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

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**Abstract**

The extent of the impacts of supply chain disruptions depends on how individual firms adjust prices and quantities after a shock. This paper develops a mechanism of adjustment to shocks that advances the understanding of firm-level responses to supply chain disruptions. It does so by exploring a major fire outbreak that closed a beef processing plant owned by Tyson that produced 6% of the beef in the United States. We document increases in marginal costs after the fire that curiously did not pass-though to Tyson's products. We rationalize price changes post-fire with an empirical model of bilateral bargaining between processors and retailers that incorporates higher uncertainty in the delivery of products by processors after a drop in production capacity. We argue that higher delivery uncertainty presses markups for the processor that loses capacity, which may result in lower retail prices for products by that processor after the shock. Counterfactual simulations point to heterogeneous price effects of disruptions across processors.

*JEL Codes:* Q13, Q18, L13, D81

*Keywords:* delivery uncertainty, pass-through, 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.

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# 1 Introduction

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

Concerns about supply shocks have led policymakers to consider measures to reduce their depth and extent.[1] However, being able to predict the costs and benefits of such measures depends critically on understanding how the individual firms that make up the chain respond to disruptions. Many firm-specific factors will be key for the final pass-through of cost shocks to consumers: their pricing rule, the vertical relationships between manufacturers and retailers, the magnitude of the shock relative to marginal costs, reputation effects, and changes in expectations after a shock. (Magnolfi et al., 2022a; Glover et al., 2023; Cajal-Grossi et al., 2023; Grossman et al., 2023). Although an important topic, the literature still lacks a depth of empirical evidence on the importance of each of those factors, hindering policymakers' ability to effectively aid companies in distress. We believe this is partly due to data availability and identification issues when dealing with large shocks that can potentially also have demand effects.

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

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

pricing conditions. After the fire, we document an increase in marginal costs across the industry. These higher costs lead to higher retail prices for beef products from all processors but, surprisingly, *not* for the products owned by the processor directly affected by the fire. We show that traditional models of cost pass-through cannot rationalize these price movements. To explain the price changes post-fire, we propose a new mechanism of price adjustment that incorporates uncertainty regarding stockouts in a model of bilateral negotiations between beef processors and retailers.

The US beef processing consists of four major processors — Tyson Foods, Cargill, JBS, and National Beef — that collectively process 80%-85% of the US beef. The fire shut down Tyson's largest plant in Holcomb, Kansas, which accounted for 15-20% of Tyson's capacity and 5-6% of the US capacity, from early August to December of 2019. Unlike other recent economic-wide disruptions (e.g., COVID-19), the fire can be interpreted as a rather isolated shock exclusive to the production capacity of the beef industry with minimal effects on demand. This setting offers a natural experiment to examine the effect of a temporary and significant supply-chain shock on firms pricing decisions in an oligopolistic competition setting with heterogeneous products.

We start with reduced-form evidence showing that the fire had significant economic impacts on the cost of beef processing, with a decrease in weekday slaughtering, a 10% increase in overtime work, and an increase of 1% in wages in the animal slaughtering industry. Uncertainty about future slaughter capacity also led to lower future prices for cattle after the fire, but a short-lived decline in cattle cash prices.[2] The consequential increase in average wholesale prices of beef (11% for ground beef and 10% for high-quality cuts) confirms the higher costs of processing that apply to Tyson plants in particular.

Unexpectedly, we find that the shock had no significant effect on the retail prices of Tyson products, while products from other major manufacturers experienced increases in the retail price of 5%, on average. These findings are counter-intuitive because traditional models of cost pass-through under imperfect competition predict that an increase

[2]Notice that most cattle procurement uses formula contracts. Formula contracts are contracts that guarantee the supply of cattle at a future date to processors. Prices are determined a few weeks before delivery by a formula that uses realized cash prices at a region. The overall prices processors pay for cattle are an average of all prices paid at different plants.

in marginal cost leads to either an overall increase in prices for all firms, or a decline in competitor's prices (Magnolfi et al., 2022b) – none of which are observed in our data.

We rationalize these price movements by arguing that the Holcomb fire increased the probability of Tyson faltering in the delivery of products to retailers, potentially causing stockouts in retail stores. Stockouts of beef are costly to retailers, particularly close to periods of demand peak (Campo et al., 2003; Ailawadi et al., 2008; Briesch et al., 2009; Matsa, 2011). The heightened uncertainty around the availability of Tyson's products at groceries reduced retailers' expected payoff from negotiating with Tyson right before a major grilling holiday, the US Labor Day. In our structural model, the reduction in expected retailer payoff affects retail prices through a bilateral bargaining process between the retailer and the processor, which reduces margins and caps price increases for Tyson's products, but not for its competitors. We show empirically that large supply disruptions may not lead to an overall price increase – not even a considerable price increase for products offered by the firm directly affected by the shock – if the need to maintain a relationship with retailers makes manufacturers absorb the shock during the price negotiation.

We develop a structural model of the industry that allows us to translate the observed shock into changes in marginal cost and expected sales to then perform counterfactual shocks at other processors that are not Tyson. By doing so, we can evaluate which are the most consequential shocks to consumers. Our paper follows previous work on differentiated products and model demand for beef products using a discrete-choice approach (e.g., Nevo, 2001; Villas-Boas, 2007; Bonnet and Dubois, 2010; Conlon and Gortmaker, 2020). We bridge these demand models with a model of expected sales that mimics key aspects of the beef industry, namely, the negotiation of processor-retailer prices and scheduled delivery of beef way ahead of demand realization. On the supply side, we show that price negotiations between processors and retailers can nicely describe the pricing conduct of beef markets, similarly to other industries as described in Grennan (2013). We use a model selection approach as in Duarte et al. (2023) to provide evidence that the supply side we propose better explains the price movements observed in the US

beef market than traditional supply-side models.

With the models of supply and demand in hand, we estimate demand and supply pre-fire to then predict equilibrium outcomes post-fire. Our random coefficient nested logit demand model pre-fire is able to generate realistic substitution patterns across beef products. Post-fire, we are able to match price and quantity patterns observed in our reduced-form evidence by increasing marginal costs and decreasing Tyson's delivery reliability parameter, as long as stockouts generate costs for retailers beyond current sales loss.

Fires are common in food processing plants (Verzoni, 2022). Hence, we conduct counterfactual exercises that simulate a fire impact of similar magnitude on other processors. Counterfactual simulations show that shocks of similar magnitude to other beef processors lead to heterogeneous price effects — retail prices may fall or increases in various degrees across manufacturers. For example, a similar shock on National Beef would decrease the prices of its products by more than 1.5%. The same shock would increase the prices for JBS products by more than 1%.

We contribute to the literature as one of the first empirical studies on the impact of supply chain disruptions in successive oligopolistic markets where prices are bargained to settle, and where delivery uncertainty is considered. By proposing a novel pricing mechanism and using detailed scanner data, our structural model rationalizes market impacts that conventional frameworks of pass-through tend to overlook. This finding has critical implications regarding policy design that aims at improving supply-chain resilience or foster firm adaptation post shocks by changing market structure or bilateral negotiations between firms.

# 2 The US Beef Industry

Beef industry has the highest retail value in the US agricultural sector— 106 billion USD in 2018 and 111 billion USD in 2019 (USDA, 2022). The US beef market is highly self-sufficient with net imports accounting for less than 0.5% of domestic beef consumption in

recent years. In this section, we highlight key structural features of the US beef industry and introduce the data for our empirical analysis.

## 2.1 Data sources

We collect information about the beef supply chain from different sources. The information on retail prices and sales comes from the Kilts NielsenIQ Scanner Dataset. NielsenIQ Scanner data is organized by universal product codes (UPC) in weekly reports for several retail stores. There are 961 beef Universal Product Codes (UPCs) in the dataset. The data reports sales numbers and information about products characteristics, including measures of volume sold. The NielsenIQ Retail dataset consists of more than 21,000 fresh-beef-selling stores from some 130 retail chains (henceforth retailers), and 49 U.S. states.

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

## 2.2 Supply chain structure

The US beef supply chain comprises roughly three stages: cattle production, meat processing, and retailing. The entire cycle of a single calve, from offspring to maturity, takes around three years. The cycle starts at cow-calve operations, where weaning calves start gaining weight. After reaching the desired weaning weight, calves are sold to stockers and backgrounders and follow to feedlots to reach maturity, and then to packing plants where the first stage of processing begins (Cowley, 2022). Packing plants harvest mature cattle and pack them into primal cuts. Nowadays, most plants further process primal cuts into case-ready beef products that consumers buy at grocery stores. In the U.S., more than two-thirds of beef is consumed fresh and purchased in grocery stores (Hahn, 2001).

Concentration across the beef supply chain has risen since 2000. Generally, slaughtering, processing, and packing are conducted by the same plants, hereafter referred to as processors. Geographically, the bulk of cattle slaughtering is conducted in the US Great Plains, where most of the cattle raising takes place (Crespi and Saitone, 2018). Beef packers have consolidated during the 2010s with the top four largest beef packers slaughtering around 85% of the available cattle in the United States and also engaging in further meat processing (Crespi et al., 2012; Crespi and Saitone, 2018). Meat packing 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 output (Hadachek et al., 2024). In recent years, the concentration of beef retailing has risen along with a higher concentration in food retailers (Hamilton et al., 2020).

Retail stores offer a diverse beef product line that comprises different beef cuts. The different beef cuts are grouped according to similar characteristics, and each of the groups is referred as a complex. For example, rib-eye steak is a cut that is part of the rib complex, strips and tenderloins are part of the loin complex, chuck roasts are part of the chuck complex, and top rounds are part of the round complex (Ortez et al., 2021). Historically, ground beef represents the highest share of the national market in retail by volume, close to 45% (Peel, 2021).

Beef products are branded by manufacturers as well as retail chains. The brands owned and managed by retail chains (e.g., Great Value of Walmart) are called private labels, while brands owned by manufacturers are often referred to as national brands. In recent years, about 150 national brands (NB) occupy about 30% of the US fresh beef market, while the rest is taken by some 80 private labels (PL, retailer owned brands). However, there is considerable variation in the market share of NBs at the local market level. Specifically, at the Designated Market Area (DMA) level, NB products jointly contribute 43.7% of volume sold on average with a standard deviation of 31.40%, suggesting importance of studying the bargaining between NBs and retailers at the local market level.

Retailers mostly procure beef cuts by negotiating directly with processors, with price

bids in the spot market as a complementary channel. The majority of retailers receive case-ready fresh beef from processors which are negotiated and scheduled for delivery weeks in advance. This calendar dictates advertisement and the availability of some cuts by specific processors. For example, the holiday of Fourth of July and the Labor Day represent annual peaks of beef demand. A retailer needs to order more beef from specific processors weeks ahead to meet the demand surges around a coming holiday. We revisit this issue in the next sections, where we discuss our data and present several stylized facts of the beef industry.

# 3 Impacts of Supply Disruption: The Case of Holcomb Fire

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

The fire at the Holcomb plant generated uncertainty regarding the availability of beef product in the market. The impact of the fire to Tyson's costs are well documented in agricultural news outlets of the time. The Holcomb plant procured cattle from a large geographical radius, mainly from the High Plains of Texas to Nebraska, and Tyson had to diverge cattle to be harvest cattle at smaller plants that produce at lower scale throughout the US Great Plains (Gabel, 2019; Ishmael, 2019). In conversations with industry insiders and other regulators, we learned that Tyson had some capacity slack in other processing plants, but the divergence of cattle to plants with smaller capacity was likely costly.

The uncertainty regarding beef availability also increased across the supply chain after the fire. Upstream the beef supply chain, cattle producers and feeders worried that other processing plants would not be able to offset the loss in production by Tyson, leading to a decline in cattle harvesting and an increase of cattle on feed. For example,

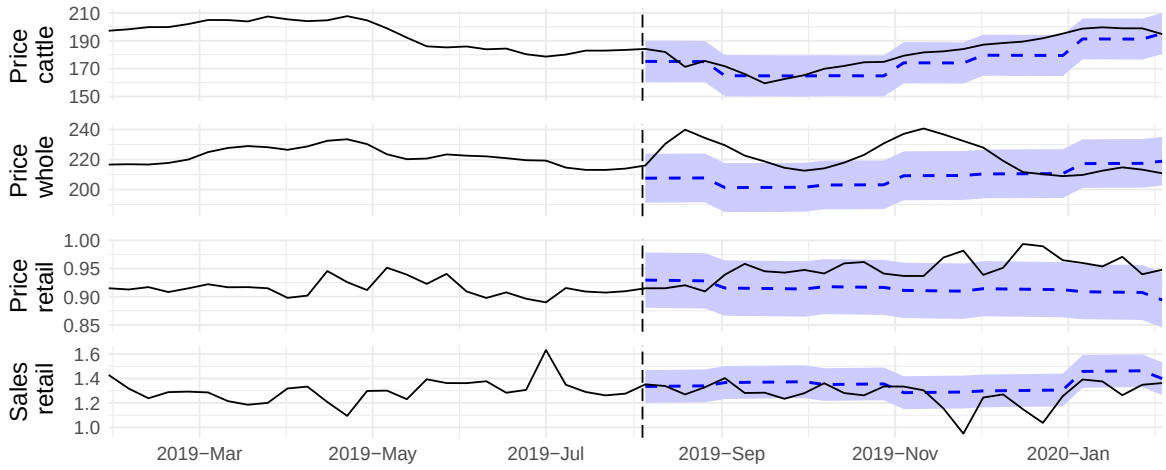
after the fire, the Texas Cattle Feeder Association informed their members that "*beginning Saturday morning (August 10, 2019), TCFA [the Texas Cattle Feeders Association] staff and leadership reached out to Tyson, Cargill, JBS and National to assess the impacts of the Holcomb plant fire and determine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

Downstream the supply chain, retailers worried about beef stockouts one month before Labor Day, a traditional holiday for grilling in the US (Dennis, 2020). Uncertainty amounted as retailers started procuring beef to secure levels of supply that would be consistent with their promotion schedules for the holiday, putting further pressure on wholesale prices after the fire. In fact, conversations with regulators and insiders revealed that negotiations of delivery schedules between retailers and processors tend to happen with weeks, and sometimes months in advance. This is because beef is a product that tend attract consumers to stores, particularly around celebratory dates.

Whoelsale prices increased after the fire alongside adjustments in the supply chain. In figure 1, we show the evolution around the time of the fire of nationwide average prices from markets at different stages of the beef supply chain, and the aggregate retail sales of beef. We contrast the actual price and quantity series observed after the fire (solid line) with what would have been expected based on the trend and seasonality from the three years before the shock (dashed line).[3] We also observe a consequential reduction in aggregate sales of beef approaching the end of 2019. We don't, however, observe a significant impact on the negotiated spot prices between processors and cattle ranchers. Next, we discuss the details on how agents across the supply responded to the fire.

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

**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.

## 3.1 Fire impacts in detail

The fire triggered different reactions from the cattle, wholesale and retail markets. At the brand level, there is also considerable heterogeneity in the impact when comparing Tyson against other brands and across beef cuts.

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

Lower cattle prices likely had a limited effect on Tyson's marginal costs. The prevalence of formula contracts in cattle procurement likely limited the benefits of lower future prices. Under formula contracts, feedlots contract cattle to processors for future delivery, and prices are pegged to a formula that uses cash prices across regions close to delivery dates (MacDonald, 2006; Garrido et al., 2022). In accordance with figure 1, Dennis (2020) shows that cash prices recovered fast across regions limiting the benefits of lower futures prices for cattle after the fire.

**Table 1:** Fire Effects on Prices of Cattle Futures

| | log(Feed Cattle Futures) | log(Live Cattle Futures) |
|---|---|---|
| | (1) | (2) |
| Fire | **−0.018** (0.008) | **−0.029** (0.007) |
| Fire (Nov-Dec) | **0.058** (0.010) | **0.085** (0.008) |
| Adj. $R^2$ | 0.068 | 0.612 |
| Num. obs. | 1006 | 1006 |

*Note:* Data on first expiring futures contract for live cattle and cattle on feed from 2016 to 2019. All specifications account for month and year fixed effects.

The increase in cattle slaughter during the weekends helped sustain the supply of beef to consumers during the second half of 2019. Table 2 shows an increase in Saturday slaughters after the fire— although imprecisely estimated— at the same time that weekday slaughter numbers fell. The substitution of weekday slaughter with weekend slaughter is consistent with the large decrease in capacity from the Holcomb plant.

As a result of the increase in weekend slaughter, there is a slight increase in wage rates after the fire. Using aggregate data from the BLS, we observe a 1% nationwide average wage increase received by employees in the animal slaughtering industry, as Table 3 shows. Notice, however, that there is a small increase in the total overtime hours post-fire for production workers in the animal slaughtering industry, but a small decrease in the total time hours post-fire for all employees in the animal slaughtering industry. The fire led to an increase in inactive workers, who are unable to work at

**Table 2:** Fire Effects on Weekday and Saturday Slaughter (1,000 heads)

| | Weekdays | | Saturday | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Fire | −3.867 (2.379) | **−4.989** (2.399) | 3.043 (3.173) | 0.664 (3.469) |
| Fire (Nov-Dec) | | 2.775 (4.630) | | 5.551 (5.669) |
| Adj. $R^2$ | 0.149 | 0.148 | 0.676 | 0.676 |
| Num. obs. | 1041 | 1041 | 209 | 209 |

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

Holcomb, pulling down the average work hours. To compensate for working hours lost, a smaller group of active workers tend to work overtime a lot more.

**Table 3:** Fire Effects on Wages and Working Hours

| | log(wage) | log(Hours) | log(Prod. Hours) | log(Overtime) |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Fire | **0.003** (0.001) | −0.012 (0.006) | −0.007 (0.008) | **0.098** (0.040) |
| Fire (Nov-Dec) | −0.000 (0.002) | 0.010 (0.007) | 0.016 (0.009) | −0.067 (0.050) |
| Adj. $R^2$ | 0.856 | 0.942 | 0.886 | 0.597 |
| Num. obs. | 60 | 60 | 60 | 60 |

*Note:* Bureau of Labor Statistics national data for NAICS code 311611 from 2016 to 2019 on a monthly frequency. *Work Hours*: total work hours of work in slaughtering, including administrative staff. *Prod. Work Hours* : total hours of work in slaughtering, excluding administrative staff. *Overtime*: total hours of Saturday slaughtering. All specifications control for year and month fixed effects.

**Wholesale market** At the wholesale level, boxed beef cutout values have been following a positive trend since 2016 and natural seasonality, with lower prices during the second half of a year relative to the first half.[4] However, in the month of August, right after the fire, we observed significantly higher wholesale prices for the boxed beef cutout. This jump in price reflected the higher costs of beef processing and also retailers' and

[4]This seasonality comes mainly from the fact that in the U.S., most calves are spring-born and fall-weaned.

processors' concerns about the industry's capacity in the coming months. We do not find strong evidence that the impact of the fire had different magnitudes depending on the cut of beef (see table 4 in the appendix B).

**Table 4:** Fire Effects on National Wholesale Beef Prices

| | log(Price Select) | log(Price Choice) | log(Ground Beef Price) |
|---|---|---|---|
| | (1) | (2) | (3) |
| Fire | **0.095** (0.012) | **0.026** (0.012) | **0.105** (0.021) |
| Fire (Nov-Dec) | −0.006 (0.022) | **0.067** (0.020) | −0.027 (0.045) |
| Adj. $R^2$ | 0.460 | 0.491 | 0.509 |
| Num. obs. | 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 account for week, month, and year fixed effects.

**Retail market:** Figure 1 shows an upward shift increase in the retail beef price only in the last two months of 2019. In column (1) of table 5, we quantify that, after conditioning on product, time, and market characteristics, retail prices increased by 1.4% on average post-fire, with an average increase of 2.7% in the last two months of the year.

We leverage the brand-level data from NielsenIQ to investigate if the retail-price impacts on Tyson products differ from the impacts on other brands. As column (2) in table 5 shows, the post-fire period dummy reduces the average retail price of Tyson's products in relation to non-Big4 products by some 1.5%. Other major NBs and PLs enjoy 3-7% price increases. These price changes are economically significant, considering the the spread between retail and wholesale prices at the national level has been around 42% in recent years (U.S. Department of Agriculture, 2022).

One could argue that the decreased capacity of Tyson may have caused its residual demand to shift in and the residual demand for other brands to shift out. However, the fire had a positive impact on Tyson's volume sales (see Appendix B). Some other brands experience increases in volume sales, and some do not.

**Table 5:** Fire Effects on Retail Beef Prices

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

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

## 3.2 Rationalizing the impacts of the fire

Results in the tables above suggest that Tyson's capacity reduction and the shift towards overtime, and production at other Tyson plants represent an increase in the marginal cost of processing for Tyson. In the meantime, the empirical results show that Tyson's retail prices experienced price reductions on average, while retail prices for the other three big national brands and private labels increased significantly. We show that traditional models of supply cannot rationalize the price dynamics after the fire.

Following the spirit of Magnolfi et al. (2022b), we illustrate the intuitive predictions based on a few classic models of firm conduct and explain why none of them can rationalize the patterns of data that we observe. The detailed mathematically derivation is shown in Appendix D. Consider a differentiated-product environment, the change in retail prices for a multi-product retailer depends on the pass-through of shocks on the marginal cost (MC) of manufacturing. In our context, the pass-through of an increased MC at Tyson to retail prices of multiple products carried by the retailer is the key

driving force.

We consider a few classic models. 1) There is perfect competition and hence no retail or wholesale markup. An increase in Tyson's MC would only pass-through fully to Tyson retail prices and would not affect retail prices of other manufacturers. 2) There is Bertrand-Nash competition among retailers and no wholesale markup. The products are strategic complements, implying positive pass-through of Tyson's MC on Tyson as well as on other products made by manufacturers. The same rationale applies to a model with no retail markup and Bertrand-Nash competition among manufacturers. 3) There is Cournot competition among manufacturers and no or constant retail markup. The pass-through of an increase in Tyson's MC would be positive for Tyson products and zero for other products. 4) The manufacturer and retailer perfectly collude and adopt two-part tariff pricing. Retail prices are set to maximize the joint profits which are allocated between manufacturer and retailer via lump-sum transfers. The pass-through of an increase in Tyson's MC would be positive for retail prices of Tyson products, but negative for products by other manufacturers. The models share the prediction that prices of Tyson products would rise due to increased Tyson MC, which contradicts the data patterns summarized in subsection 3.1, though they imply different price effects on other packers' products.

The discussion so far suggests that allowing the fire to affect retail prices only through the direct impact on marginal cost cannot rationalize the price patterns observed in the data post shock. To rationalize the effect of the fire, we model two key elements of the beef market after the shut down of the Holcomb plant: 1) the uncertainty regarding the ability of Tyson to deliver beef products to retailers as described by Dennis (2020) and Ishmael (2019), and 2) the ability of bargaining prices of beef that stem from long-term relationship of processors and retailers in this market. In what follows, we will argue that equilibrium post fire consists of Tyson reducing its markup to compensate for its unanticipated, reduced reliability of delivery. If the reduced delivery reliability is large enough to offset the effects of higher MC for Tyson, there can be a negative effect on retail prices. Competing beef manufacturers, in contrast, may charge larger markups

thanks to their relatively high delivery reliability.

Next, we provide structural models of demand and pricing that we can bring to the data and allow us to simulate the impact of shocks on marginal cost and expected delivery on the wholesale price bargaining between processors and retailers during the Holcomb fire.

# 4 Structural Model

We present the structural model of demand and supply for the US beef supply chain. We focus on the processing and retail level of the chain and take the cattle raising part as an exogenous aspect of processors marginal cost.[5] We first characterize the demand for fresh beef products by extending the discrete-choice model of Berry et al. (1995) to incorporate uncertainty if beef delivery by processors. On the supply side, we construct a model of negotiated beef pricing that accounts for bargaining between retailers and processors and can incorporate delivery uncertainty in an empirically tractable way.

### 4.0.1 Demand with delivery uncertainty

Our framework describes the relationship between processors and retailers in two stages. In the first stage, beef processors and retailers negotiate wholesale and retail prices for beef deliveries in the second stage. Retail and wholesale prices are kept fixed during the second stage, when delivery and sales are realized. For reasons correlated with processors' characteristics, we allow for randomness in the amount of beef that is actually delivered. Before the first-stage negotiations take place, both processors and retailers form expectations about the probability of delivery based on their information sets.

In what follows, we construct the sales expectation that retailers and beef processors rely on when negotiating prices in the first stage. Let $\mathcal{J}$ be the set of all possible products that can be supplied to a given store in a given market (period-DMA), $t$. For exposition

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

purposes, we suppress the market subscript. In the second stage, a product $j \in \mathcal{J}$ is either delivered or not (shelf presence). Consumer $i \in I$ maximizes utility by choosing between beef products from a set of *available* products $J \subset \mathcal{J}$ and an outside option of not buying beef.

The indirect utility of this consumer from choosing product $j$ with brand $b$ is:

$$u_{ij} = X_j'\beta_i - \alpha_i p_j + +\tilde{\xi}_j + \epsilon_{ij}, \tag{1}$$

where, in reference to the researcher, $X_j$ and $\tilde{\xi}_j$ are the observed and unobserved characteristics for product $j$, respectively, $p_j$ is the price, and $\epsilon$ is the residual random term assumed to be distributed according to the standard Type I extreme-value (T1EV) distribution. The deterministic part of the outside option utility (i.e., not buying beef) is normalized to zero.

The average choice probability, $\rho^C$, for product $j$ takes the form:

$$\rho^C(j|j \in J_t) = \int \frac{\exp\left[X_j'\beta_i - \alpha_i p_j + \tilde{\xi}_j\right]}{1 + \sum_{k \in J_t} \exp\left[X_j'\beta_i - \alpha_i p_j + \tilde{\xi}_j\right]} f(\mu_i) d\mu_i, \tag{2}$$

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

Let $\mathcal{S}$ be the set of all subsets of $\mathcal{J}$ that has the outside option as an element. We model delivery uncertainty by imposing a probability distribution $\rho^D$ over elements of $\mathcal{S}$. Assume that the event of a firm's product delivery is independent of the delivery from other firms and what happened in previous periods. Assume also that products from the same brand are delivered in batch, i.e. we only need to focus on the probability of delivering the batch and not on individual products.[6] If every period there is a mass $M$ of consumers, then we can calculate the expected aggregate sales during the second

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

stage for the product $j$ owned by the processor $f$ that supply the batch $J_f$ as:

$$\mathbb{E}[q_j] = M \sum_{\{J \in \mathcal{S} | J_f \subset J\}} \rho_f^D \times \rho^C(j|J_f \subset J). \tag{3}$$

Note that equation 3 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 $\tilde{\xi}_j$ from the data. We must thus assume that in "business-as-usual" periods, such as the months before the fire, deliveries are made with probability normalized to one.[7]

A delivery probability shock for processor $f$ is denoted by $\Gamma_f \leq 1$. The expected sales share for any product $j$ owned by $f$ in the case of a delivery shock $\Gamma_f$ is:

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

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

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

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

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

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

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

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

### 4.0.2 Bargain pricing decision

After expectations over delivery and sales are formed, retailers and processors bargain over the retail and wholesale prices in the first stage. The nature of retail beef products is different from other grocery goods. As in almost any supermarkets retail margins are close to zero. Based on conversations with industry insiders, some beef cuts are used as a loss leader to attract consumers to shop at the store, a practice that finds theoretical justification for larger retailers (Chen and Rey, 2012).

Armed with these insights, we model the negotiation between retailers and beef processors by assuming that retail margins are zero and that the parties have opposing incentives when bargaining over the wholesale price.[8] While processors want to set prices to maximize profits in the supply chain, retailers want to maximize consumer experience over the beef product assortment by reducing prices. Specifically, for a given retailer-processor pair $(r, f)$, the Nash-Bargain objective takes the form:

$$\max_{[p_j]_{j\in\mathcal{J}_f^r}} \left( \mathbb{E}\left[ \sum_{j\in\tilde{\mathcal{J}}_f^r} q_j(p, \tilde{\mathcal{J}}_f^r)(p_j - c_j) \right] \right)^a \left( \mathbb{E}\left[ W(p, \tilde{\mathcal{J}}^r) \right] - \mathbb{E}\left[ W(p, \tilde{\mathcal{J}}_{-f}^r) \right] \right)^b \tag{4}$$

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

We make the standard assumption that parties take the negotiation of others as given and that there is no replacement threat by retailers or processors.[9] 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

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

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

payoff for processors is zero. In our context, the delivery probability of Tyson products is reduced after the fire ($0 < \Gamma_{Tyson} \leq 1$), while other processors' probabilities of delivery are fixed at one.

The negotiation between retailers and processors depends on the importance of the processors' products for the overall expected consumer experience. For consistency with our logit assumption on demand and for tractability, we use the inclusive value of the consumers as a measure of the expected consumer shopping experience. We assume that any delivery missed has a negative retailer-specific impact, $F_r$, on retailer's payoffs that is beyond the effect that it has on the current period. For example, there could be a reputational or goodwill effect that hits the retailer, when consumers face stockouts (Matsa, 2011).[10]

Formally, the expected consumer experience in the scenario where only Tyson has a shock on delivery probability, $\Gamma_{Tyson} < 1$, is:

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

In particular, the expected consumer experience if the retailer does not have a supply contract with Tyson is $\mathbb{E}[W(p, \tilde{\mathcal{J}}_{-Tyson})] = V(p, \tilde{\mathcal{J}}_{-Tyson})$, i.e., there is no more delivery uncertainty.

The solution of the pricing game for any product $j$ owned by firm $own(j)$ takes the form:

$$a \frac{\mathbb{E}[s_j] + \sum_{k \in \mathcal{J}_{own(j)}} \mathbb{E}\left[\frac{\partial s_k}{\partial p_j}\right](p_k - c_k)}{\sum_{k \in \mathcal{J}_{own(j)}} \mathbb{E}[s_k](p_k - c_k)} = b \frac{\mathbb{E}[s_j]}{\mathbb{E}[(V(p, \tilde{\mathcal{J}}) - V(p, \tilde{\mathcal{J}}_{-own(j)})]} \tag{5}$$

where $s_j$ is the market share of product $j$, and expectations are taken over the randomness of the realized assortment. Note that if retailers have zero bargain weight ($b = 0$),

[10] 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.

then equation 5 is the standard Bertrand-Nash pricing equation. Conversely, as retailers' bargaining weight increases relative to processors' ($a \to 0$), prices are set lower to increase consumers' expected shopping experience.

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

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

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 $(j,k) = \frac{b}{a}\frac{\mathbb{E}[s_k]\mathbb{E}[s_j]}{\mathbb{E}\left[(V(p,\tilde{\mathcal{J}}) - V(p,\tilde{\mathcal{J}}_{-own(j)})\right]}$ if the products are owned by the same firm, and zero otherwise.

Most of the terms in equation 5, i.e., expected shares pre-fire and inclusive values, stem directly from the demand system. We can also simulate inclusive values when product $j$ drops for the market (see Conlon and Gortmaker, 2020). What is left out is measure of $F_r$, and an estimation of bargaining weights $a$ and $b$. We discuss the full empirical implementation next.

# 5 Empirical Implementation

We make further functional form assumptions to estimate the demand model. Let $t$ be the market index. We project the common taste term $\delta$ into a set of observed characteristics, including price: $\delta_{jt} = X_{jt}'\beta$. The idiosyncratic component of preferences is projected on a set of demographic information interacted with product characteristics: $\mu_{ijt} = d_i X_{jt}'\Pi$. We decompose the unobserved taste component into a brand fixed effect, market fixed effect, and product-market unobservable: $\xi_{jt} = \xi_b + \xi_t + \Delta\xi_{jt}$.

We lack information about $F_r$, the parameter that captures the loss in sales in the chain after the stockout of beef. There is some evidence that stockouts have a heterogeneous effect on sales. Around 30% to 50% of consumers delay purchases or leave stores when facing a stockout (Zinn and Liu, 2001). We take of those estimates to feed the supply side of our model and assume $F_r$ to be 40% of the total sales of the processor

missing deliveries. We will carry this value to our empirical exercise.

## 5.1 Identification of demand

The presence of market shares in equation 3 requires the standard instruments used to identify the demand for differentiated products under discrete choice (Berry and Haile, 2014). We use the local version of differentiation instruments (Gandhi and Houde, 2019), its intersection with median income, the share of products in a retailer to capture the shelf space, prices predicted by product characteristics (see Backus et al., 2021), and several costs shifters. While the differentiation instruments and shelf space allow for variation within and between markets, the costs shifters (prices of cattle, hay, corn, and soybeans, electricity price, fuel price, and hourly wages at meatpacking) allows variation across time.[11]

Armed with the instruments $Z_{jt}$ and a functional form for $\xi_{jm}$, we construct the moment conditions for each market $\mathbb{E}[\xi_{ij}Z_{jt}]$. Its sample analogue depends upon the parameters of the indirect utility, $\theta$, which can be estimated by GMM based from the minimization of $g_D(\theta) = \frac{1}{N}\sum_{jt}\xi_{jt}Z_{jt}$. In that regard, the way of our demand model operates, therefore, is identical to the well-known BLP model. We supplement $\mathbf{g_D}$ with micro-moments in the spirit of Backus et al. (2021).

## 5.2 Supply models comparison

We also test the strength of our bargaining pricing model against competing models of product pricing that, from our institutional knowledge, could potentially characterize the behavior of retailers and beef processors.[12] We use Rivers and Vuong (2002) model selection approach, popularized to our context by Duarte et al. (2023), to check which

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

[12] Based on the discussion from section 3, we already discard supply models that imply unrealistic fire pass-through. Conversations with professionals in beef retail procurement and executives at meatpacking guided us in the selection of alternative pricing mechanisms.

model better fits the pricing pattern before the fire.

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

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

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

Two-part tariff with zero retail margins is a common way that to model grocery goods price decisions (e.g., Miller and Weinberg, 2014). Under this mode of conduct, first-order conditions take the matrix form of $p = \Delta^w + c$, where, again, $p$ is prices, $\Delta$ refers to markup, $w$ refers to processors, and $c$ is marginal costs. If retailers set prices, the first-order conditions take the matrix form of $p = \Delta^r + c$ under this pricing model, where $r$ refers to retailers.

We also consider a model of linear pricing. Linear pricing assumes that processors decide their margins at the wholesale level first, sell their products to retailers that set their margins by choosing retail price of beef products. We further assume that private labels are vertically integrated. The pricing behavior of national brands generates dou-

ble marginalization model similar to Villas-Boas (2007) where the first-order condition assumes the form $p = \Delta^r + \Delta^w + c$.

Finally, we test the bargaining model. We do not have data on the ratio of bargaining weights for processors and retailers, $b/a$. Hence we assume that the the bargaining weights for retailers and processors are the same, on average. This leads a the ratio $b/a$ to equal 1. This is a strong assumption, so we test the lack of fit of this assumption against other modes of conduct using the process described in Duarte et al. (2023).

# 6 Estimation Results

With the model of demand and competing models of supply, we estimate demand and supply for beef in the US before the Holcomb fire. Estimation outcomes from the demand and supply models are discussed.

## 6.1 Sample construction

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

We aggregate the beef data by fresh meat classification, size, and brand for each market. Here, *brand* refer to the parent brand. Large beef processors typically own multiple sub-brands. For instance, Tyson owns Tyson, Jimmy Dean, Hillshire Farm, and others. We aggregate sub-brands to the parent brand. Appendix table A2 displays

the market shares by volume for the Big Four processors from 2018 to 2019. Private labels products dominate our sample, but market shares of Cargill, JBS, National Beef, and Tyson are sizeable.

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

Summary statistics of the sample for estimation are presented in table 6. The number of products by market ranges from 10 to 204, with an average of 77. The average share of products offered by one of the Big Four is 1%, up to the maximum 9% in one of the markets. Private labels take on average 11% of markets, and the outside option reaches an average of more than 85% and no more than 95% across all markets. Average real-dollar price per pound is $5.82.

**Table 6:** Sample Summary Statistics

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

*Note:* Authors' creation based on NielsenIQ Retail Scanner Data.

## 6.2 Demand results

We start with results in table 7. All specifications include dummies for quarter-year, for DMAs, retailers, and products offered by the Big Four. Column 1 presents parameters from a simple logit demand specification. Column 2 shows the results from a nested logit model. We find that nesting by type of beef cut in the demand system leads to demand

elasticites more in line with the literature.[13] Column 3 displays results from a random coefficient nested logit model (RCNLM) that uses micro-moments to aide estimation of parameters. The first form of micro-moments matches average income markets for those who consume beef across. The second form of micro-moments matches the covariance of prices and income for those who buy beef across markets.

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

**Table 7:** Demand Estimates

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

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

Our demand model generates reasonable substitution patterns, too. Table 8 shows average diversion ratios across beef cuts. Primarily, price shocks in a particular cut (represented by the rows in table 8) lead consumers to deviate to the outside good, but a significant share of consumers deviate to the most popular beef product, namely, ground beef with higher fat content. Consumers buying ground beef tend to stick with ground beef or substitute away to the outside good when prices increase.

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

**Table 8:** Average Diversion 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.

## 6.3 Supply results

On the supply side, we follow closely the RV tests 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 marginal revenue implies sample moments and a GMM objective function. We, therefore, define fit by a GMM objective function by which we derive the RV tests. Differentiation instruments (Gandhi and Houde, 2019) are used to form the GMM function that turn out to be strong for the exercise.

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 previously discussed, we assume equal bargaining ratios to generate markups for the bargaining model to conduct the RV test. Table 9 shows that the RV tests favors the bargaining model over all other models.

**Table 9:** RV Test Results

| | Test Stat. | | | | F-stat | | | | MCS |
|---|---|---|---|---|---|---|---|---|---|
| | 1. | 2. | 3. | 4. | 1. | 2. | 3. | 4. | |
| 1. RM | | 3.89 | 9.76 | 8.76 | | 3.13 | 423.63 | 2.48 | 0.00 |
| 2. PM | | | -2.59 | 43.59 | | | 2.93 | 71.56 | 0.01 |
| 3. DM | | | | 7.59 | | | | 2.38 | 0.00 |
| 4. Bargaining | | | | | | | | | 1.00 |

*Note:* RM refers to a two-part tariff model with retailers making price decisions. PM is a two-part tariff with processors making price decisions. DM refers to a model of double marginalization with vertical integration for private labels, and Bargaining refers to the model of bargaining.

With the best fit for the supply model in hand, we calibrate the model to match the observed price dynamics post fire. The target for price changes comes from the results in table 5. The reduced-form regressions suggest that Tyson's prices moved down, while its largest competitors– the other Big-Four processors – experienced a price increase on 5%, on average.

Conditional on a cost of stockout $F_r$ of 40% of realized sales, we show that a industry-wide increase in marginal costs aligned with a decline in the inclusive value for Tyson's products rationalize the post fire price dynamics observed in section 3.1. Column 2 in table 10 shows that we can get close to an average increase in prices of 5% for all products by increasing marginal costs of all processors by 6% in relation to their pre-fire levels. Notice, however, that an industry-wide increase in marginal costs sharply increases Tyson's prices, too, without considering delivery uncertain, which contradicts the reduced-form evidence. The third column of 10 shows that only increasing the post-fire marginal cost for Tyson by 6% barely changes prices for products of other processors, which also maligns with observed data patterns.

The fourth column fully rationalizes the price dynamic immediatly post fire. By increasing marginal costs for all firms by 6% and adjusting the delivery uncertainty

parameter for Tyson to $\Gamma_{Tyson} = 0.4$ (i.e., a substantial decrease in delivery certainty by Tyson), we get to a muted change in Tyson's prices after the shock and closer to 5% change in price of other processor, reflecting price changes post the Holcomb fire.

**Table 10:** Percentage Changes in Marginal Costs Post Fire

| Manufacturer | ↑ MC, Industry | ↑ MC, Tyson | ↑ MC, Industry and ↓ Tyson's Delivery Uncertainty |
|---|---|---|---|
| Cargill | 4.92 | 0.00 | 4.92 |
| JBS | 4.73 | 0.01 | 4.89 |
| National | 4.12 | 0.01 | 4.62 |
| PL | 3.77 | 0.02 | 3.92 |
| Small processors | 5.26 | 0.01 | 5.41 |
| Tyson | 4.46 | 3.56 | 0.17 |

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

# 7 Counterfactual Analysis

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

A fire of the magnitude of the Holcomb plant can generate heterogeneous changes in market equilibrium depending on which processor is hit. The market effects of fire out-

breaks in different food processing plants depend on the market share for each processor and retailer, the cross-price elasticities of demand in each market, and market structure.

To understand the heterogeneity of supply shocks on market outcomes, we simulate a disruption similar to the Tyson fire on different large processors. Specifically, we simulate a post-fire market where industry-wide marginal cost increase by 6%, and delivery uncertainty for a processor increase 60%. These magnitudes correspond to the parameters used for calibration in table 10 that rationalize market outcomes after the Holcomb fire.

The results in table 11 highlight how supply outbreaks on different processors lead to different market outcomes. Had an outbreak of similar magnitude of that presented in table 10 happened to Cargill, average prices for Cargill products would have increased by 0.40%, slightly more than the 0.17% increase in prices for the Tyson from table 10. A similar shock on JBS would lead prices for JBS products to go a full percentage point higher than Tyson's , while a shock on National Beef would decrease the prices of National Beef by 1.72%.

In general, pricing based on bargaining allows firms to absorb supply shocks via changes in delivery uncertainty. The same negative shock in delivery uncertainty decreases the ability of each processor to maintain markups at the pre-shock levels. This is because consumer' inclusive values fall after the shock, decrasing retailer payoffs. Additionaly, the costs associated with stockouts decrease retailer's payoffs even further capping markups and price increases. The magnitude of changes in consumers' inclusive value and in costs of stockouts, in turn, depend on how important products of each firm are for retailers. When processors have low ability to maintain markups after a shock, the negative impact of the fire on own-prices tend to be higher.

**Table 11:** Percentage Changes in Prices Post Counterfactual Shocks

| Manufacturer | Shock on Cargill | Shock on JBS | Shock on National Beef |
|---|---|---|---|
| Cargill | 0.40 | 5.03 | 5.20 |
| JBS | 4.97 | 1.32 | 5.24 |
| National Beef | 4.59 | 5.18 | -1.72 |
| PL | 4.21 | 3.80 | 3.77 |
| Small processors | 5.47 | 5.44 | 5.39 |
| Tyson | 4.47 | 4.98 | 4.90 |

*Note:* We simulate price changes by assuming a industry-wide increase in marginal cost of 6% and a decline in processor-specific delivery certainty $\Gamma$ of 60%.

# 8 Concluding Remarks

The 2019 fire on Tyson's Holcomb plant was a major disruption in the capacity to process beef in the United States. We have documented the widespread effect that the fire had in the beef industry. We show that the fire likely increased marginal costs of beef processing firms by increasing weekend slaughter, wages, and overtime for workers employed by processing plants right after the fire.

Despite increased marginal costs for the industry, Tyson's products did not experience any significant increase in retail prices. Products for other processors, on the other hand, did experience significant increases in retail prices post Holcomb fire. We argued that traditional supply models on pass-through are unable to rationalize these price dynamics. We then build a model of bargaining with processor-specific delivery uncertainty that fully rationalizes the changes in prices observed after the fire.

Delivery uncertainty harms consumers' experience and retailers payoffs through the increase likelihood of stockouts. We assume that stockouts incur reputational costs to retailers. This potential decline in retailers' payoff is absorbed by the bargaining pricing dynamics post the fire, resulting in substantial decline in the markup for Tyson.

The decline in markups for Tyson, then, leads to a relative softer price increase for Tyson products, despite the increase in marginal costs for the industry. Prices of other processors, on the other hand, increase accordingly.

Counterfactual simulations show that shocks of similar magnitude to other beef processors lead to heterogeneous market outcomes. Price post shock can vary from -1.72% to 1.32% depending on which processor is directly affected by the shocks. In summary, we show that negative supply shocks can lead to a range of market outcomes – including retail-price declines – for industries in which the price dynamics are characterized by bargaining. Any policies or regulations that distort the bargaining process after a major shock incur the risk of harming consumers by inducing higher prices.

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# A Additional Summary Statistics

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

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

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

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

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

**Table A2:** List of Brand Volume Shares 2018-19

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

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

# B Impacts of the Fire

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

**Table B1:** Fire Effects on Retail Prices across US Regions

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

*Note:* Computed using the Nielsen IQ data.

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

**Table B2:** Fire Effects on Beef Sales and Assortment

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

*Note:* Computed using the Nielsen IQ data.

# C Proof

**Proposition 0.1.** *For $n \in \mathbb{N}$, $(x_1, ..., x_n, 0) \in \mathbb{R}^{n+1}$, and $(\alpha_1, ..., \alpha_n)$ a random vector with $\alpha_i \sim T1EV$ i.i.d., let $\mathcal{B} := \{B \subset (0, 1, ..., n) | 0 \in B\}$ and*

$$\beta_B = argmax_i\{x_i + \alpha_i | i \in B\}$$

*Given an random variable $\gamma$ from the simplex of $\{\beta_B : B \in \mathcal{B}\}$, there exist $(z_1, ..., z_n, 0) \in \mathbb{R}^n$ s.t.*

$$argmax\{z_i + \alpha_i | i \in (0, 1, ..., n)\} = \gamma$$

*Proof.* The proof is by construction. For a given $n \in \mathbb{N}$, let's take one element of the simplex of $\{\beta_B : B \in \mathcal{B}\}$, $a \in [0, 1]^{2^n}$. We can construct $(z_1, ..., z_n, 0)$ according to the following system of equations:

$$\frac{1}{1 + \sum_{j=1}^{n} \exp(z_j)} = \sum_{B \in \mathcal{B}} \left[ \frac{a_B}{1 + \sum_{j \in B} \exp(x_j)} \right]$$

$$\exp(z_i) = \left( 1 + \sum_{j=1}^{n} \exp(z_j) \right) \left[ \sum_{B \in \mathcal{B}^i} \frac{a_B \exp(x_i)}{1 + \sum_{k \in B} \exp(x_k)} \right], \quad \forall i \in \{1, .., n\}$$

where $\mathcal{B}^i \equiv \{B \in \mathcal{B} : i \in B\}$. □

# D 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 $\kappa$. For a given market $t$ (e.g., a retailer-DMA-quarter combination), the equilibrium price takes the form $p_{jt} = \Delta_{\kappa t}(s(p)) + c_{jt}$, with $c$ being the MC and $\Delta = p_{jt} - c_{jt}$ the markup.

The simple logit demand implies market shares in the form below

$$s_{jt} = \exp(\delta_{jt})/(1 + \exp(\delta_{1t}) + \exp(\delta_{2t}), \tag{6}$$

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 $\rho_\kappa$ 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

$$\rho_{bert} = \frac{(1-s_1)^2(1-s_2)^2}{1-s_1-s_2} \begin{bmatrix} \frac{1}{1-s_2} & \frac{s_1 s_2}{(1-s_1)^2} \\ \frac{s_1 s_2}{(1-s_2)^2} & \frac{1}{1-s_1} \end{bmatrix}. \tag{7}$$

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

$$\rho_{cour} = \begin{bmatrix} \frac{1-s_1-s_2}{1-s_2} & 0 \\ 0 & \frac{1-s_1-s_2}{1-s_1} \end{bmatrix}. \tag{8}$$

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

Finally, the manufacturers and the retailer may adopt a two-part tariff and jointly

maximize the profits. Suppress the subscript for market, $t$, the corresponding pass-through matrix is

$$\rho_{tpt} = \begin{bmatrix} 1 - s_1 & -s_2 \\ -s_1 & 1 - s_2 \end{bmatrix}. \tag{9}$$

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