3)	(4)
	log(Price Boxed Beef)	log(Price Select)	log(Price Choice)	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. Significant coefficients at the 95% confidence level are shown in bold.

Retail market: We leverage the product-level scanner data to investigate the effects of the Holcomb fire on retail prices. The NielsenIQ Scanner data allow for a decomposition of the price effect by packer. In the US market, beef labeled by brands owned by retail chains (i.e., private labels) is often processed by several packers. Detailed data on which packer processes each private-label product are unavailable. We, therefore, group private labels as one single category and abstract away from identifying the effect of the fire on private labels because the mix of beef from different processors can endogenously change after the fire.

By comparing beef retail prices in September through December of 2019 with the average price observed in August, prices have increased around 4% after the fire.[8] Table 4 breaks down the effect on retail prices by packer. Surprisingly, Tyson's products declined on average by about 2% following the fire, suggesting a differential effect on Tyson's pricing behavior relative to other beef processors. This decline was most pronounced in September and October and accentuated in the last two months of the year. In contrast, we observe price increases for products of other packers and private labels from September to December.

Table 4: Percentage Changes in Beef Retail Prices Relative to August 2019

	2019 Month				Semester
	Sep.	Oct.	Nov.	Dec.	Avg.
	(1)	(2)	(3)	(4)	(5)
All products	3.72	4.34	3.58	5.66	3.72
Tyson	-2.45	-4.41	-0.98	-0.71	-2.14
Others	3.95	4.67	3.74	5.93	4.57
Cargill	2.71	2.90	1.65	2.95	2.55
JBS	7.28	9.15	-4.13	10.16	5.62
National Beef	2.55	3.50	3.45	4.43	3.48
Private label	4.76	5.43	4.61	6.81	5.41
Small brands	0.56	1.70	2.42	3.33	2.00

Note: The table calculates monthly weighted average percentage change in beef product prices in relation to the average price observed in August of 2019 using product level data from NielsenIQ. Weights are the product's volume sold in August of 2019.

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

[8] We use the whole month of August as reference for calculations since retail prices deviations from trend in the second half of August are small and unlikely to have been driven by the fire. The results are qualitatively identical and quantitatively even stronger, if we either take early August as the reference period or if we take the average prices for May, June, and July as reference and compute the price percentage change for September, October, November and December.

stemming from higher processing 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 (e.g., cut and size) using data from January 2017 to early-August 2019. We then compute trend-implied retail beef prices by projecting equation 1 on the data after the fire. Specifically, for product j owned by processor b in time t:

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

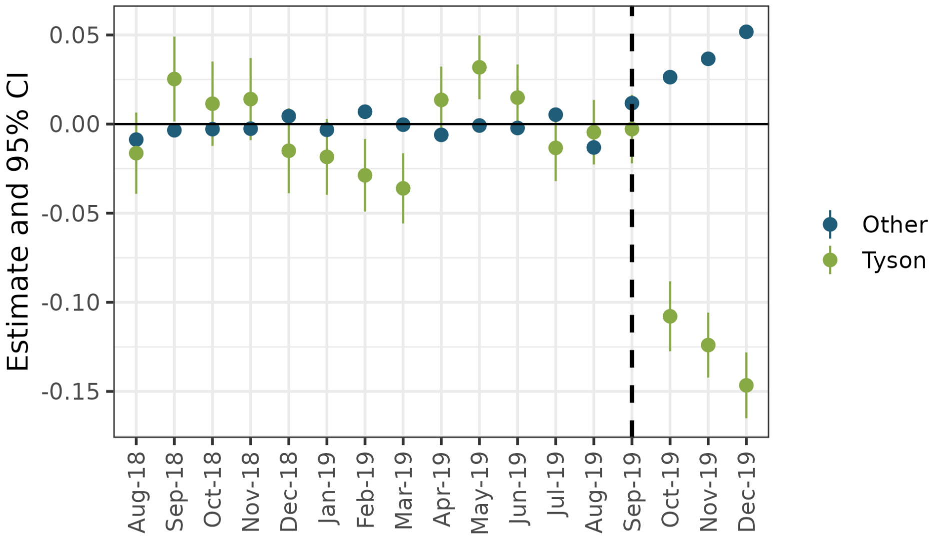
The second step consists of assessing the differential effects of the fire on Tyson and other processors. We do so by using equation 2, which comprises of an event-study around the fire. We estimate the average deviation from trend-implied beef prices (i.e., $\Delta \log(p_{jbt}) = \log(p_{jbt}) - \widehat{\log(p_{jbt})}$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

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

We show the results of the two-step approach in Figure 2. 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. Prices do not seem to have major deviations from trend before the fire. Together, Table 4 and Figure 2 suggest a price effect of the fire on Tyson's products that is different from price effects on other packers, and the patterns cannot be explained by packer-specific pre-fire trends.

Appendix B provides information on cold storage of beef and wholesale prices of other meats (e.g., pork), showing little impact of the fire. The appendix further offers a detailed discussion of the heterogeneity in the fire's effects, including decomposing Figure 2 for other packers. Furthermore, Table B6 shows that most of the variation in price deviation post fire (i.e, $\Delta log(p_{jbt})$) can be attributed to retail and processor

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



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. Confidence intervals at a 95% level.

fixed effects, as well as the cuts that these firms are offering. DMA fixed effects explain little of the variation in price deviations, suggesting that the effect post-fire is largely related to firm features and product specialization, not spatial heterogeneity. Similarly, through a variance decomposition exercise, we find that most of the variation in impact across Tyson products sold by different retailers in different DMAs can be attributed to differences in retailer characteristics and cuts, with minimal variation across geographic markets. We also show that the negative price deviations from trend and seasonality for Tyson products are primarily driven by ground beef — consistent with the Holcomb plant's specialization in ground beef processing — and concentrated among large retailers, specifically those in the top quartile of pre-fire beef sales.

Overview of impacts: Based on the preceding discussion, we identify four key effects of the Holcomb fire: 1) a rise in processing costs for packers — especially for Tyson — driven by increased utilization of remaining capacity and elevated labor expenses; 2) a corresponding increase in the average wholesale price of boxed beef cutouts; 3) a rise in retail prices for non-Tyson beef products ; and 4) a *decline* in retail prices for Tyson products.

3.2 Rationalizing the impacts of the fire

When evaluating the transmission of changes in marginal costs to retail prices in settings of differentiated products, most articles assume a fixed markup at one level of the supply chain, usually retailers, and an equilibrium pricing behavior of Bertrand-Nash (Berry et al., 1995; Nevo, 2000; Miller and Weinberg, 2014) or Cournot-Nash (Berry et al., 1999; Feenstra and Levinsohn, 1995) among firms at the other level. Other articles have allowed the possibility of double marginalization (Villas-Boas, 2007; Bonnet and Dubois, 2010; Duarte et al., 2024), collusion (Nevo, 2001a; Michel et al., 2024; Sullivan, 2017), or a simple cost multiplier (Magnolfi et al., 2022a) throughout the supply chain when quantifying the effects of changes in upstream marginal costs. We argue that, because all these models imply a positive pass-through to the prices of products owned by the firm that directly bears higher marginal costs, none could rationalize the pricing patterns observed in our context. In Appendix C, we provide detailed discussion on the pass-through rates under the conventional models cited above.

Tyson's 2019-2020 financial statement suggests a possible explanation. According to the statements in the Beef Segment, the increasd spread between preexisting contractual agreements and the cost of fed cattle was "partially offset by price reductions offered to customers" (Tyson Foods, 2020).[9] Wholesale price discounts after the fire could explain the observed negative pass-through for Tyson's products.

To rationalize the emergence of wholesale price discounts after a supply shock, we start with three key elements of the beef market. First, beef is a crucial product for attracting consumers to grocery stores (FMI, 2018), but demand fluctuations are common in beef retailing. Second, beef is perishable, and retailers hence rely on the processor's ability to deliver beef as scheduled and upon emergency (Dennis, 2020), instead of maintaining inventory, to prevent stockouts. Third, retailers and processors have bargaining power

[9] Although the financial statement cleared mention wholesale price discounts, it is not clear if it was a response to shocks triggered by the Holcomb fire or COVID. Nevertheless, we take it as anecdotal evidence of processors behavior after unexpected supply shocks.

when negotiating wholesale prices and are willing to adjust the terms under new economic circumstances in order to preserve the relationship.

Stockouts can be extremely costly for retailers.[10] To mitigate the risk of stockouts, retailers are willing to pay a premium for suppliers that can make quick adjustments to supply and reduce the probability of stockouts. There are several ways suppliers can offer delivery flexibility. In particular, having slack capacity plays a critical role in enabling suppliers to promptly manage unforeseen shocks and reduce delays in product delivery (Hendricks et al., 2009).

After the Holcomb fire, it is unlikely that Tyson had much slack capacity left, if any. Holcomb represented around 20% of Tyson's beef processing capacity, and diversion of cattle from Holcomb to other plants probably took up Tyson's slack capacity on weekdays and Saturdays. Therefore, Tyson ended up with little room to respond to unexpected retailer orders for the rest of 2019. Retailers, logically, would be unsure about Tyson's ability to meet unexpected orders, which likely increased the probability of stockouts if they kept Tyson as its supplier. Hence, if retailers had the ability to negotiate for more favorable terms, then the reduced reliability of Tyson's deliveries could have led to a decrease in wholesale prices for Tyson's products.

The characteristics of the beef industry suggest that most retailers have bargaining power when negotiating beef contracts. There has been a steady increase in scale and concentration in the US retail sector for the last 30 years, with warehouse clubs and supercenters owned by retailers with multi-market presence now enjoying sales dominance over smaller retail formats (Ellickson, 2016). Increased scales put retailers in a better position to negotiate with suppliers. Insiders of the beef industry suggest, during the negotiation process, retailers frequently make counteroffers that are justified by market conditions, for example, the entry of new competitors or changes in the popularity of the manufacturer's brand. It is hence reasonable to assume that, retailers had the ability to make counter-offers on wholesale prices and adjust the negotiated margins based on the

[10] In addition to losing sales of goods that experience stockouts, retail stores may lose sales of other goods due to consumers' one-stop shopping behavior (Thomassen et al., 2017) and even future customers due to reputation damage (Matsa, 2011). Zinn and Liu (2001) provide evidence that some 30% to 50% of consumers delay purchases or leave the store after a stockout.

new environment after the fire.

In addition, the importance of beef in attracting consumers and the high concentration at retailing and processing levels make long-term relationships important, as the search for new partners can take time and be extremely costly (MacDonald et al., 2023). The desire to maintain long-term relationships makes both parties willing to adjust the contractual terms facing shocks (Ksoll et al., 2023; Cajal-Grossi et al., 2023).

Put together, we argue that Tyson's capacity loss from the fire likely led to weakened confidence of retailers regarding Tyson's ability to deliver beef products as scheduled or on the spot for the rest of 2019. To account for the decline in Tyson's delivery reliability, negotiations over beef prices may have resulted in lower markups for Tyson and better terms for retailers. This reduction in markups could have been large enough to offset the higher marginal cost in processing, resulting in negative price changes for Tyson's products. In contrast, the delivery reliability of competing packers was much less affected by the fire as their slack capacity largely remained and implied a positive pass-through of higher marginal costs. In the following sections, we present a structural model that formalizes the mechanisms described above.

4 Structural Model

We present the structural models 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.[11] 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 reliability 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

[11]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).

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. 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 probability of beef actually delivered is incorporated. Before first-stage negotiations are settled, retailers form expectations about the probability of delivery from each processor based on their information sets.

4.1 A demand model with stockouts

In what follows, we construct the sales expectation that processors and retailers rely on when negotiating prices in the first stage. Let $\mathcal{J}_t$ be the set of products contracted by the retailer to be supplied to its stores in a given market t (e.g., retailer-DMA-year-month). In the second stage, a product $j \in \mathcal{J}_t$ is delivered or not and consumer $i \in I$ maximizes utility by choosing between beef products from a set of *available* products $J_t \subset \mathcal{J}_t$ and an outside option of not buying beef.

The indirect utility of consumer i from choosing product j of brand b in market t is

$$u_{ijt} = X_{jt}^{'}\beta_i - \alpha_i p_{jt} + \xi_{jt} + \epsilon_{ijt}, \tag{3}$$

where X_{jt} and ξ_{jt} are the observed and unobserved characteristics for product j, respectively, p_{jt} 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.

For easier exposition, we suppress the market subscript. The average choice probability, ρ, for product j takes the form

$$\rho(j|j \in J) = \int \frac{\exp\left(X_j^{'}\beta_i - \alpha_i p_j + \xi_j\right)}{1 + \sum_{k \in J} \exp\left(X_j^{'}\beta_i - \alpha_i p_j + \xi_j\right)} dH(i), \tag{4}$$

where H is the cumulative density function 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 reliability by imposing a probability distribution γ^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 the probability of delivering the batch and not individual products.[12] If there is a mass of M consumers in every period, then we can calculate the expected aggregate volume sales of product j during the second stage:

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

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 data alone. We, therefore, assume that in "business-as-usual" periods (e.g., the months before the fire), deliveries are made with probability normalized to one and deal with deviations from this normalization for individual processors.[13] To ease notation, we denote a deviation over the "business-as-usual" probability by processor f as $\gamma_f^D \leq 1$.

Given that a deviation γ_f^D only happened for firm f, there are only two relevant product sets: the full contracted set $\mathcal{J}$, and the set without f products, $\mathcal{J}_{-f}$. The expected sales share for any product j owned by f is:

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

[12] This implies that the probability of any given subset in $\mathcal{S}$ is the multiplication 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 $\gamma_1^D \times \gamma_2^D \times (1 - \gamma_3^D)$, where γ_j^D is the delivery probability of brand j.

[13] 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.

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

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

Finally, the T1EV assumption for the error term implies that the average *ex ante* expected maximum utility that consumers derive from facing the actual assortment $\tilde{\mathcal{J}}$ and price vector p is:

$$V(p,\tilde{\mathcal{J}}) = \int \frac{1}{\alpha_i} \log \left[\sum_{j\in\tilde{\mathcal{J}}} \exp(X_j^{'}\beta_i - \alpha_i p_j + \xi_j) \right] dH(i)$$

By taking expectations over delivery events, we can express the expected inclusive value during the first stage as:

$$\mathbb{E}[V(p,\tilde{\mathcal{J}})] = \gamma_f^D V(p,\mathcal{J}) + (1-\gamma_f^D)V(p,\mathcal{J}_{-f}).$$

4.2 Bargaining game

After expectations for delivery reliability are formed, retailers and processors bargain on wholesale prices in the first stage. Discussions with industry experts reveal that beef cuts are often employed as loss leaders by supermarkets to entice customers to shop in their stores. To take into account the character of the loss leader, we model the negotiation between retailers and beef processors setting retail markups to zero.[14]

The parties have opposite incentives when bargaining: 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:

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

[14]The results would be the same if we assume that retailers set a fixed uniform markup across products and that the margin does not change after a shock in delivery expectations. Other studies on US retail markets confirm this assumption (Duarte et al., 2024).

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

The negotiation between retailers and processors depends on the importance of the processors' products for the expected consumer experience, $W(p, \tilde{\mathcal{J}})$. For consistency with our demand setup and empirical tractability, we use consumers' average inclusive value, $V(p, \tilde{\mathcal{J}})$, as a measure of the expected consumer shopping experience.

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).[15] Formally, the expected consumer experience in the scenario where only firm f has a shock on delivery probability, $\gamma_f^D < 1$, is:

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

In expression 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.[16] 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.

The solution of the game for any product j that is part of the batch $\mathcal{J}_f$ owned by

[15] 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.

[16] 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).

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 expectations are taken over the randomness of the realized assortment. Note that if retailers have zero bargaining weight ($b = 0$), then equation 7 is the standard Bertrand-Nash pricing equation. In contrast, as the bargaining 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 the equilibrium price vectors as

$$\mathbf{p} = \mathbf{c} - (\mathbf{\Omega} - \mathbf{\Lambda})^{-1}\mathbf{s}, \tag{8}$$

where $\mathbf{\Omega}$ 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 $\mathbf{\Lambda}$ 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.

5 Empirical Implementation

Our empirical exercise aims to rationalize the differential price movements across packers after the Holcomb fire by adjusting marginal costs and the parameter of delivery reliability. To match the price dynamics post-fire, we first estimate structural parameters for demand and supply based on data before fire and then calibrate marginal costs and Tyson's delivery reliability to the post-fire data. In what follows, we discuss the assumptions of functional form that we make to estimate the structural models and present the instruments used to construct moment conditions.

5.1 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 NielsenIQ Home Scanner Data (HMS) about market-level consumers characteristics (e.g., income) and use the matrix of parameters Π to govern the interaction with 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: 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 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 interaction with median income, the share of products of a brand 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). The differentiation instruments and shelf space allow for variation within and between markets, and the costs shifters allows variation across time.[17]

Moreover, we supplement market-level moments with micro-moments derived from consumer-level decision data from the HMS. Specifically, we calculate two moments: the average income of households who opt to buy beef and the covariance between the price paid and the income of households. We use the derived choice probabilities to construct the analogous moment from the model and include additional estimation conditions based on the difference between the sample and model moments. The final vector of conditions used in the generalized method of moments (GMM) formulation includes both the aggregate and micro-moments.

5.2 Supply

We estimate the supply model as in equation 7. We lack information on F_r, the parameter that captures the loss in sales in the chain after the stockout of beef. There is some

[17] Prices of cattle, hay, soybeans, and corn are obtained from the USDA, the price of energy is obtained from the Energy Information Administration (EIA) at the regional level, and the BLS provides hourly wage for meatpacking workers.

evidence that stockouts have heterogeneous effects 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 worth 40% of the total beef sales in a market.

We also need values for the ratio of bargaining weights for processors and retailers, $\frac{b}{a}$. In principle, we could estimate this ratio. Since markups are determined in equilibrium, we would need instruments that exogenously shift them. Like other empirical papers on vertical relationships, we have no clearly valid source of variation that generates strong instruments for the estimation of bargaining weights. Instead, we compute a pairwise model fit comparison among non-nested pricing models that, to our institutional knowledge, could potentially characterize the behavior of retailers and beef processors. 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, as discussed by Magnolfi and Sullivan (2022).

Specifically, we use Rivers and Vuong (2002)'s model selection approach as described in Duarte et al. (2024) to check which conduct model best fits the pricing pattern before the fire. The method allows for a model selection based on a pairwise comparison of each alternative supply model and accounts for the endogeneity of markups in a tractable way. We consider four 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 markups are zero, (2) a two-part tariff in which the processor sets prices for beef products with zero retail markups, (3) a model of linear pricing across the supply chain, and (4) a bargaining model with equal weights for processors and retailers.

The two-part tariff with zero retail margins is a common way to model grocery goods price decisions (e.g., Miller and Weinberg, 2014). Following our notation in equation 8, the equilibrium pricing equation in this conduct takes the usual Bertrand-Nash form of $\mathbf{p} = \mathbf{c} - \mathbf{\Omega}^{-1}\mathbf{s}$, with zeros in the Ω matrix determined by the ownership structure among processors. The expression for the conduct with retailers setting prices is analogous, except for the ownership structure driven by retailers. In the linear pricing model, processors decide wholesale prices before retailers set retail prices. This creates a double marginalization pricing framework as in Villas-Boas (2007), where processors fully account for the retail pass-through when setting the wholesale price. In all conducts, we assume that private labels are vertically integrated with retailers, and private-label products hence have no processor markups.

5.3 Sample construction

Because pricing and assortment decisions are typically made at the retailer level rather than the store level (DellaVigna and Gentzkow, 2019), we define a market as a retailer-DMA-month combination. The size of market is defined as the total potential beef sales by consumers who shop in the market. To approximate this, we estimate the number of customers using total sales of eggs and milk within each retailer-DMA-month, following a methodology in Backus et al. (2021) (see Appendix A for more details). To ensure that our measure is representative of a retailer's total sales, we restricted our sample to DMAs with high coverage in the RMS data, ending up with a total of 5,622 markets that spread out over the United States.

Fresh beef products involve little processing other than cutting and packaging, and the only ingredient is the flesh itself. Thus, we aggregate the UPC level data and define a product based only on package sizes (pounds per package), cuts (ground beef lean/fat, patty, steak, and others) and brand. Here, *brand* refers to the parent brand or the packer. Large beef packers typically own multiple sub-brands. For instance, Tyson owns Tyson, Jimmy Dean, Hillshire Farm, and others. We observe 142 brands, many being brands owned by small local packers.

Table 5 presents summary statistics for products and markets. A typical market has 12 products and 5 brands, with around 2 products per brand. There is considerable heterogeneity in price and market shares between products. We also observe a large market share for the outside option, with about 79% of the retail customer not buying beef. This is not surprising, as all other meats such as poultry and pork, are left as part of the outside option. In Table A1, we describe the distribution of sales across processors.

Private-label products dominate sales for most of our sample, but the market share of branded beef by Cargill, JBS, National Beef, and Tyson are substantial in some markets, reaching more than 30% of sales in some cases.

Table 5: Sample Summary Statistics

	Mean	Std. Dev.	Min	Q1	Median	Q3	Max
Products per market	12	5	3	8	12	15	31
Brands per market	5	2	1	3	5	6	16
Products per brand-market	2	3	1	1	1	2	15
Price ($/lb.)	5.88	2.85	1.93	4.11	5.46	6.82	24.09
Product Share	0.02	0.03	0.00	0.00	0.01	0.02	0.68
Outside option share	0.79	0.16	0.00	0.70	0.83	0.91	1.00
Size (lb.)	1.46	0.96	0.25	1.00	1.00	2.00	5.00

Note: Authors' creation based on 2018-2019 NielsenIQ Retail Scanner Data. A market is a retailer code × DMA × month. Product is a brand×cut×size.

6 Results

We present and discuss the results of the demand and supply estimation in this section. Counterfactual analysis is performed to show heterogeneous pass-through rates among firms, when similar fire shocks hit different beef packers.

6.1 Demand results

We start with the demand results in Table 6. 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 instrument the nest with the number of products per nest, a common practice in the literature (Conlon and Gortmaker, 2020). We find that nesting by grouped cut in the demand system leads to demand elasticities more in line with the literature. Column (3) displays results from a random coefficient nested logit (RCNL) model that uses micro-moments to aid the identification of parameters.

All models estimate a downward-slopping demand system with own-price elasticities varying between -1.2 and -4.4. The RCNL model 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 6: 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	66,829		66,829		66,829	

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 7 shows average diversion ratios across grouped cuts. Primarily, price shocks in a particular cut (each row in the table) lead consumers to deviate to the outside good, but a significant share of consumers deviate to the most popular cut, namely, ground beef with relatively high fat content. Consumers buying ground beef tend to stick to ground beef or substitute with the outside good when prices increase.

Table 7: 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.

6.2 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. We use differentiation instruments (Gandhi and Houde, 2019) to form the GMM function and find them 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 bargaining ratios to generate markups for the bargaining model to conduct the RV test. Test statistics in Table 8 shows that the RV tests favor the bargaining model over other models.

Table 8: 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 (b=a)							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 linear-wholesale pricing with vertical integration for private labels as in Villas-Boas (2007), and Bargaining refers to the model of bargaining defined before. MCS is the model confidence set of Hansen et al. (2011). F-stat is the weak instrument test statistic of Duarte et al. (2024); all pairs are above the appropriate critical value for worst-case size of 0.075 and best-case power above 0.99.

Table 9 presents the marginal costs and markups derived from the bargaining model. The costs are plausible, with less than 2% of the ground beef observations showing negative marginal costs. As expected, steak incurs significantly higher marginal costs compared to other cuts due to its labor-intensive processing. Besides, lean ground beef has higher marginal costs than fattier options, likely due to its pricier cut composition.

The Learner indices are similar for all packers, except for National Beef which enjoys

Table 9: Supply Model Results

(a) Marginal Cost Estimates by Beef 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 Brand

	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	-

Note: Marginal cost is in \$/lb. Lerner Index is the retail price minus marginal cost over the retail price. Information on gross margins is obtained from Bureau van Dijk (2025), and refers to the ratio of revenue minus cost of goods sold over revenue in 2018.

a higher average markup.[18] As a sanity check, we compare the implied markups with gross margins from the accounting data of the two public companies in our sample. The comparison suggests that the model generates reasonable margins not far from the actual margins set by firms in this industry.[19]

6.3 Fitting post-fire price movements

We rationalized the post-fire movement in beef prices by arguing that the closure of Holcomb led to 1) an increase in processors' marginal costs, and 2) a decline in Tyson's delivery reliability. We now show that we can empirically explain the negative pass-through of Tyson's products and positive pass-through of other processors' products by

[18]Branded products for National Beef were present in fewer markets than other Big-Four processors. Additionally, the median income of markets where national beef locates are about 30% higher than median income in markets where other large processors place their products, which can partially explain its higher Lerner Index.

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

calibrating wedges in marginal cost and delivery probability in equation 8. We continue to set the stockout cost, F_r, at 40% of the sales realized throughout the calibration exercise.

We present three scenarios in Table 10 to argue for the necessity of adjusting both marginal costs and Tyson's delivery reliability. The first scenario adjusts the industry's marginal costs to match the average price increases post-fire. By adjusting marginal costs (increase by 5.50%), we can explain the average increase in beef prices post-fire (4.3%), but not the decline in prices for Tyson's products. Starting from the increase in marginal costs found in the first scenario, the second scenario sequentially adjusts Tyson's delivery reliability ($\gamma^D_{Tyson} = 0.34$) and the industry's marginal costs to match both the average decline in Tyson's price (2.1%) and the average increase in beef prices for other processors (4.5%) based on column (5) in Table 4. Finally, the third scenario adjusts the marginal costs and the delivery reliability parameter only for Tyson, but we can hardly match any price changes for other processors.[20]

Table 10: Calibrated Percentage Changes in Prices Post Fire

	(1) ↑ Industry MC	(2) ↑ Industry MC ↓ Tyson's Delivery Probability	(3) ↑ Tyson's MC ↓ Tyson's Delivery Probability	Observed
Tyson	4.06	-2.10	-2.17	-2.14
Others	4.35	4.46	0.15	4.57
$\tilde{\gamma}^D_{Tyson}$	1	0.342	0.365	
MC_{all}	↑ 5.50%	↑ 5.45%		
MC_{Tyson}			↑ 6.00%	

Note: The calibration exercise in column (1) targeted the average change in retail prices for *all beef processors* by changing the marginal cost of all industry participants. An increase of 5.5% in marginal costs from pre-fire levels successfully calibrated the model. In column (2), the calibration exercise targeted two measures, the observed change in prices for Tyson after the fire and the average change in prices after the fire for other processors. To match both averages, we iteratively adjusted marginal costs for the industry participants and changed Tyson's delivery reliability parameter, γ^D_{Tyson}. The iteration finished with an increase in marginal costs of 5.45% from pre-fire levels, and $\gamma^D_{Tyson} = 0.342$. Column (3) matches the average change in beef prices for Tyson only. It does so by iteratively changing Tyson's marginal costs and Tyson's delivery reliability, and the iteration successfully ended with an increase of 6% in Tyson's marginal cost and a decline in $\gamma^D_{Tyson} = 0.365$. Based on previous literature, we assume a cost of stockout of 40% of the sales share for the processor products throughout the exercises.

[20] The 5% increase in marginal costs of processing makes sense given institutional features of beef processing. See Appendix D for a detailed discussion based on some back-of-envelop calculation.

6.4 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 Holcomb fire outbreak we examine here is only one, albeit a consequential one, of thousands of fires that occur in US agrifood plants every year. In 2022, for instance, more than 11,000 fires occurred (Verzoni, 2022) in some of the 41,080 food and beverage processing plants in the nation (Bureau of the Census's County Business Patterns, 2022).

From a policy perspective, it is important to evaluate the resiliency of the supply chain to unexpected disruptions and to identify potentially weak links. A fire similar to the Holcomb fire could generate heterogeneous changes in market outcomes depending on which plant is hit. The pass-through of the shock to consumers depends on a number of factors, such as the plant size, capacity utilization, how much lower delivery reliability becomes, the market shares of each processor and retailer, the cross-price elasticities of demand in each market, etc.

To compare short-term price effects of potential fire hitting different plants, we leverage the estimates from our structural models to run counterfactual simulations.We focus on the largest plant of the Big-Four packers. Plant-level, confidential capacity data come from USDA-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 Big-Four packers are included in the dataset.

We make two additional assumptions for tractability of simulation. First, once a fire is imposed on a plant, we reduce the probability of delivery (γ^D) for the packer in a way that is proportional to what is observed for Tyson's plant. Specifically, we assume a power function, $\gamma_i^D = (X_i)^a$, where $X_i \in [0, 1]$ is the portion of the active capacity of packer i after its largest plant shuts down. The delivery probability equals 1 if $X_i = 1$ and equals 0 if $X_i = 0$. We use the observed point on this function that comes from the Holcomb fire, $X_{Tyson} = x^*$ (i.e., the remaining capacity of Tyson as a percentage after the Holcomb plant closes) and $\gamma^D_{Tyson} = 0.34$, to help back out the value of a, which is assumed to be equal between packers. Once we have a, we can impose different γ_i^D for different packers after the fire.[21] Second, the increase in the marginal cost of processing is set at 5.0% because the scale of the largest plants among packers is similar to Tyson's Holcomb plant, implying comparable needs for the industry to increase use of remaining capacity to make up the lost capacity.

The results in Table 11 highlight the heterogeneous price impacts induced by the hypothetical shocks. Cargill, for instance, presses markups of its products significantly due to its low delivery reliability like Tyson does, whereas JBS would absorb the increased marginal costs in processing to a much less extent. A shock on the National Beef plant, in contrast, has a near-unit pass-through to retail prices, meaning National Beef barely changes its markups. This is because National Beef sells products in markets where demand elasticity is relatively low. Even as its delivery reliability falls, it is able to pass most of the increased costs to consumers with relatively inelastic demand (see Table 9 for more discussion the markups of National Beef products).

Table 11: Percentage Changes in Prices Post Counterfactual Shocks

	Shock on			
Avg. % change in	Cargill	JBS	NB	Tyson
Cargill prices	-2.53	4.21	4.49	4.10
JBS prices	4.18	0.53	4.73	4.12
National Beef prices	3.96	4.47	4.64	3.96
PL prices	4.00	3.50	3.46	3.60
Small processors prices	4.63	4.56	4.55	4.54
Tyson prices	3.69	4.21	4.43	-2.49

Note: We simulate price changes by packer, assuming a industry-wide increase in marginal cost of 5.0%. The simulations are conducted considering July 2019 as the normal-time market conditions.

7 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

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

the marginal costs of beef processing for packers after the fire by increasing Saturday slaughter and overtime wages for workers.

Despite higher marginal costs of processing, Tyson's products experienced lower retail prices after the fire. Products owned by other processors, in contrast, experienced price increases. We show that non-bargaining firm conducts fail to rationalize the price dynamics documented. We build a model of bargaining with processor-specific delivery reliability that fully rationalizes the observed changes in prices. Tyson experienced a considerable decrease in delivery reliability due to the closure of its Holcomb plant, while other packers maintained the near-normal-time reliability of delivery. Retailers sourcing from Tyson hence face relatively high risks of stock-outs of beef because Tyson is less able to respond to stochastic demand with little slack capacity left after the fire. Through bargaining, Tyson ended up with lower markups which more than absorbing higher marginal costs due to the fire.

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 decrease in delivery reliability, the structure of the market, and the local demand.

Our findings suggest that supply chain disruptions can generate a wide range of market outcomes if prices are shaped by bilateral bargaining between firms. The insights have critical policy implications. In particular, policy intervention that distorts the bargaining process risk unintentionally harming consumers by increasing the pass-through of supply shocks to retail prices. In the example we study, Tyson's partial absorption of cost increases due to the fire was likely motivated by the threat of losing retail shelf space to competing beef suppliers. This highlights the importance of maintaining competitive options for retailers and suggests that reduced pass-through may be an underappreciated benefit of competition in a supply chain, one that merits greater attention in ongoing policy debates (see Garrido et al., 2022 for a discussion of the current debate on competition in the US beef processing). Regarding the allocation of government budgets on fire or hazard prevention, priority could be given to protecting facilities operated by processors that are least capable of absorbing cost shocks — those most likely to fully pass shocks on to consumers through higher prices — instead of equally spreading the subsidies among firms (see Jia et al., 2024 for empirical evidence on substantial efficiency improvements of targeted subsidies *versus* equal-to-all subsidies).

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A Market Definition & Sales Distribution

Market size: We define the market size as the potential volume of beef purchases by all consumers visiting a given retailer in a specific DMA (Designated Market Area) during a month. To construct this measure, we first estimate the monthly customer flow for each retailer-DMA. Following the approach of Backus et al. (2021), we proxy the number of customers using purchases of fresh milk and/or fresh eggs, which are commonly and regularly purchased products. The construction proceeds in four steps:

1. Compute the total volume of fresh milk and fresh eggs sold in each retailer-DMA-month using NielsenIQ RMS data.
2. Use HMS data to calculate the total volume of milk and eggs purchased by households shopping at the same retailer-DMA in the same month.
3. Compute the average household purchase of milk and eggs for each retailer-DMA-month using the NielsenIQ HMS data.
4. Estimate the number of customers purchasing milk or eggs at each retailer-DMA-month by dividing the total RMS volume (for milk or eggs) by the corresponding average HMS household purchase. Take the maximum of the two resulting estimates (milk-based and egg-based) as the estimated number of customers for that market.

With this estimate of consumer flow, we then compute the market size for beef by multiplying the average household beef purchase (from HMS) by the estimated number of customers. The inside share of a beef product is calculated as the RMS volume sold of that product in a retailer-DMA-month divided by the estimated market size. The outside share is simply one minus the sum of all inside shares for that market.

DMA sampling: We further refine our final sample by selecting markets within DMAs that have similar characteristics to DMAs with high coverage by Nielsen. We do so in three steps. We start by including DMAs with high coverage by Nielsen, as discussed Backus et al. (2021). To expand the geographical coverage of our sample, we compute the average and standard deviation of the outside share of beef for these high-coveraged DMAs. With both values in hand, we select other DMAs with average outside share within 1 standard deviation of the average outside share of markets with high coverage. This results in 62 DMAs covering most of the territory of the United States. We use products sold in markets within these DMAs as our final sample.

Sales distribution: Table A1 presents summary statistics for the market shares of the inside options, disaggregated by the Big-Four packers, private labels, and other packers. Among the customers who purchase beef, approximately 64% opt for private label products. This indicates that, on average, private labels account for the majority of beef sales. National brands still play a significant role in certain markets, as evidenced by the upper quartile of their market share distributions. In addition, beef sales within individual markets tend to be highly concentrated among a few brands, with an average Herfindahl-Hirschman Index (HHI) of approximately 0.7.

Table A2 presents summary statistics by cut of beef. High-fat ground beef is available in nearly all markets and accounts for the largest share of revenue — approximately 55% — followed by low-fat ground beef, patties, and steaks. High-fat ground beef is

Table A1: Market Share Distribution (2018-19)

	Markets	Mean	Std.	Q1	Median	Q3
Total volume/Market Size	5622	0.190	0.150	0.070	0.140	0.250
Volume/Total volume						
Cargill	1289	0.170	0.180	0.040	0.100	0.230
JBS	915	0.200	0.260	0.020	0.070	0.240
National	315	0.250	0.260	0.030	0.200	0.360
Other	5542	0.360	0.330	0.070	0.260	0.610
Private labels	4616	0.640	0.330	0.340	0.780	0.940
Tyson	1070	0.190	0.250	0.000	0.090	0.260
Volume HHI	5622	0.717	0.206	0.535	0.729	0.916

Note: The volume shares are measured in percentage, and represent the average of the inside share of beef volume sold across markets.

also typically sold at a lower price and in larger package sizes compared to other cuts. However, there is substantial variation in the revenue share of each cut across markets, as reflected in the high standard deviations of shares by cut.

Table A2: Summary Statistics by Cut

	Markets	Price, $/lbs		Revenue share		Size, lbs	
Ground, high-fat	5615	3.88	(1.09)	0.55	(0.19)	2.14	(0.94)
Ground, low-fat	4800	5.79	(1.21)	0.24	(0.12)	1.17	(0.32)
Others	2013	5.07	(2.61)	0.04	(0.04)	1.43	(0.94)
Patty	5380	5.40	(1.41)	0.15	(0.13)	1.45	(0.43)
Steak	4145	9.75	(4.1)	0.12	(0.13)	0.86	(0.53)

Note: Statistics are computed across product-market for the period of 2018-19 using NielsenIQ data. Standard-deviation is shown in parenthesis. Low fat refers to fat content below 15%.

Table A3 examines whether firms concentrate their volume sales in specific beef cuts. The results show that high-fat ground beef is the primary product for all major brands, consistently accounting for more than 50% of total volume sold. There is also evidence of some product specialization among the Big-Four packers. For instance, Cargill focuses primarily on ground beef, while JBS has a relatively higher volume share of patties, and National Beef concentrates more on other cuts. In the case of Tyson, high-fat ground beef remains the most important product, but the company also records non-negligible sales of steak and patties.

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

	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
Private labels	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

In this section, we present additional results about the impacts of the fire for each level of the US beef supply chain.

Cattle market: Table B1 presents the evolution of cattle futures prices during the second half of 2019, controlling for both seasonality and trend. As discussed in section 3, the fire at the Holcomb plant had a limited but noticeable impact on cattle prices, primarily within the first 30 days following the closure. During this period, prices declined by approximately 9%, largely due to uncertainty surrounding processing capacity of Tyson after the fire. The uncertainty prompted many cattle ranchers to close contracts for near-maturity cattle prematurely, resulting in a short-term oversupply of cattle. In November 2019, following Tyson's announcement that the plant would be fully restored by the end of the year, cattle prices rebounded.

Table B1: 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 the 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 in January 2017.

Table B2 shows that cattle spot prices were less affected by the fire compared to futures prices. While spot prices exhibited a similar pattern — a decline in the first month following the fire, followed by a rebound beginning in November — the magnitude of the decrease was more modest, at approximately 3.5% relative to the expected level after accounting for trend and seasonality. Furthermore, this impact was consistent across regional markets.

Wholesale market: We also examine two more potential effects of the fire on wholesale markets: cold storage and the prices of other non-beef meats. Table B3 presents the change in beef cold storage levels following the fire, relative to the trend and seasonality observed since 2016. The results indicate a slight decline in storage in most of the second half of the year of around 5%, although the estimates are imprecise. Nevertheless, it is unlikely that this reduction in storage could meaningfully offset the loss in processing capacity caused by the Holcomb plant closure, given that cold storage accounts for only a small fraction of total beef consumption in the nation — less than 2% — and the vast majority of beef sold to households is fresh.

Table B4 compares the evolution of wholesale beef prices during the second half of 2019 with those of pork and chicken. Our estimates indicate that the fire had no significant

Table B2: Evolution of Cattle Spot Prices After the Fire

	National	TX-OK	KS	NE	IA-MN
	(1)	(2)	(3)	(4)	(5)
mid Aug	−0.035 (0.017)	−0.039 (0.019)	−0.035 (0.018)	−0.041 (0.019)	−0.037 (0.020)
Sep	−0.038 (0.019)	−0.050 (0.021)	−0.033 (0.019)	−0.041 (0.020)	−0.041 (0.019)
Oct	0.015 (0.017)	0.030 (0.018)	0.005 (0.018)	0.016 (0.017)	0.014 (0.018)
Nov	0.018 (0.018)	0.019 (0.019)	0.015 (0.020)	0.019 (0.017)	0.016 (0.018)
Dec	0.051 (0.023)	-	0.052 (0.025)	0.045 (0.023)	0.040 (0.023)
R^2	0.913	0.892	0.902	0.902	0.902
Adj. R^2	0.905	0.883	0.893	0.894	0.893
Num. obs.	261	256	261	261	261

Note: Standard errors in parenthesis. Data on national and regional spot prices from 2015 to 2019. All specifications are estimated in log-levels, and account for month-seasonality and a quadratic time trend with a trend break in January 2017. Prices in the Texas-Oklahoma region are not available for December of 2019.

Table B3: Evolution of Beef Cold Storage After the Fire

	All	Bone-in	Boneless
Sep	−0.050 (0.025)	−0.081 (0.092)	−0.046 (0.023)
Oct	−**0.078** (0.026)	−0.025 (0.100)	−**0.082** (0.026)
Nov	−0.038 (0.034)	−0.030 (0.080)	−0.039 (0.036)
Dec	−0.047 (0.045)	−0.093 (0.099)	−0.045 (0.046)
Adj. R^2	0.666	0.203	0.661
Num. Obs.	48	48	48

Note: Standard errors in parenthesis. Data on national beef cold storage in lbs from 2016 to 2019. All specifications are estimated in log-levels, and account for month-seasonality and a quadratic time trend.

impact on the wholesale prices of these other meats. This suggests that substitution effects or spillovers to pork and broiler markets were at most limited in the immediate aftermath of the Holcomb plant closure.

Retail market: Figure B1 presents a breakdown of the fire's impact on Tyson and non-Tyson brands, controlling for processor-specific trends. The observed increase in average retail prices was primarily driven by products from small local packers and private labels. Products from the other members of the Big-Four showed a slight decline in their prices relative to trend, but not meaningfully different from the patterns implied by trend and seasonality over the previous two years.

Table B5 presents the estimated impact of the fire on beef sales volumes and the number of products offered, relative to trend. As discussed, we observe an increase in sales of Tyson products alongside a decline in sales of products from the other Big-Four" packers, consistent with the price dynamics reported in Table 4. Changes in product assortments in retail stores following the fire were minimal (i.e.,less than one product for most processors). The only notable exception was National Beef, which experienced an average reduction of two products in the post-fire period.

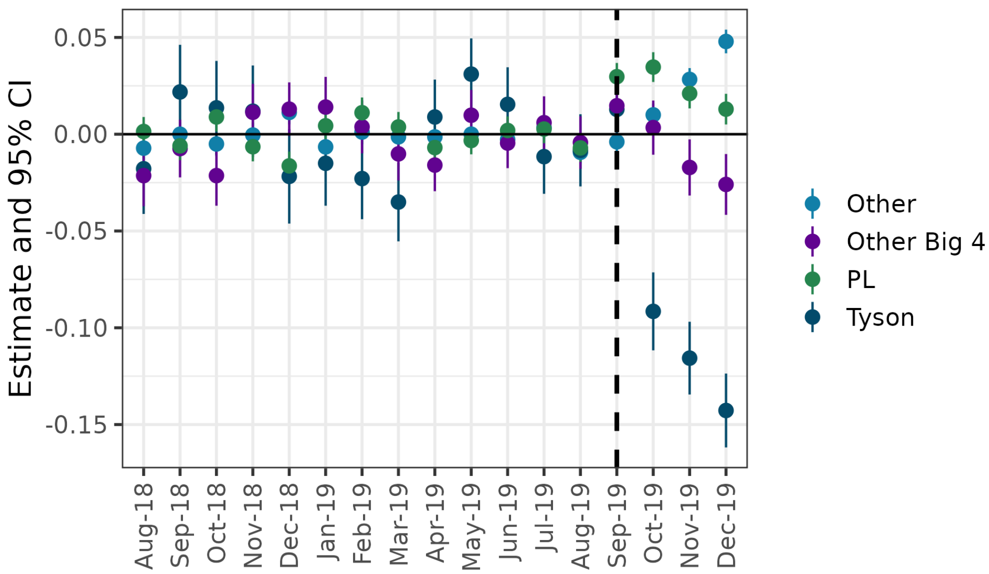
Effect heterogeneity: We now discuss the heterogeneity of price deviations post-fire. The first row of Table B6 decomposes the variance of price deviations from the trend-

Table B4: Fire Effects on Wholesale Prices of Meats

	log(Pork)	log(Broiler)	log(Beef)
	(1)	(2)	(3)
mid Aug	0.025 (0.032)	−0.042 (0.027)	**0.120** (0.015)
Sep	0.075 (0.052)	**−0.059** (0.027)	**0.083** (0.015)
Oct	0.044 (0.024)	0.013 (0.022)	**0.096** (0.018)
Nov	−0.016 (0.046)	−0.034 (0.021)	**0.124** (0.019)
Dec	0.006 (0.030)	−0.006 (0.020)	**0.038** (0.019)
Adj. R^2	0.244	0.793	0.538
Num. obs.	208	209	208

Note: Data on meat prices come from www.lmic.com. We control for seasonality using week fixed effects, a linear trend, and we include a dummy for 2019 in the broiler regression to control for an uncharacteristic strong inventories relative to demand in the broiler market that year, as reported by the USDA's *Livestock, Dairy, and Poultry Outlook* throughout 2019.

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. Confidence intervals are shown for a 95% level.

implied and seasonally-adjusted prices (i.e., the dependent variable in equation 2) for all products. DMA fixed effects explain little of the variation in price deviations, and the effect of fire is largely due to retailer and processor fixed effects and cut of beef.

Figure B2 further shows that average price deviations of Tyson were negative for the majority of DMAs, and the second row of table B6 shows that most of the variability in price deviation post-fire for Tyson products can be explained by the cut of beef and retailer fixed effects, echoing our key finding that firm-to-firm bargaining shapes the pass-through of costs in a critical way.

In light of the results of the variance decomposition results, Table B7 investigates which types of cut had the most pronounced effects after the fire. Most of the price

Table B5: Fire Effects on Beef Prices, Sales, and Assortment, Under a Common Trend

	log(volume)	Number of products
	(1)	(2)
Fire	0.113 (0.020)	−0.047 (0.050)
× Tyson	**0.164** (0.036)	−**0.270** (0.059)
× Cargill	−**0.106** (0.044)	−**0.991** (0.079)
× JBS	−**0.091** (0.039)	−**0.841** (0.071)
× NBF	−**0.260** (0.062)	−**2.051** (0.130)
× Private labels	−**0.168** (0.014)	−**1.054** (0.036)
Adj. R^2	0.505	0.674
Num. obs.	402560	402560

Note: Data from NielsenIQ from 2017 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, a common trend, and fixed effects for DMA, processor (regional brands are grouped in one category), year, and retailer. The reference category is regional brands. Numbers in bold are statistic significant at a 95% confidence level.

Table B6: Variance Decomposition for the Log Difference

	Retail	Processor	DMA	Year-Month	Type	Error
All products	18.39	61.13	0.93	0.88	27.94	62.56
Tyson products	15.06		3.07	1.98	74.56	27.24

Note: Data consist of price deviations estimated using equation 2 in the main text for the first row and Tyson's products price deviation for the second row. We remove DMA-retailers combination with a very small number of products to avoid numerical problems in the decomposition. DMA fixed effects explain a small portion of the variance of the difference between observed prices and trend-implied prices.

declines observed in Tyson-branded products stemmed from a decrease in the price of ground beef. This is consistent with the fact that Tyson's Holcomb plant mostly processed ground beef.

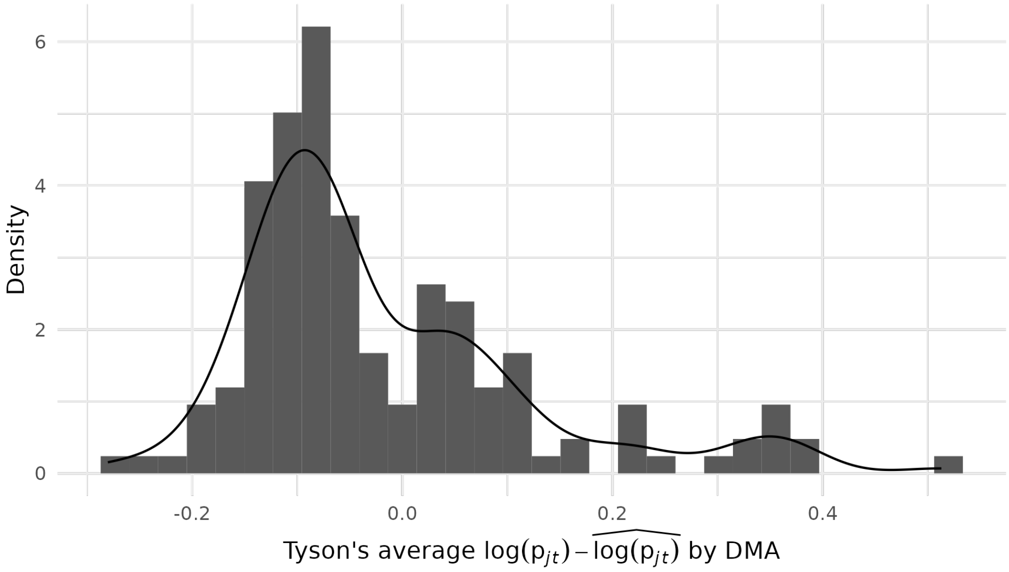
Table B7: Average Log Difference by Cut of Beef

Type	Others	Tyson
Ground, high fat	0.02	-0.16
Ground, low fat	0.01	-0.16
Others	0.07	0.18
Patty	0.02	0.04
Steak	0.02	0.01

Note: The table shows the average of price deviation post fire for Tyson and all the other processors by cut of beef.

Finally, we find some evidence that retailer size may influence the extent of price deviations from trend for Tyson's ground beef. Table B8 shows the relationship between the average post-fire price deviation at a retailer and the average volume of Tyson ground beef sold pre-fire, with retailers grouped by quartiles of volume. The results indicate that retailers selling larger volumes of Tyson products tend to have more negative price deviations. The price deviations stemmed from the fire, and not by some retailer-specific trend. Figure B3 shows an event study around the fire for the sample of products sold in

Figure B2: Deviation of Tyson's prices from trend+seasonality implied prices, averaged by DMA



Note: The figure shows the average Tyson's price deviations at each DMA estimated using equation 2 in the main text.

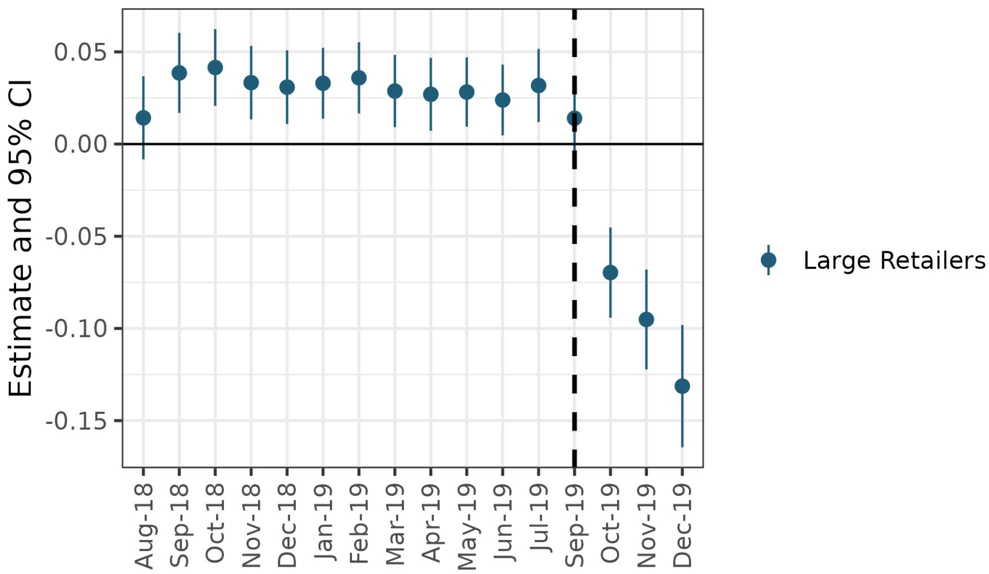
retailers in the 4th quartile of B8. The outcome variable is the deviation of Tyson ground beef products from retailer-specific trend-implied prices. Before the fire, Tyson ground beef were trending above August deviations, but sharply decline after August when the fire occurred.

Table B8: Price Deviation by Retail Size

Quartile of Ground Beef Volume Distribution	Median Volume (000 lbs) Pre-fire	Median Price Dev. Post Fire
1	0.01	0.28
2	13.24	0.03
3	54.03	0.14
4	1708.36	-0.10

Note: Sample of average ground beef price deviation by retailers. The sample contains 15 retailers offering Tyson products post-fire. Volume of Tyson ground beef is in thousands of pounds, and refer to the average volume sold across retailers pre-fire. The largest quartile contains a few outliers in terms of volume sold, which also experienced price declines.

Figure B3: Deviation of Tyson's Ground-Beef Prices



Note: The chart shows price deviation from retailer-implied trend before and after the fire. The sample includes products sold at retailers with the largest presence of branded-Tyson products, and corresponds to retailers included in the fourth quartile of table B8. The reference month is August 2019. Confidence intervals are at 95% level.

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 following form:

$$s_{jt} = \exp(\delta_{jt})/(1 + \exp(\delta_{1t}) + \exp(\delta_{2t})), \tag{9}$$

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

$$\rho_{bert} = \frac{(1-s_1)^2(1-s_2)^2}{1-s_1-s_2} \begin{bmatrix} \frac{1}{1-s_2} & \frac{s_1 s_2}{(1-s_1)^2} \\ \frac{s_1 s_2}{(1-s_2)^2} & \frac{1}{1-s_1} \end{bmatrix}. \tag{10}$$

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

$$\rho_{cour} = \begin{bmatrix} \frac{1-s_1-s_2}{1-s_2} & 0 \\ 0 & \frac{1-s_1-s_2}{1-s_1} \end{bmatrix}. \tag{11}$$

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

If the manufacturers and the retailer may adopt a two-part tariff and jointly maximize the profits, then the corresponding pass-through matrix is

$$\rho_{tpt} = \begin{bmatrix} 1-s_1 & -s_2 \\ -s_1 & 1-s_2 \end{bmatrix}. \tag{12}$$

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

Finally, in the case of a double marginalization model, the pass-through of opponents cost shocks can either be positive or negative depending on the level of market shares, but the pass-through from an increase in costs on the firms own prices is invariably positive. The pass-through equation takes a complicated form, as wholesalers internalize the response of the retailer to changes in the wholesale price. After algebraic manipulations, we can show that the pass-through matrix takes the form:

$$\rho_{LPDM} = \begin{bmatrix} h(s_1, s_2)^2 f(s_1, s_2) & h(s_2, s_1)^2 g(s_1, s_2) \\ h(s_1, s_2)^2 g(s_2, s_1) & h(s_2, s_1)^2 f(s_2, f_1) \end{bmatrix}, \tag{13}$$

where $f(s_i, s_j) > 0,\ \forall (s_i, s_j) \in [0, 1]^2,\ s_i + s_j \leq 1$.

D Post-Fire Marginal Costs of Processing

In the empirical literature on economies of scale, 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.

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}. We are unable to report specific capacity statistics due to confidentiality of the data.

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.[22]

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

$$\frac{MC^{67\%}}{MC^{100\%}} = \frac{mg(0.67q)^{g-1}}{mgq^{g-1}} = 0.67^{g-1}. \tag{14}$$

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 2-4%, thus, is likely the lower bound.

[22] 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.