Market Concentration and Resilience in Agricultural Supply Chains

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Abstract

U.S. agricultural supply chains are arguably among the most efficient in the world. Recent global events, however, have disrupted these supply chains, exposing a fundamental lack of resilience. Policy critics suggest market concentration is one reason for this lack of resilience, yet little empirical evidence supports this claim. In this paper, we develop a model to test the effect of market concentration, both in the supplier and retail markets, on supply chain resilience. We measure resilience using the time it takes price spreads—the difference between retail and wholesale prices—to return to their previous levels after a major disruptive event. We test our model using data from the U.S. beef supply chain following a packing plant fire in 2019 that temporarily removed 6% of the beef supply from the market. Using an event-study approach, we find that supplier and retail concentration improve recovery times by about 1.45%. Our results, therefore, demonstrate that market concentration may not necessarily be a culprit for supply chain resilience. Hence, policies targeting market concentration may be misguided and incentivizing new competition counterproductive.

Keywords: concentration, supply chain resilience, prices, food systems, econometrics.

JEL Codes: D43, L13, M31

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1 Introduction

In the aftermath of the COVID-19 pandemic, the U.S. food system exhibited an almost stunning lack of resilience (Chenarides, et al. 2023). Although we know quite a bit about what it takes for firms to be resilient in the face of extreme disruption (Rice & Caniato 2003; Ponomarov & Holcomb 2009; Pettit, Fiksel & Croxton 2010; Blackhurst, Dunn, & Craighead 2010; Pettit, Croxton & Fiksel 2013, 2019; Tukamuhabwa, et al. 2015; Ali, et al. 2017; Stone & Rahimifard 2018; Behzadi, et al. 2017; Behzadi, et al. 2018; Ali, et al. 2022) there is very little empirical research on resilience at a system level. Understanding how firm decisions aggregate up to the level of the system is important in order to better understand how features of the system affect resilience, the role of firms within a complex adaptive supply system (CAS, Choi, et al. 2001; Carter et al. 2015; Novak et al. 2021; Wieland & Durach 2021), and whether we can expect food supply networks to be resilient to future disruptions. Conceptually, supply networks are complex systems that adapt, evolve, and change over time, but consumers still expect at least a relatively normal flow of services from the system, at reasonable prices, and without delay (Carter, et al. 2015). In this paper, we offer a new empirical measure of system resilience, demonstrate its value as a means of understanding systems performance, test the importance of theoretical drivers of system resilience, and provide insights as to whether the food system failed in a key test of its resilience: A meat-packing plant fire that removed fully 6% of the U.S. supply of beef for a 4-month period.

Scale is critical in studying the concept of resilience. Novak, et al. (2021) note that ignoring the importance of temporal and spatial scale in defining resilience risks misunderstanding whether a system is truly resilient. While individual firms may lack resilience at a very micro-level scale, the system itself may indeed exhibit resilience if buyers are able to switch quickly among suppliers, there are few barriers to entry so new firms can enter quickly, and production does not depend on a single (or highly concentrated) source of supply. Indeed, Principle 1 from Novak, et al. (2021) states that "Firm resilience is not a proxy for supply chain resilience," so we adopt this notion as a guiding principle for our empirical analysis. Even if individual firms or dyads attempt to control their supply relationships, the

interaction of self-interested agents in a free market necessarily generates complex outcomes if those interests are not completely consistent with each other (Choi, et al. 2001). We focus on resilience at the level of the system, not of the firm.

There are many definitions of resilience in the literature, and we do not intend to repeat them all here. Instead, we synthesize more recent definitions of resilience from the CAS literature (Carter, et al. 2015; Kauffman, et al. 2018; Adobor 2020; Wieland & Durach 2021; Novak, et al. 2021) with those from the "engineering and control" literature (Simchi-Levi, et al. 2014; Simchi-Levi, et al. 2018; Gao, et al. 2019) in deriving practical and useful measures of what it means for a supply system to be resilient in the face of a disruption. In general, we understand a resilient system to be one that can either "...shift and adapt to an alternative steady state..." (Novak, et al. 2021, p. 326) or one that has the "...adaptive capability...to prepare for and/or respond to disruptions, to make a timely and cost-effective recovery..." (Tukamuhabwa, et al. 2015, p. 8) or some variation thereof. Our approach is agnostic as we focus only on measurable outcomes from a supply network – prices.

Our focus on prices as a sufficient statistic for supply chain resilience reflects a more expansive view of resilience that regards supply chains as complex adaptive systems (Choi, et al. 2001; Pathak, et al. 2007; Carter, et al. 2015; Novak, et al. 2021, and others). Just as the structures and functions of a complex adaptive system evolve over time, and in response to shocks from either the supply or demand side, prices evolve over time as an indirect indicator of the ability of the system to not only fulfill its core functions to buyers and sellers within the system but to the greater needs of society if they appropriately reflect externalities within the system.[1] Prices for a particular end product will only disappear if the product is no longer useful or obsolete – think of the rotary phone or the horse-drawn plow – so we restrict our attention to products for which there is an ongoing demand, and the disruption in question does not threaten the existence of the product class itself. In this sense, prices,

[1]For example, once viewed as a means of simply raising government revenue, agencies now frame gasoline taxes more appropriately in terms of a means of forcing players in the fuel system to internalize at least some of the many externalities involved in the use of fossil fuels. While gasoline prices hardly reflect the full cost to society of the resources either used or damage in their production and use, prices potentially serve as the primary signal to all stakeholders in the fuel system to transition to alternatives, such as solar, wind, or nuclear.

or more appropriately, their variation over time, are an ideal measure of resilience and the ability of a system to either recover, adapt, or evolve to something different.

While there are a wide range of system attributes that may be important to a system's resilience (Rice & Caniato 2003; Ponomarov & Holcomb 2009; Pettit, Fiksel & Croxton 2010; Pettit, Croxton & Fiksel 2013, 2019) we study the effect of concentration – both in the upstream supplier market and the downstream consumer market – as their combined impact remains unresolved in the literature. Specifically, while Hadacheck, Ma & Sexton (2023) find that concentration in the output market reduces resilience, others find the opposite, namely that greater concentration means that firms develop closer relationships, are more likely to exchange information are less likely to default on supply obligations, each of which promote system resilience (Polyviou, et al. 2023; Jiang, et al. 2023). From first principles, less concentrated supply chains whether upstream or downstream are more diversified, and leverage the well-understood risk-reducing portfolio effects due to spreading out risks in order to reduce the importance of any one part of a system. On the other hand, supply-chain cooperation and information exchange relies on partners interacting as equals, building dependency relationships and coordinating production schedules (Cajal-Grossi, et al. 2023; Jiang, et al. 2023 - check). Highly concentrated output markets can be either beneficial to a system's resilience as large, sophisticated sellers coordinate with equally sophisticated buyers, each earning relatively high margins that serve as buffers to changing costs, or detrimental as strategic interaction among sellers leads to destructive competition, exit, and excessive control in too few hands (Saboo, et al. 2017; Kim & Zhu 2018; Gu, et al. 2024). We attempt to resolve this debate by considering the effect of concentration in both supplier and buyer markets on prices, and margins at the retailer level.

Our empirical setting considers a disruption that removed some 6% of the U.S. beef supply from the market for several months – a fire at Tyson Inc.'s plant in Holcomb Kansas in August of 2019 (henceforth, the "Holcomb Fire," Dennis 2021). We use the Holcomb Fire in a treatment-effect empirical framework, and consider prices in other, non-affected fresh food categories as control. In this way, our setting provides a quasi-experimental framework to test the resilience of the US retail food-supply system, and allows us to interpret our findings as causal in nature.

We propose a measure of supply chain resilience based on prices for a narrowly defined set of items, or more specifically price spreads between the prices received by sellers and the prices they pay to their suppliers.[2] If each member of a supply chain is compensated a competitive amount for the value they add to a product, and their costs of production are relatively stable, then variation in price spreads should reflect the extent to which firms in the supply chain either absorb (add resilience) or accentuate (detract from resilience) variation in the prices they pay. In this way, price spreads are clear, observable measures of supply chain performance. Consider the market for food as an example. Although there were clear disruptions in the distribution channels for food during the COVID-19 pandemic, the demand for food is arguably constant over time, unless there are a substantial number of people becoming obese, or, more likely, many more going without food (Gundersen, et al. 2021; Park, et al. 2022).[3] If the amount of food flowing through the system is roughly constant, then prices are a good indicator of how close the system may be operating to prior levels of performance. Prices are a key measure of service delivery: If there is an excess of demand over supply at one point in the supply chain, then prices will rise, and vice versa. If a supply chain returns quickly to its previous level of performance following a disruption, then prices will stay relatively constant. If the system evolves to something better in the sense of Novak, et al. (2021), then lower prices suggest firms have found a more efficient way to meet prior demands.[4]

Focusing on prices as our indicator of the stability of supply-network service flow, we define a measure of system resilience analogous to time-to-recover (TTR) developed in Simchi-Levi et al. (2014); Simchi-Levi, et al. (2018); Sodhi & Tang (2019); Gao, et al. (2019); Behzadi, et al. (2020). Instead of defining the measure as the level of the firm, as done in these applications, we define the measure at level of the supply chain system. As tradition-

[2]Price spreads such as this are also known as "gross margins" as they represent the difference between per-unit revenues and per-unit cost-of-goods-sold without including any fixed costs of selling. Throughout, we retain the term "price spread" to avoid any ambiguity.

[3]Gundersen, et al. (2021) project dramatically higher food security rates in many local US areas, based largely on income and unemployment data from the U.S. Current Population Survey and American Community Surveys. However, both measures rose quickly following the shutdowns in early 2020, so their projections likely overstate the actual rate of food insecurity in 2020.

[4]In fact, much of the literature on food insecurity during COVID-19 argues that food insecurity rose due to higher prices, so the demand for food is clearly endogenous to system performance.

ally applied, however, TTR is not appropriate in a CAS perspective as the notion of recovery presumes an equilibrium that the system will ultimately return to. Therefore, we define a measure of the time to recover that only reflects the fact that the system appears to be providing the same services that it was prior to the disruption in the sense that price spreads return to something near their pre-disruption levels. We make no assumptions regarding the nature of the services or quantities that are moving through the system as prices only reflect the value placed on system services by the buyers, and the cost of providing those services (place any markup adjustment for market power) by the suppliers. Our notion of system recovery, therefore, is not the same as TTR as applied in the literature as we account for the fact that the system may not return to its former state at all.

We test our hypotheses regarding the mechanisms underlying system resilience using an econometric approach that is ideally suited to measure the temporal dimension of price adjustment. Economists use the notion of "price transmission" to describe the rate at which prices respond to either shocks to production costs, or to disruptions that emerge from the demand-side of the market.[5] To this end, we define a supply-chain disruption that affects equilibrium prices in the market as a discrete event, and adopt an event-study approach to test the ability of one particular food supply chain to recover as a function of a range of structural attributes of the system itself. With this approach, we are able to estimate the scale of the disruption, the rate at which price stabilize, whether they stabilize at all, and any factors that may influence the extent and speed of adjustment. Our measure of recovery, therefore, estimates the precise time a system takes to return to its former function and, if prices are lower, improve the efficiency of service provision from a consumer perspective.[6]

We examine retail price variation around a disruption – a fire at a Tyson beef processing plant in Holcomb, KS in August 2019 – that removed 6% of the U.S. beef supply for a period of 4 months. Our example provides clear econometric identification as the disruption

[5]See Peltzman (2000) for an early review of the literature, and Frey & Manera (2007) for a more recent treatment of the econometric literature on price transmission. Price transmission is also referred to as "pass-through" in the economics literature, so see Miravete, Seim, & Thurk (2018,2023) for recent, and rigorous econometric treatments of this concept.

[6]Obviously, lower prices would not represent an improvement if the focal agent is a firm instead of a consumer, but system efficiency tends to be measured by the degree of competitiveness, and competitiveness is associated with lower resource use, lower cost, and lower prices to the end user.

was truly exogenous, it logically could not have affected the prices of other, non-substitute grocery products that form our empirical counterfactual, and occurred at a single point in time (Callaway & Sant'Anna 2021; Goodman-Bacon 2021). Retail prices are appropriate for our purposes as they are directly comparable to prices for other non-impacted food products, are adjusted by retailers at a relatively high frequency in response to wholesale price changes (Miravete, Seim, & Thurk 2018), and reflect consumer valuations, almost in real time.

Our data are from the NielsenIQ / Kilts retail scanner data set, which tracks retail sales and prices on a universal product code (UPC) basis for stores in highly granular geographies We collect retail prices and volume movements for our focal category – fresh beef – and four other grocery categories that are likely to be independent of beef disruptions and broadly representative of consumer grocery-shopping experiences: Fresh apples, potatoes, grapes, milk, and eggs. We choose stores from five geographically disparate markets (New York, Chicago, Dallas, Los Angeles, and Atlanta) in order to capture empirical experiences in different parts of the country. We define all of our retail markets on a designated market area (DMA), and capture retail sales on a weekly basis over a time period defined as 52 weeks prior to the disruption (August 19, 2019) and the 29 weeks following the disruption, but prior to the spread of the COVID-19 pandemic.[7] We combine our retail scanner data with data from the NielsenIQ / Kilts consumer panel in order to capture household attributes at the market level, and with wholesale price data from the USDA, Agricultural Marketing Service (Market News Service) to measure wholesale prices in each category, the Bureau of Census for retail inventories, and the USDA to measure the number of cattle on feed. By combining these rich data sets, we are able to test a wide range of hypotheses regarding the attributes of resilient food systems.

We find that the Holcomb fire caused retail price spreads, or the difference between retail and wholesale prices, to narrow by some 39% in response to the shortage in supply as wholesale prices rose dramatically and retail prices remained relatively fixed. Price spreads for retailers that tend to buy from fewer suppliers, or when the beef supply chain is relatively

[7]Goodman-Bacon and Marcus (2021) outline the threats to identification presented by studying events surrounding the COVID-19 pandemic, so we choose to avoid these issues rather than address them econometrically.

concentrated, recover some 14.4% faster than otherwise. Although greater supply-chain concentration may indeed place more bargaining power in the hands of suppliers (Gu, et al. 2024) it appears as though the benefits associated with closer relationships with major suppliers dominates when it comes to maintaining the resilience of the supply chain. Examining the effect of rival concentration, or the number of competing retailers in each market, we find a similar improvement in resilience. In our base-case scenario price spreads recovered in about 3.5 weeks, but those in highly concentrated retail markets recovered in almost exactly 3.0 weeks. Because retailers in more highly concentrated markets are likely to have some market power in the output market, they appear to be able to restore margins more quickly, and pass along some of the higher wholesale prices to consumers.

We contribute to the supply chain management literature on supply chain resilience, the operations literature on managing risk, and the empirical operations literature on testing theoretical models based on the CAS perspective of resilience. By focusing on the role of concentration as a critical determinant of system resilience, we attempt to reconcile the difference between the economics (Hadacheck, Ma, & Sexton 2023) and supply chain management literatures (Saboo, et al. 2017; Kim & Zhu 2018; Polyviou, et al. 2023; Jiang, et al. 2023; Gu, et al. 2024) as to the true role of large firms in either promoting or detracting from supply chain resilience. Our findings suggest more concentrated supply chains are more resilient, with the clear implication that large firms are not likely to be the source of anything other than absolute failure risk as a cause of fragility. Second, from a methodological perspective we contribute to the supply-chain resilience literature by defining an alternative measure of resilience, based on prices and price spreads, and demonstrate that prices can serve as objective measures of the time to recovery for our case-study supply chain (Simchi-Levi, et al. 2018; Gao, et al. 2019). We argue that prices are particularly valuable in this regard because they are more readily available than volumes or service flows in settings like ours and that they serve as sufficient statistics for the value of supply-chain services as prices embody all relevant information at each point in time.[8] Third, we contribute to the policy literature on resilience as our findings suggest that self-organizing supply chains appear

[8]This is the well-understood "efficient markets hypothesis" (Fama 1970) extended to markets in which rational expectations can be expected to at least approximate reality (Muth 1961).

to return to normal relatively quickly, and any attempt to engineer a market structure to achieve resilience goals may in fact be counterproductive.

In the next section, we frame our empirical hypotheses in the theoretical and empirical findings of the recent literature on supply chain resilience, focusing on food supply chains. We then describe the empirical model we use to test these hypotheses in section three, and explain why it is particularly well suited for this purpose. In section four we describe the sources for our retail and wholesale data, and the empirical constructs we use to capture each supply-chain attribute relevant to measuring resilience. In this section, we also explain our identification strategy, and examine some patterns in the data that support our notion of resilience, and why prices are relevant measures of resilience. We explain and interpret our empirical results in section five, and offer some policy recommendations that follow from our findings. Section six concludes, and offers some suggestions for future research in this area, and some of the weaknesses in our approach.

2 Background

Our theoretical framework draws on conceptual and empirical findings from the supply chain resilience literature. It highlights the importance of testing market concentration on supply chain resilience by considering prices as a measure of supply chain resilience. Given that the vast majority of empirical research on supply chain resilience is at the level of the firm, not the system (i.e., the supply chain), our challenge in this section is to develop theoretical constructs that capture what we know about the relationship between market concentration and resilience at the firm level and are robust to aggregating to the supply chain level.

2.1 Supply Chain Resilience

2.1.1 The Engineering Versus the Ecological View of Resilience

The supply chain management literature has largely adopted two perspectives of supply chain resilience. The first one builds on the "engineering view" of resilience [**?**]; [**?**], which considers a system as an engineerable system that operates at an equilibrium. A resilient system returns to this equilibrium after experiencing a disturbance. Resilience, therefore,

is measured as return time, with more resilient systems returning to their pre-disturbance steady state faster than non-resilient systems. According to [?, ?], "If it is assumed that only one stable state exists or can be designed to so exist, then the only possible definitions for, and measures of, resilience are near-equilibrium ones— such as characteristic return time." In the supply chain context, supply chain resilience is, therefore, defined as the ability of the supply chain to return to normal operations after a disruption [?];[?]. Indeed, most supply chain resilience literature adopts this view and measures resilience as "time to return to normal" or "time to recover" with lower values being optimal (e.g., [?];[?];[?]).

The second perspective builds on the "ecological view" of resilience [?]. Ecological resilience refers to the "amount of disturbance that can be sustained before a change in system control and structure occurs" and "focuses on persistence, change, and unpredictability [. . .]" [?], p. 33). In other words, the system does not return to an equilibrium steady state after it experiences a disturbance, but it can shift to a completely different state [?]. Indeed, supply chains are considered to be complex adaptive systems [?]; [?]; [?]: they are neither linear nor predictable but are a dynamic network of interconnected entities; they adapt to environmental changes, such as demand changes or supply disruptions; their behavior is not dictated by the behavior of one entity but by the interactions among the entities in the system; and they self-organize [?]. Viewing supply chains as CAS means we must consider them not as engineerable systems but as constantly-evolving ones, especially following a disruptive event after which they learn and grow [?]. Assessing resilience in CAS, however, is more difficult, with limited empirical research adopting this perspective. In this study, we approach supply chain resilience from the CAS perspective, as we are interested in when the supply chain reaches a price equilibrium after a disruption and what that equilibrium is.

2.1.2 Supply Chain Resilience: Firm Versus Supply Chain Perspectives

The literature offers various definitions of resilience, with most studies focusing on the firm as their unit of analysis and not the system (i.e., the supply chain) [?]. Some adopt the engineering view of resilience, as discussed above. For example, [?] define supply chain resilience as "[a firm's ability to recover from disruptive events]", following the engineering view of resilience. Others adopt the ecological view. For instance, [?] define supply chain

resilience as the ability of an organization to "survive, adapt, and grow in the face of turbulent change" (p. 1). [**?**] are an exception as they define supply chain resilience at the scale of the network as "[...the adaptive capability of the supply chain to prepare for unexpected events, respond to disruptions, and recover from them by maintaining continuity of operations at the desired level of connectedness..."(p. 131), which captures the key CAS notions of evolution and adaptation that ensures a system provides a level of services, regardless of what those services look like in terms of their physical structure.

In this study, we develop our expectations regarding the relationship between concentration and resilience at the system level but build our hypotheses from the micro-foundations of how firms operate, interact with each other, and aggregate their performance into market outcomes.

2.1.3 Market concentration: Supplier and retailer concentration

We focus on concentration as a key variable affecting supply chain resilience as industrial structure is both an important and topical policy matter (POTUS 2021; MacDonald, Dong, and Fuglie 2023), and there is academic disagreement as to whether more or less concentrated industries are likely to be more resilient (Jiang, et al. 2023; Polyviou, et al. 2023; Stevens & Teal 2024; Hadacheck, Ma, & Sexton 2024). In this section, we explain how we expect concentration to affect resilience, how it applies to our empirical example, and our hypotheses on how we expect each to affect systemic resilience.

As a theoretical construct, two forms of concentration are relevant to resilience at the consumer-facing level of the supply chain: Supplier concentration, or the reliance of a retail buyer on a small number of manufacturers or processors, and seller concentration, or the number of competitors in the downstream market (Saboo, et al. 2017; Kim & Zhu 2018; Jiang, et al. 2023; Polyviou, et al. 2023; Gu, et al. 2024). Both are generally measured by the Herfindahl-Hirschman Index (HHI), the CR4 (four-firm concentration ratio), or a similar index.[9] If supplier concentration is relatively high, the system may be unduly affected by

[9]HHI is calculated as the sum of the squared market shares of all firms in the market, times $10,000$. A monopoly market, therefore, has an HHI of $10,000$, whereas a competitive market converges to an HHI of 0. For antitrust purposes, the Antitrust Division of the U.S. Department of Justice regards an industry with an HHI of $2,500$ or higher as "concentrated." CR4 is the sum of the market shares of the four largest firms, by share, in the industry. In general, a CR4 of 70% or higher represents a highly concentrated industry. There

disruptions to any single supplier as retailers have few options to replace lost supply and may be forced to raise prices to ration limited supply in the face of relatively constant demand (Tang 2006; Steven, et al. 2014; Hadachek, Ma & Sexton 2024). However, to the extent that suppliers in concentrated industries can earn higher margins, they will have a greater ability to absorb shocks and not pass them on to downstream suppliers via higher wholesale prices [**?**]. Further, high concentration suggests buyers are better able to maintain close, collaborative, likely lower-cost, and consistent-volume relationships with fewer partners [**?**]; [**?**]. In the downstream market, a more concentrated retail market suggests sellers will also be able to charge higher margins and absorb cost-based disruptions instead of passing them on to consumers as higher retail prices (Weyl & Fabinger, 2013; Miravete, Seim,& Thurk, 2018). Each of these mechanisms, however, is highly nuanced and may manifest in different ways in our empirical example.

Resilient supply chains tend to be more flexible, and flexibility is likely to depend on the concentration level, albeit in different ways. In general, flexibility refers to the ability of firms in a supply network to change quickly, and a high degree of flexibility "...facilitates coordination processes and enables organisations to cope with high levels of environmental and operating uncertainty..." (Manuj & Mentzer 2008; Scholten, et al. 2014 p. 215) should a situation demand it. Reviewing the supply chain management literature on resilience, Ali, et al. (2017) find that flexibility is the second-most common attribute of resilient supply chains, next to network design, or structural features, and above redundancy. To the extent that decision-making tends to be more centralized in highly concentrated industries, concentration can promote flexibility. On the other hand, firms in highly concentrated industries tend to be more profitable, so they may not have the same sort of cost discipline that forces change and adaptation in the face of disruption. Whether concentration impairs or promotes flexibility, therefore, is an empirical question.

Flexibility, however, is also directly related to the notion of buffering developed in Bode, et al. (2011); Manhart, et al. (2020); and Novak, et al. (2021) who argue that buffering strategies are those that seek to "...minimize the firm's exposure to risk by building inventory,

are no similar standards for category-level concentration or thresholds for concentration's effect on system resilience.

capacity, lead-time, and cost buffers..." (p. 330). In economic terms, operating margins provide agents anywhere in the network the ability to absorb cost increases or price reductions that may result from a supply chain disruption (Simchi-Levi, et al. 2018; Novak, et al. 2021). Firms in highly competitive networks are less likely to be flexible as they are price-takers in their downstream market, and cannot absorb cost shocks by maintaining production and reducing margins (Tang & Tomlin 2008). In our context, firms in more highly concentrated retail markets are more likely to have higher operating margins, a greater ability to absorb cost shocks, and therefore to shield downstream consumers from disruptions that occur in input markets. From a consumer perspective, more concentrated markets will appear to be more resilient.

From a CAS perspective, firms that recognize the complex and adaptive nature of their supply networks, and are more likely to adapt and evolve quickly after a disruption, are more likely to survive over time (Choi, et al. 2001; Wieland 2021). When there are formal controls placed on the system, or complete contracts designed to capture every eventuality, ostensibly to improve the efficiency of vertical relationships, they may remove the essential element of flexibility from the supply network so are more likely to impede resilience and its ability to adapt (Choi, et al. 2001; Kauffman, et al. 2018; Wieland 2021). Beefpacking is highly contract-dependent (cite, cite), so the contracting feature of imperfectly competitive food supply chains could reduce retailers' flexibility to adjust prices and their resilience from our price-based perspective.

Highly concentrated industries are likely to have greater end-to-end visibility. Visibility is "...the ability to see from one end of the supply chain to the other..." (Scholten, et al. 2014, p. 214) and implies that one agent, a retailer for example, is able to see inventories at the wholesale level and production rates that feed into inventories, and demand rates that bring them down (Christopher & Peck 2004; Juttner & Maklan 2011; Pettit, Croxton & Fiksel 2013; Jain, et al. 2017). At least partial visibility in many "commodity" supply networks is mandatory, through regulatory requirements specified in either price reporting or food-safety inspection requirements (USDA-AMS, 2023). Indeed, limits on visibility in complex supply networks may be partly responsible for a lack of adaptive capability as each agent in the system has little visibility beyond its immediate partners one link above or

below in the system (Carter, et al. 2015). If networks self-organize and evolve based on the self-interests of each of their constituent agents, then this sort of myopia is likely to lead to a lack of resilience as disturbance-responses will be reactive, not proactive. From a systems perspective, therefore, the type of visibility that is necessary involves systemic visibility, or the ability to see outcomes at each point in the system, by each agent. In the beef industry, the fact that all the players are large and highly interconnected with their buyers, operating in an industry with mandatory price-reporting, concentration is likely to promote visibility and hence resilience.

Concentrated industries are less complex from a network perspective, simply because there are fewer players, by definition. Complex systems mean more alternative sources of supply, but may also be more vulnerable to disruptions somewhere in the system due to layered interdependencies (Craighead, et al. 2007; Blackhurst, et al. 2011; Kim, et al. 2015; Wiedmer, et al. 2021). From a network perspective, complexity refers to the number of nodes in a supply system (supply complexity), the number of arcs, or relationships between the nodes (logistics complexity), and the number of products moving between the nodes (Wiedmer, et al. 2021). Kim, et al. (2015) argue that resilience falls in the number of nodes and arcs in the system, as points of potential failure rise exponentially in the number of interconnections in the system and a firm's ability to coordinate with supply partners falls in the number of connections that must be managed. With a constant probability of failure at each point of interconnection, increasing the number of interactions in the system increases in a non-linear way with the number of agents in the network. However, Portfolio Theory suggests that if the probabilities of failure at each point in the system are independent then resilience should rise with complexity as the variance of the entire set of suppliers falls (Markowitz 1952; Wiedmer, et al. 2021). With respect to our empirical example, commodity systems tend to be relatively simple, or non-complex, but the risk of supply failure tends to be highly correlated (e.g., drought affects wide areas, disease spreads quickly). At the processor level, however, supply complexity is much lower as there are relatively few national suppliers. In general, therefore, we expect concentration to improve resilience through this complexity mechanism.

When each of the buying-retailers and selling-processors are large and highly engaged in maintaining relationships, they are more likely to collaborate (in the legal sense of the term). Collaboration includes the entire suite of activities that constitute "bridging strategies" in the sense of Bode, et al. (2011), Manhart, et al. (2020) and Novak, et al. (2021). Bridging strategies involve "...strengthening relationships with suppliers and other stakeholders [and] are concerned with building adaptive capacity via boundary-spanning activities..." such as asking farmers to hold cattle at greater weights, or asking retailers to reduce Labor Day promotions in the case of the Tyson fire in Holcomb (Dennis 2021). In this way, bridging strategies seek to build external relationships in order to enhance resilience capabilities, and are akin to the collaboration strategies in Christopher & Peck (2004) and Scholten, et al. (2014). In fact, Christopher & Peck (2004) argue that firm-level collaboration strategies help contribute to system-level resilience. Wieland & Wallenberg (2013) emphasize the notion of "relational competencies" and Cajal-Rossi, et al. (2023) to "relationality" which both refer to the quality of the relationships between supply-chain parties, measured in terms of investments in the quality of communication and cooperation between supply chain members, and the extent of integration vertically through the supply chain. Collaboration can take many forms, and involves different degrees of integration depending on the strategy being adopted, including information sharing, joint planning, logistics cooperation, goal congruence, decision synchronization, incentive alignment, resource sharing, collaborative communication, and joint knowledge creation (Cao, et al. 2010; Scholten and Schilder 2015; Qi, et al. 2022). However, it may be the case that collaboration among firms provides the link between firm-level and systems-level resilience outcomes (Scholten & Schilder 2015), but resilience at the systems level still derives from the independent actions of self-interested firms, and collaboration along many of these lines tests the boundary of the firm both legally and economically. In our case, Dennis (2021) documents the nature of collaboration in the beef supply chain following the Holcomb fire, which would not have happened in a less concentrated market environment.

Finally, resilient supply chains are better able to build and maintain redundant resources than otherwise. Redundancy is a means of gaining flexibility (Scholten & Schilder 2015; Kamalahmadi, et al. 2016) but represents a specific type of flexibility that derives from having

backup resources should the primary sources fail (Sheffi 2005; Sheffi 2015). Redundancy is a critical argument in many models of supply chain resilience – in the fundamental tradeoff between efficiency and resilience, the cost of achieving a higher degree of adaptive ability, or resilience, is the loss in efficiency due to maintaining redundant resources (Sheffi 2005; Sheffi, et al. 2015; Ponomarov & Holcomb 2009; Pettit, Croxton, & Fiksel 2010; Pettit, Fiksel, & Croxton 2013; Blackhurst, et al. 2011; Juttner & Maklan 2011). In that sense, the value of resilience can be measured by the cost of efficiency firms are willing to forego to achieve it. Excess inventories, longer lead times, multiple suppliers, or a geographically diverse supply base are just a few examples of network designs that may not maximize efficiency, but they are redundancies intended to improve resilience. In the beef supply chain, only large and well-capitalized retailers and process are able to support redundant systems.

In general, therefore, our net expectation regarding all the different dimensions and mechanisms through which concentration operates leads us to believe that more concentrated systems are likely to be more resilient. In the next section, we describe the data we use to test these theoretical hypotheses and the empirical measures we use to proxy each of the above theoretical constructs.

3 Data

In this section, we describe our data sources and provide model-free evidence from our data that appears to support our hypotheses. We explain our identification strategy and discuss the primary challenges to econometric identification we face and how we overcome them. We explain our logic in using retail scanner data for the purposes at hand and why we believe these data are ideal, although relatively unexploited, for examining supply chain resilience.

3.1 Data Sources

Our primary data source is the Kilts/Nielsen scanner database hosted by the Kilts Center at the Booth School of Business at the University of Chicago. Although Kilts offers both "consumer panel" and "store level" scanner data sets, we use the store-level retail scanner data because our interests lie in explaining price behavior at the supply chain level and

assessing supply chain performance using retail prices on a category level. Our data spans all weeks in 2018, the 32 weeks in 2019 preceding the Tyson Holcomb fire (August 8, 2019; Dennis 2020), and the 29 weeks after the fire but before the COVID-19 outbreak. We define the start of the COVID-19 pandemic era as February 1, 2020, which is before any state-level shelter-in-place orders but conservatively avoids any demand or supply disruptions that may be associated with the COVID-19 pandemic.

Our data include category-level prices for five of the largest retail markets in the U.S. (DMAs, or "designated market areas"in Nielsen terminology): Atlanta, Chicago, Dallas, Los Angeles, and New York. Our sample design ensures geographic coverage that is as broad as possible, while remaining empirically tractable. Including markets at different distances from the source of the disturbance (Holcomb, KS) also allows us to detect any differences in regional effects in our statistical model.

We focus on the beef category but collect data on four other retail food categories for robustness checks: Fresh milk, eggs, apples, and potatoes. We chose these other categories because their prices are likely independent of beef prices, and we can observe wholesale prices for each from the USDA-AMS Market News Service. In the NielsenIQ RMS data, the fresh produce category is the top dollar-sales category (%B...in 2019), while beef, milk, and eggs are all in the top 10. Note that we cannot use data from other fresh meat categories (e.g., pork, chicken, and fish) because doing so would violate the stable unit treatment value assumption (SUTVA, [**?**]), meaning that a treatment can only impact the treated observations and not the control observations. Because pork, chicken, and fish are likely protein substitutes for beef, any change in the retail price of beef is likely to affect the demand for these other products, violating the independence assumption implicit in SUTVA.[10]

For each category, we define a price index that consists of a sales-weighted average of weekly sales of all items in the category (or product module). Using sales-weighted averages means that the role of each item in the price index varies from week to week, which is both

[10]In the Nielsen RMS data, all "fresh meat" items reside in a single product module, including chicken, turkey, pork, and other meats, so we extract all fresh beef observations from the fresh meat module by analyzing the Universal Product Code (UPC) description for the Nielsen "BF" code. We also exclude all frozen beef product modules as frozen beef moves through a different supply network than fresh beef and, as a storeable commodity, is not subject to the same supply shocks as fresh beef.

necessary and realistic: If the composition of category sales changes from week to week, the average category price should reflect both changes in item prices and the mix of items sold each week. If relative prices for the items in the category change over time, consumers will likely substitute from one category to the other and change the actual cost of the category in their grocery budget. Price indices need to reflect these changes to accurately reflect category prices.[11] With this simple approach, we also do not need to exclude products that stock out or are otherwise unavailable during any given week as our index fluctuates naturally with availability, and we assume consumers substitute for like-quality products. Change in these price indices captures any disturbances in the upstream supply chain caused by exogenous reductions in capacity of the type we have in mind in our empirical example.

Prices are formed at many different points in the upstream supply chain (e.g., prices paid to farmers, processors, distributors, or packers are all readily available for some products and could equally reflect the effect of shocks to the supply system), so our choice to focus on retail-level prices is deliberate.

First, prices above the retail level are rarely available in units that are directly comparable. For example, some prices refer to raw, unprocessed products that lose weight in processing, so the finished-good price represents something different from the raw-product price. For example, cattle are priced at the farm gate in terms of dollars per hundredweight (cwt) of live animal, whereas processed meat refers to the dollar per cwt of actual meat.

Second, prices for different products are almost never comparable on a spatial scale. For example, the reference price for fresh potatoes may be Eastern Oregon, whereas the price for live cattle may refer to farm-gate prices in Kansas or Oklahoma.

Third, the retail level is the only point at which attributes of the vendor can be held constant, and all other factors that may affect the "price"' are held constant to permit direct comparison. For example, potatoes and beef sold through a Kroger store reflect only differences in the wholesale price paid by Kroger for the two products and category-level

[11] Others use fixed-weight price indices that mimic the U.S. Bureau of Labor Statistics' Consumer Price Index calculation method more closely (Leung 2021; Renkin et al. 2022), but at the cost of chain drift, or the difference between a fixed-weight index and one that uses chained, or updated, weights over time. We eliminate chain drift by using contemporaneous sales-weights in calculating our store-level price indices.

pricing strategies by Kroger. All other variables that may lead to differences in the prices between the two items are the same, by definition, for items sold in the same retailer.

Fourth, and perhaps most importantly, retailers may pass through changes in wholesale prices to consumers at different rates - or indeed not at all - depending on their particular pricing strategy. In fact, there is empirical evidence of asymmetric pass-through, in which retailers pass-through wholesale price increases more quickly and completely than they do wholesale price reductions (Peltzman 2000; Chandra & Tappata 2011), and of retail prices that are held at fixed levels, despite highly variable wholesale prices.[12] However, the vast majority of research on retail price fixity (Anderson & Simester 2010; Anderson, et al. 2017; Ilut, et al. 2020), the "rockets and feathers" problem (Peltzman 2000; Chandra & Tappata 2011; Richards, et al. 2014), and national-level price setting by retailers (DellaVigna & Gentzkow 2019; Hitsch et al. 2021) concerns consumer-package goods (CPG) categories or those that are sold in the center-of-store by the vast majority of retailers.

Our example here instead concerns a perishable, or "random-weight" category with retail prices that tend to reflect wholesale price variation much more closely, and hence the retailer's acquisition cost (Lan et al. 2022). Retailers tend to price random-weight categories in a way that more directly reflects changes in supply chain cost, particularly given their increasing adoption of revenue management software and services (Kok & Fisher 2007; Berbeglia, et al. 2022) in which retail prices are set to maximize profit over variable wholesale prices. In these categories, consumers expect to see much more variation in the retail price as they understand they are purchasing "commodity" goods that are much closer to unprocessed foods than the CPGs sold elsewhere in the store, so retailers are less reluctant to vary prices in a way that will maximize their profit over a weekly purchasing cycle.

We exclude all stores that are not in the "Food" or "Mass Merchandisers" channel to capture prices that reflect direct competitors in the consumer market. We also exclude all stores with fewer than 52 weeks of sales in 2019 and less than completely represented in the part-years of 2018 and 2020. Our price index, therefore, compares stores that are direct competitors and should not reflect any entry or exit effects over the sample period.

[12]Retailers may hold prices fixed due to the costs involved in changing prices, they are reluctant to antagonize consumers, or consumer demand is highly elastic for specific items (Dellavigna& Gentzkow 2019).

3.2 Data Summary and Identification

We complete this section by summarizing our data and showing some model-free evidence of how beef prices changed during and after the Holcomb plant fire at both the retail and wholesale levels. We also explain how we measure market concentration (supplier and retailer concentration) and argue why the effects of both types of market concentration are econometrically identified in our data. We end this section by showing an event-study plot that establishes the lack of any pre-disruption trend in retail-wholesale beef price spreads and offers some visual evidence of the price-spread recovery process for our sample retailers.

Table 1 summarizes our data and shows considerable variation, over time and across retailers, in the focal price spread (beef) and each of the other price spreads we use in our robustness checks below. Table 1 also documents that supplier and retailer concentration varies over observations in our data set. Consequently, there appears to be sufficient cross-sectional and time-series variation in our data to identify the relationships between price spreads and market concentration that we seek.

[Table 1 in here]

More specifically, retail prices for perishable items typically vary much more over time than packaged items yet still reflect retail-chain-specific pricing strategies more than wholesale market conditions (Dong & Astill, 2023). In Figure 1, we show the retail price indices for our focal category (beef, choice cuts) and four other categories for comparison purposes. Retail prices for items in all categories vary over time, and beef prices do not appear to show any particularly remarkable behavior around the time of the Holcomb fire. However, retail prices only show some of the story.

Indeed, wholesale beef prices exhibited a much stronger response to removing capacity due to the Holcomb fire, as expected. In Figure 2, we show wholesale beef prices from the Livestock Market Information Center (LMIC), also on a weekly basis, over a similar time period to that shown in Figure 1, and for the same item (choice beef cuts). In this figure, we retain data through 2020 to show the dramatic effect on wholesale beef prices associated with COVID-19-related beef-packing plant shutdowns. Relative to the well-publicized (cite,

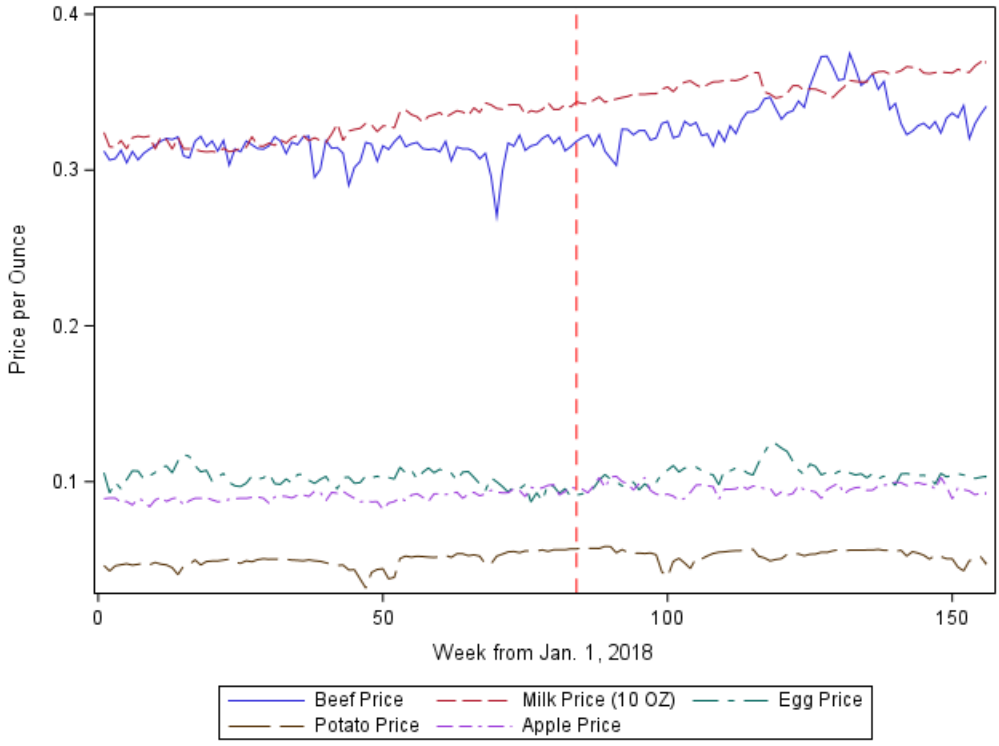


Figure 1: Retail Price Indices, by Category and Week, 2018-2020

Note: Data from Kilts / Nielsen RMS (store level) data, 2018-2020, sample of retail stores in Atlanta, Chicago, Dallas, Los Angeles, and New York. Price represents indices of choice beef cuts over all items and stores by week. The reference line captures the week of the Tyson beef-packing plant fire in Holcomb, Kansas. All non-beef price indices are value-weighted averages across all items sold in all stores each week.

cite) impact of the COVID-19 shutdowns on wholesale beef prices, the Holcomb fire was a relatively small event. Despite this, the data in this figure show that the fire did have a substantial effect on wholesale beef prices and that the shock to wholesale markets lasted for more than a few weeks.

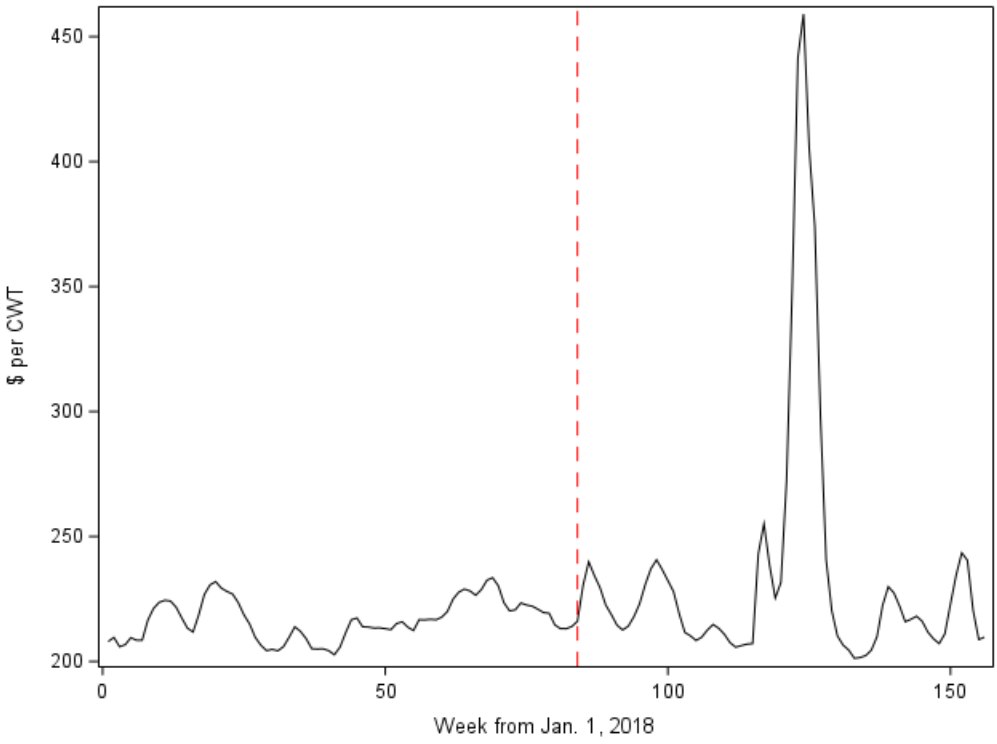


Figure 2: Wholesale Beef Prices, Choice Cutout, US, by Week, 2018-2020
Note: Data from LMIC on $ per hundredweight basis, 2018-2020, for a U.S. national-average sample. Sharp increase at week 121 in the data represents the effect of COVID-19-related plant shutdowns on wholesale beef prices.

Next, we use the data in the previous figures to provide model-free evidence of how beef price spreads changed in the time period immediately preceding the fire relative to immediately after. Table 2 shows that beef price spreads were significantly higher before and after the fire, while those in the other categories differed very little between the three sub-periods in our data. Although we account for greater week-to-week granularity in our event-study analysis below, this table does suggest that the disruption affected beef price spreads differently relative to its own prior and subsequent spreads and those of other commodities.

[Table 2 in here]

We argue that market concentration is likely important to a system's ability to recover after a disruption through any of the mechanisms described above. From a retail perspective, two types of concentration matter: supplier concentration and retailer (or rival) concentration. We measure supplier concentration as the Hirschman-Herfindahl Index (HHI) of brand concentration for each retailer, in each market, for each week of our sample data set.[13] In forming this supplier HHI (SHHI), we assume that each brand represents a separate source of supply, which may not be strictly true for some multi-brand suppliers.

In the retail market, however, brands tend to be managed by separate contracts, with different representatives from the supplier, so our approximation is likely a better description of reality than if we were to aggregate all brands up to the supplier level. In the output market, others in this literature (Saboo et al. 2017; Kim & Zhu 2018; Jiang et al. 2023; Gu et al. 2024) measure buyer concentration as the HHI among individual buyer firms. While this may be relevant for industrial concerns that sell to only a limited number of buyer accounts, the buyer market for retailers is arguably atomistic. However, rival concentration is an important measure (MacDonald, Dong, & Fuglie, 2023) as it captures the potential for imperfectly competitive pricing in the downstream consumer market. Therefore, we calculate a weekly retail HHI (RHHI) for each retailer by squaring and summing retailer-level market shares in each of our sample markets.

Each measure of concentration is arguably endogenous in that concentration may be correlated with unobservables that also affect retail-wholesale beef price spreads over time and across retailers (Berry et al., 2019; Miller et al., 2022). However, we address this issue in several ways. First, our pricing data represent weekly decisions, whereas our concentration measures are determined months or years in advance of the realization of our pricing data. Second, our preferred event-study specifications below contain store, week, and store-by-week fixed effects, as well as a full complement of control variables. By accounting for features unique to each store in this way and trends over time that may otherwise be correlated

[13]Formally, an HHI for store s in week t is calculated as $HHI_{st} = \sum_{i=1}^{N} 10,000 * w_{ist}^2$, where w_i is the share of supplier i to store s in a particular category and week t. For antitrust purposes, the Federal Trade Commission (FTC) regards any HHI value over $2,500$ as being "highly concentrated," but our analysis does not carry any antitrust implications.

with either measure of market concentration if left to the residual, we believe there is little left that may induce bias (Ellickson & Grieco, 2013). Third, our case study involves pricing decisions for only a small part of each store. Because it is highly unlikely that store managers compete on the basis of beef prices alone, even if there is a concentration effect left in the residual of our pricing model, it will be small. Fourth, several studies show how retail prices for most product categories are relatively fixed at the chain level (Della Vigna & Gentzkow 2019; Hitsch, Hortacsu, & Lin 2019; Dong & Astill 2023), so local pricing does not reflect local market power conditions. Therefore, we argue that our estimates of the impact of supplier and rival concentration will not be contaminated with endogeneity bias.

On a more fundamental level, however, econometric identification requires that each measure of market concentration exhibit sufficient variation both over time and across stores (SHHI) and markets (RHHI) in our panel data set. Figure 3 shows how RHHI varies by week in each of our sample markets, while Figure 4 shows the average SHHI by market over the same sample weeks. In the case of RHHI, the level of rival concentration varies substantially over time for each sample market and, as a side note, reaches well above problematic levels for at least two sample markets. Concerning SHHI, Figure 4 shows a surprising amount of turnover among brands over time, but retailers maintain a considerable amount of supplier flexibility. In neither case, however, does concentration appear to change as a result of either the Holcomb fire disruption or the later COVID-19 disruption (that we exclude from our estimation strategy).

Finally, we show the path of retail-wholesale price spreads around the Holcomb fire for each market (Figure 5). We again include the data through 2020 to compare our focal disruption to the COVID-19 time period for comparison purposes, but note how price spreads appear to have shrunk significantly during around the Holcomb fire but appear to have recovered quickly. Interestingly, note how the spread sometimes goes below zero as retailers appear to absorb wholesale prices that they are unwilling to pass fully along to consumers. More generally, the data in this figure reveal the level of variability in retail-wholesale price spreads and how reversion-to-normal appears to be a reasonable expectation in this market. How much is attributable to supply chain attributes, however, requires econometric estima-

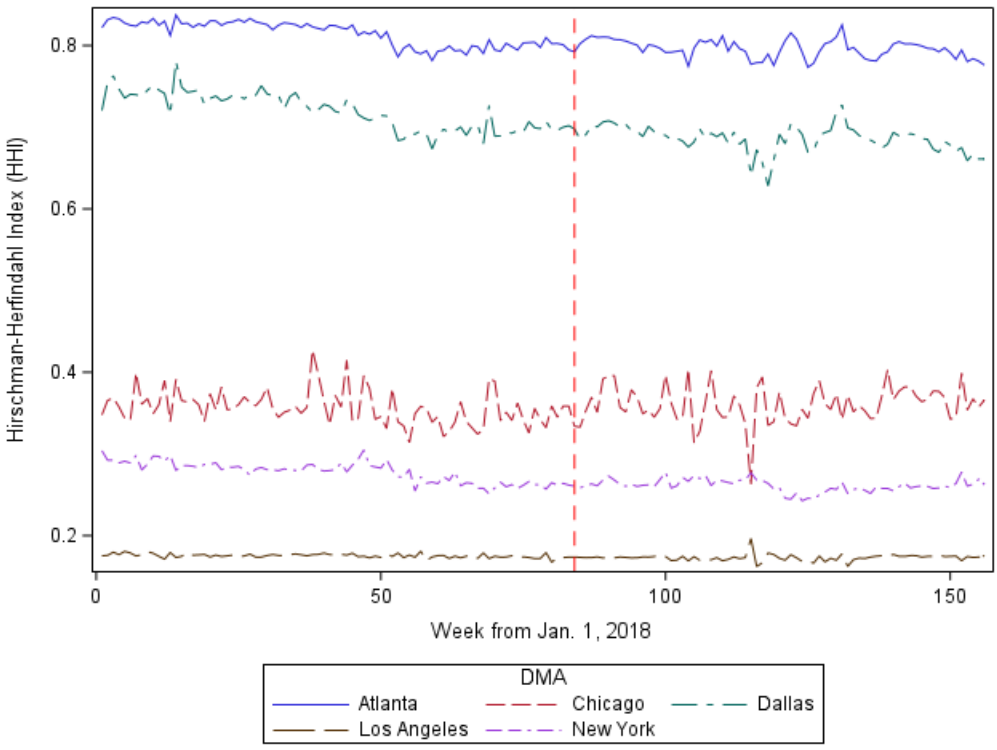


Figure 3: Retail Concentration (HHI), by Market and Week, 2018 - 2020

Note: Retail HHI estimated from NielsenIQ RMS data over the 2018 - 2020 sample period, by week, using store-level market shares in each week of the data. Markets are defined on a DMA basis, reflecting "banner-level" concentration in each market week. For our HHI-calculation purposes, each banner under each ownership group is considered a separate entity. This is a reasonable assumption in the retail food industry because if banners share a common ownership group, they tend to be managed separately and target different sub-markets within each DMA.

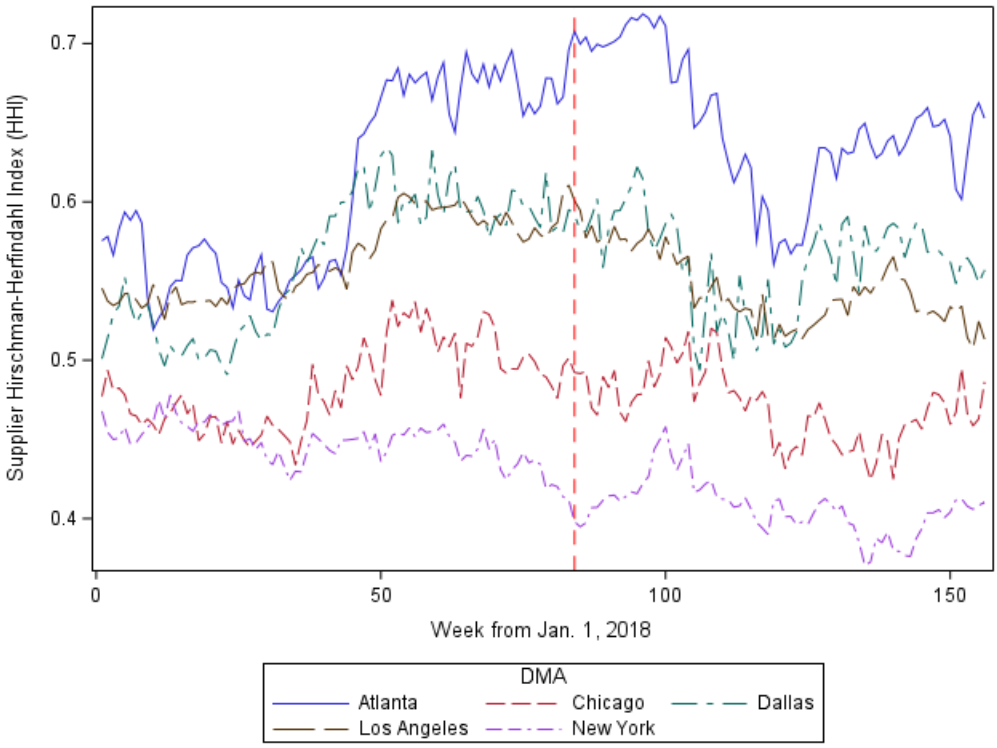


Figure 4: Supplier Concentration (HHI) by Market and Week, 2018-2020

Note: Supplier HHI estimated from NielsenIQ RMS data over the 2018 - 2020 sample period, by week, using store- and category-level brand market shares in each week of the data. Markets are defined on a DMA basis, reflecting "banner-level" concentration in each market week. For our HHI-calculation purposes, each banner under each ownership group is considered a separate entity. See the note to table 3 for an explanation of this assumption.

tion to control for the other factors that may be responsible. We return to this question in the next section.

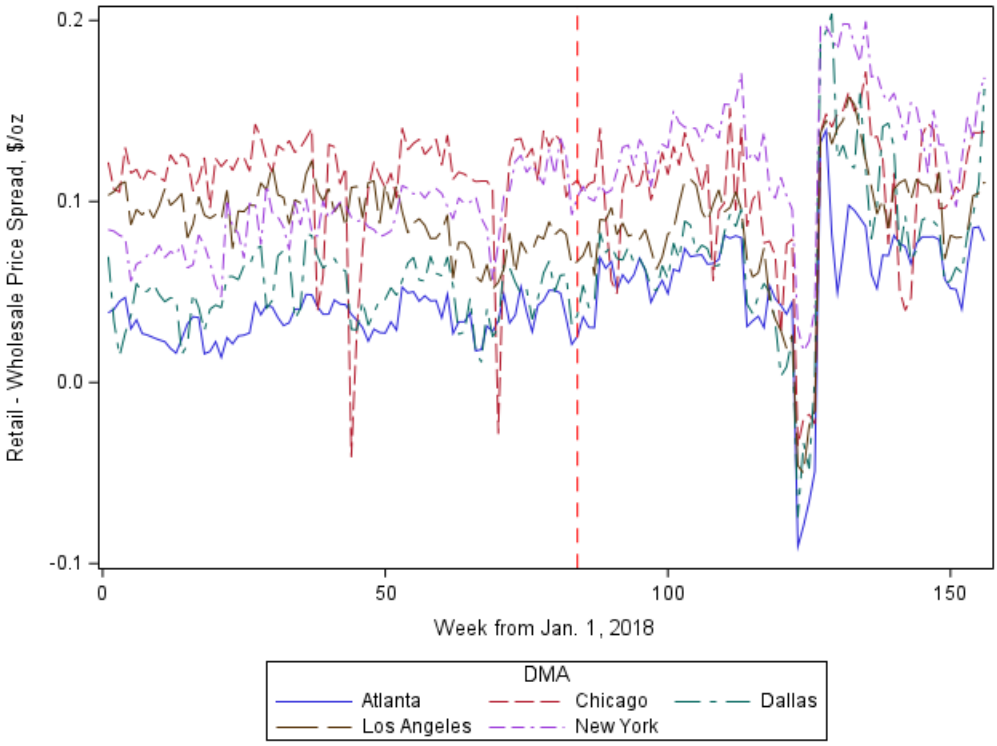


Figure 5: Retail-Wholesale Beef Price Spreads by Market and Week, 2018-2020
Note: Calculated from Kilts / Nielsen RMS (store level) data, 2018-2020, and LMIC wholesale price data for choice beef cuts, for sample of retail stores in Atlanta, Chicago, Dallas, Los Angeles, and New York. Retail price represents the index of retail prices for choice beef cuts over all items and stores by week. The reference line captures the week of the Tyson beef-packing plant fire in Holcomb, Kansas.

4 Empirical Model

4.1 Overview

Estimating the effect of each empirical construct on the time to recovery among retailers requires an econometric approach that can project system attributes into the space of price adjustment. While there are recent developments in the dynamic difference-in-difference (DiD) and event-studies literature streams that may be appropriate for the identification strategy we propose here (Callaway & Sant'Anna 2021; Goodman-Bacon 2021), these linear methods only represent approximations of the true time it takes for a price series to adjust

to an external shock. Therefore, we adopt a simple, event-study approach (Borusyak et al. 2024) in which the rate of price-spread adjustment depends on past values of the price spread.

4.2 Event-Study Model

We estimate our model with different definitions of a "price spread" but develop the model explanation below using the most usual definition of the difference between the retail price and wholesale price of the same commodity and in generic notation to allow later generalization. With this definition, a disruption in the wholesale market implies that spreads should narrow initially as retailers absorb the supply shock to the best of their ability, which can insulate consumers from paying higher prices (and potentially blaming the retailer for higher prices).

We test the notion that the value of retail service flows in the beef category should be related over time using an event-study framework. Assuming the difference in log prices between the retail (i) and wholesale (j) in period t at store s written as $y_{ijst} = \ln p_{ist} - \ln p_{jst}$, we then begin by writing the rate of convergence over time as:

$$\Delta y_{ijst} = \beta y_{ijs,t-1} + X_{st} + \gamma_s + \phi_t + \delta_{st} + \varepsilon_{ijst}, \tag{1}$$

where Δ is the first-difference operator, so that $\Delta y_{ijst} = y_{ijst} - y_{ijst-1}$, and where $y_{ijs,t-1}$ is the lagged value of the difference in log prices, X_{st} is a vector of control variables specific to either the store or time period, γ_s is a store fixed-effect, ϕ_t is a week fixed-effect, and δ_{st} is a store-by-week fixed effect, and ε_{ijst} is an error term. In this model, the parameter β measures the rate of price adjustment and is bound on $[-1, 0]$. Values of $\beta = 0$ suggest the price series are independent of each other and do not adjust toward a long-run relationship, while values of $\beta = -1$ suggest the opposite – that the prices adjust toward each other instantaneously as if convergent to the same relative point over time. Expressed differently, a value of $\beta = 0$ indicates that the system governing both series is sufficiently complex that prices are not related to each other, while $\beta = -1$ supports more of an equilibrium perspective of food supply systems as they move quickly toward each other following a disruption. Further, in this model, X_{st} represents a set of exogenous factors that otherwise govern the relative value

of each series, such as changes in economic conditions or attributes of each supply system. In this simple model, store, time, and store-by-time fixed effects soak up any variation in the extent of co-movement that is not otherwise captured by the exogenous control variables or past values of the price relationship.

The simple two-way fixed effects model in (1), however, assumes that all adjustment follows an exponential path and does not allow us to focus on adjustment to a specific disruption. Rather, price spreads may adjust all at once if agents are particularly responsive, after a delay if there are institutional constraints to adjusting prices quickly, or not at all if the disruption moves the market away from the previous equilibrium. Moreover, our interest lies in how prices adjust back to their former equilibrium, or not, following a disruption – and not necessarily how they generally adjust over time. For that reason, we use the model in (1) as a first approximation as to how prices in the grocery channel adjust, but we use an event-study approach (Borusyak et al. 2024) as our primary method for testing how prices adjust in response to an adjustment, and how system attributes affect their rate and direction of adjustment.

Generalizing our base model above, we define D_t as an indicator variable that assumes a value of 1 during the week of a disruption ($\tau = 0$) and 0 otherwise, so the change in spread becomes:

$$\Delta y_{ijst} = \sum_{\tau=-10}^{10} \beta_\tau D_{t+\tau} y_{ijs,t+\tau} + X_{st} + \gamma_s + \phi_t + \delta_{st} + \varepsilon_{ijst}, \tag{2}$$

where $\tau = \{-10, -9, ..., 9, 10\}$ indexes our event-study window. With this specification, the β_τ coefficients have the same interpretation as the simple model above, only now expressed as a sum of changes over time, with the sum of β_τ coefficients in the positive domain of T capturing the cumulative rate of price-adjustment either back to or away from the previous level.

We use the specification in (2) to generate baseline estimates of how prices adjust over time without external influence, or at least any other factors that may govern the movement back to equilibrium levels left to the residual term, ε_{ijst}. However, we assume that there are features of the system, q_{st},independent of the X_{st} variables that affect the changes directly, influencing the rate at which prices either move toward or away from their long-run values.

We capture these features by interacting the event-study terms $y_{ijs,t+\tau}$ with the system features defined above such that:

$$\Delta y_{ijst} = \sum_{\tau=-10}^{10} \alpha_\tau q_{st} D_{t+\tau} y_{ijs,t+\tau} + X_{st} + \gamma_s + \phi_t + \delta_{st} + \varepsilon_{ijst}, \tag{3}$$

becomes the econometric model of price-resilience we use to test each of the hypotheses developed above. Namely, we test the equivalence of α_τ and β_τ both for individual elements of T and over the entire set of adjustment periods to test the importance of each q_{st} variable. If $\mid \alpha_\tau \mid > \mid \beta_\tau \mid$, for example, then q_{st} increases the rate of price-adjustment to its previous value (or price-spread adjustment, as the case may be), or if $\mid \alpha_\tau \mid < \mid \beta_\tau \mid$ then q_{st} slows the rate of adjustment. If the difference $\alpha_\tau - \beta_\tau$ is not statistically indistinguishable from zero, then the q_{st} element is not important to the rate of price adjustment, and hence resilience of the system.

Event-study plots are a useful method of analyzing the data for pre-event trends and for generating model-free evidence of the event itself and recovery in our case. In Figure 6 below, we show estimates from our base event-study model, including week, store, and store-by-week fixed effects and the controls described below to examine the recovery process visually. From our event-study diagram, it appears that price spreads remained below their "usual" levels for some five weeks following the fire before returning to their pre-disruption levels. From a summary perspective, therefore, it appears as though the time to recovery for the fresh beef supply chain was roughly five weeks. In this figure, however, we do not account for the effect of concentration on the recovery rate.

[figure 6 in here]

In the next sub-section, we explain how we define each argument in our set of resilience elements (q_{st}) and control variables (X_{st}) and how they are operationalized in the empirical model.

4.3 Variable Definitions and Construction

In terms of the empirical model of price adjustment introduced in the previous section, we use this data to define a set of scalar variables (q_{st}) that allow us to test our primary hypotheses regarding the role of market concentration (supplier and retailer concentration)

in supply-chain resilience. We also derive a set of variables considered important for supply chain resilience but are not the focus of our hypothesis testing above. These variables form elements of the control vector (X_{st}) in our empirical model.

First, we define a measure of product complexity following [?] by measuring the breadth of the beef-category assortment for each retailer and week in the data. Specifically, we operationalize product complexity as a simple count of the unique products (UPCs, universal product codes) in each category. Product complexity can affect resilience in two competing ways. If a retailer sources from a smaller number of suppliers, it is likely to maintain closer, reciprocal relationships with each. In this case, we expect greater resilience with a smaller number of suppliers (or an inverse relationship). Further, complexity may reduce resilience as retailers are likely to have less flexibility in influencing suppliers' stocking decisions if there are many different products on the shelf. On the other hand, greater complexity implies that consumers may be able to substitute among products easier, so any shock to the supply of one product will be absorbed by greater sales of other products in the same category. Ultimately, which effect dominates is an empirical question.

Second, velocity is another important element of resilience. For empirical purposes, we define velocity as the speed with which products enter and exit the retail distribution channel, measured as the time between shipments and consumer purchases. With inventory data, the ratio of sales to inventory (both in dollars) provides a measure of turnover, but we do not know the inventory amounts held by each retailer. Therefore, we proxy turnover rates in each category and market by calculating the average purchase cycle (interpurchase time) from the Kilts / NielsenIQ Consumer Panel data. Comprising a nationally representative sample of some 50,000 households across the U.S., the NielsenIQ Consumer Panel data set is the benchmark dataset for establishing stylized facts for consumer purchasing behavior (see Leung (2021) for a recent example). For each sample household, we select those who reside in our focal DMAs and calculate the number of days between purchase occasions for each category in question. The number of days between purchases is the purchase cycle or interpurchase time. We average interpurchase times for each market, week, and category and interpret our variable as the speed with which products turnover at the retail level. Products

that turnover more quickly should have a higher velocity, and hence greater resilience, than otherwise.[14]

Third, we define a measure of visibility throughout the beef supply chain. Visibility is difficult to capture empirically as it refers to relationship-specific knowledge that is not usually available as data. However, as we explain above, systemic visibility is of key policy importance in U.S. agricultural supply chains, so the U.S. government ensures that both price and the "fundamental" drivers of supply and demand are as visible as possible to all market participants. For our purposes, we use data from the "Cattle on Feed" (CoF) survey (USDA-NASS 2023). The CoF survey is administered by the National Agricultural Statistics Service (NASS) of the USDA, and captures a survey sample of the number of cattle on feed (being raised for slaughter purposes) by surveying feedlot operators in the 16 most important cattle-feeding states in the U.S.[15] The number of cattle on feed is important as cattle cannot remain on feedlots indefinitely, and must move to slaughter within only a few weeks of the date at which they are expected to reach slaughter weight ($900 - 1000$ lbs). We use cattle-number estimates from the CoF survey that are stratified by weight class, so we know how many cattle on feed that weigh between $600 - 699$ lbs, $700 - 799$ lbs, and so on. Retail buyers, and feedlot operators (sellers) use this data to gauge how many animals are likely to come to market in short-, medium-, and longer-term timeframes. Defining visibility this way, we believe that the speed of price adjustment should rise the greater the ratio of the heaviest to the lightest animals on feed as it suggests supply that is likely to come to market soon.

Fourth, we operationalize two measures to assess the extent of collaboration among beef supply chain members. Anecdotal evidence surrounding the events of August 2019 suggest that Tyson Foods warned retailers that supply shortages were likely to be forthcoming until

[14]We acknowledge that there are many other ways to define velocity in the literature (Kamalahmadi, et al. 2016), and other definitions may differ conceptually from ours, but we believe our measure captures one interpretation that is relevant to supply chain resilience.

[15]USDA describes the survey as providing "...estimates of the number of cattle being fed a ration of grain, silage, hay and/or protein supplements for the slaughter market that are expected to produce a carcass that will grade select or better. This survey is conducted in the 16 largest cattle-feeding states. About $2,000$ known cattle feeders with a capacity of $1,000$ or more head are enumerated. Feedlots with $1,000$ or more head capacity represent about 85 percent of all fed cattle in the U.S. The 16 largest states represent 98 percent of U.S. cattle on feed in lots of $1,000$ head or more capacity" (USDA-NASS 2023).

the Holcomb plant could be brought back online (Dennis 2021). Entering the key Labor Day grilling period, retailers typically promote beef products heavily in order to attract price-sensitive customers who may also buy other, more high-margin, items for the holiday weekend. In our retail scanner data, there are two measures of the extent and depth of beef promotion around the disruption: (1) the frequency of beef "featuring," and (2) the frequency of beef items on "display." We derive measures of each directly from the retail scanner data for the beef category, and express each as a sales-weighted average across all UPCs in the beef category. We expect to find each measure of collaboration to be negatively related to the rate at which prices converge. That is, retailers likely promoted beef items less during the disruption-recovery period, so price spreads in the beef category converged faster with fewer feature and display promotions.

Fifth, we measure redundancy using aggregate system inventories as a measure to which retailers had established buffers against the likelihood of something like a packing-plant fire occurring. Higher inventories in the system suggest that firms have excess capacity to draw from previous production during disruptions, either at the wholesale or the retail level (Christopher & Peck 2004; Scholten & Schilder 2015). Our scanner data does not capture retailer-specific inventory levels, but the Bureau of Census regularly surveys retailers for their "Monthly Retail Trade Survey" (MRTS, Bureau of Census 2023). We use inventory measures from the MRTS at both a "final retailer" and "wholesaler" level, on a monthly basis, in order to capture inventories at two different points in the food supply system. Our measures are aggregated over all retailers and are reported at a national level only.[16] We expect to find that higher inventory levels are associated with faster recovery times.

5 Results

In this section, we present and interpret our empirical models of supply chain resilience and examine each of the hypotheses above. We begin by examining the results from our base model in (1) above, which examines price-spread adjustment in the retail beef market in general, and then proceed to study spread adjustment with respect to the Holcomb fire

[16] Although beef processing is concentrated mainly in cattle-producing states (USDA,FSIS 2023), beef from federally-inspected plants moves throughout the country.

disruption through the event-study models in (2) and (3). We use these models to study the effect of market concentration and our control variables on price-spread adjustment over time and the recovery rate in the retail beef market.

5.1 Base Model

Our first set of results are in Table 3 below. In this model, we examine the underlying price-spread reversion process in the retail beef market to establish our expectations as to whether convergence back to a "normal" price spread should even be expected in this market. In terms of the parameters of equation (1) an estimate of β between 0 and -1 suggests that price spreads are indeed convergent, with estimates closer to -1 indicating rapid convergence and to 0 slower convergence. Our estimates in Table 3, from the preferred specification that includes the full set of control variables (Model 5), show an estimate of $\beta = -0.56, (p < 0.01)$. Hence, price spreads seem to converge back to their previous levels and at a moderate speed. Moreover, interacting the speed of adjustment with the fire dummy suggests that price spreads were some 0.02 log points slower in converging during the fire disruption. However, this interaction estimate assumes a strict distribution for the change in price spreads in the recovery phase and does not reveal the sort of heterogeneous recovery process that we expect. For this reason, we rely on our event study estimates.

[Table 3 in here]

5.2 Event Study Model

Next, we present the results from our event-study models, beginning with the simple event-study specification that underlies Figure 6 above and then adding supplier concentration and retail (rival) concentration as supply-chain attributes that may affect the speed of recovery following a disruption. Our first set of estimates is in Table 4 below, in which we estimate five different models, from a model that contains only the event-study terms (Model 1), store fixed effects (Model 2), store and week fixed effects (Model 3), store, week, and store-by-week fixed effects (Model 4), and finally, a fully saturated model in which we include the full set of fixed effects in addition to the controls explained above (Model 5). Among these models,

the estimates in Table 4 show that the parameters of interest, namely the parameter for the contemporaneous change in the spread ($t = 0$) and for each of the subsequent "lead" weeks ($t + 1, t + 2$, etc) are relatively stable and suggest a similar pattern of recovery regardless of the nature of the specification.

[Table 4 in here]

In each of the models in Table 4, the dependent variable is the percentage change in price spreads from the previous to the current period, while the main explanatory variable consists of leads and lags of the Holcomb fire disruption, which interacted with a lag of the spread. With this specification, we interpret each coefficient as the rate of adjustment of the current spread in response to the disruption. Our primary interest, therefore, lies in the magnitude of the contemporaneous adjustment of the spread of the fire in the period in which it happened (the disruption effect) and the rate of recovery back toward its previous level (the recovery effect). Each lead coefficient in the table shows how the price spread adjusts back to its pre-disruption level, interpreted in terms of percentage points of spread. In Table 4, the estimates from Model 1 to Model 5 are relatively stable, with a large contemporaneous shock and a gradual return to the pre-disruption level. In the preferred specification (Model 5), the parameter estimates show that rising wholesale prices, and relatively constant retail prices, lead to a 19.5 point reduction in the retail-wholesale price spread at the time of the fire. Subsequent reductions in the wholesale price and modest increases in retail prices allowed the price spread to widen by some 11.1 points in the first week after the fire, 1.0 points in the second week, 3.1 points in the third week, and 8.9 points in the fourth. Full recovery, therefore, took roughly 3.52 weeks after the fire.

We then include supplier concentration as a moderating attribute for the recovery rate in table 4 above. These estimates are in Table 5 below. Controlling for the fixed effect of the Holcomb fire's occurrence, as in Table 4, the estimates in Table 5 show how the price spread changes for retailers with differing levels of supplier concentration. Because the $SHHI$ variable is bound between 0 and 1, the coefficient provides an estimate of the difference in spread between a retailer with zero concentration and one with only one supplier, or perfect

concentration.[17] With this interpretation, the estimates in Table 5 show that the direct effect of the shock was much stronger for retailers with highly concentrated supply chains (38.8 points versus 19.5), but the recovery appears to be correspondingly faster: 20.3 points in the first week, 5.8 in the second, 3.4 in the third, and 9.7 in the fourth, with full recovery in 3.01 weeks after the fire. These findings are intuitive relative to our theoretical expectations above: Over-reliance on only a few suppliers increases a retailer's exposure to wholesale-price shocks that may be unique to a single source or a small set of sources, but those suppliers are likely to prioritize important retail accounts. In light of the narrative descriptions of the actions suppliers took to replace the lost supply (Dennis 2020, 2021), large suppliers in the industry were able to bring excess capacity into production, increase supplies, and stabilize wholesale markets relatively quickly.

[Table 5 in here]

Finally, we examine a different measure of concentration, $RHHI$, or the degree of concentration in the downstream, or rival, market. These estimates are in Table 6 below. While supplier concentration affects recovery through the importance of supply relationships and the relative sophistication of large suppliers, rival concentration affects recovery through competition in the consumer market. Because retailer compensation for their role in distributing products to consumers comes through the difference between retail and wholesale prices, the rival-concentration effect manifests through the retail price, not the wholesale price as in the supplier concentration effect in table 5. In table 6, we see a similar pattern as in table 5, but less uniform. That is, the shock itself was stronger for retailers in more concentrated markets (6.8 points lower, or 26.2 points of spread reduction versus 19.5) but recovered nearly all of its losses in the first week after the fire (21.8 points), only to lose ground in the next week, and fully recover by the end of the third week. The net effect means that retailers in concentrated markets recover roughly 0.5 weeks faster than those in less concentrated markets. If retail concentration implies greater market power, then clearly retailers in more concentrated markets are able to raise prices to compensate for higher wholesale prices, all else constant, relative to retailers in more competitive markets.

[17] Note that this variable definition scales the usual HHI definition by $10,000$, as the traditional definition is not useful for econometric estimation purposes.

[Table 6 in here]

We also find that some of the other control variables are relevant to the resilience of the beef retail supply chains we examine here. However, because Cattle on Feed and Retail and Wholesale and Retail Inventory only vary at a national level, by week, we use Model 2 from table 4 to estimate the effect of the full set of controls, including these three variables. Our findings for these variables are shown in table 7 below. First, we include VARIETY, or a measure of the depth of retail assortment, as a proxy for product complexity. Complexity can either reduce resilience as offering a wider range of products exposes the retailer to a larger number of shocks, from many different sources, and can reduces the likelihood of effective collaboration [**?**]. On the other hand, offering more products also raises diversification and the "portfolio effect" of spreading risks across different sources (Wiedmer, et al. 2021). In our data, the former dominates as retailers with deeper assortments in the beef category appear to be less resilient. Second, we measure a retailer's ability to collaborate using FEATURE and DISPLAY, two measures of promotional activity in the NielsenIQ data. If retailers are able to anticipate lower supplies and higher wholesale prices, they will reduce promotional activity, so expect resilience and promotional activity to be negatively correlated, which our estimates in table 7 support. Third, we proxy product velocity using interpurchase times (ITT), or the number of days between purchases in the beef category. Shorter inventory turnover times should reduce our measure of resilience as retailers hold less inventory at any given point in time, so are more likely to pass along recent wholesale price increases as higher retail prices. On the other hand, retailers are able to turnover higher-priced inventory more quickly and source lower-priced inventory from elsewhere. Further, shorter interpurchase times suggest consumers regard the items as staple goods, and are more likely to pay higher retail prices if wholesale price disruptions force retailers to raise prices. Our estimates in table 7 suggest that the former effect dominates as velocity tends to be negatively correlated with resilience. Fourth, we expect both inventory measures to be positively associated with resilience as greater redundancy in the system provides retailers more latitude to negotiate with suppliers, and to protect consumers from rapid price increases associated with recently-purchased inventory. We find that retail inventories are indeed associated with greater

resilience, but wholesale inventories are negatively related. In our case, we may be picking up the fact that beef inventories are simply usually-low so the data are not likely to reveal any opportunities for truly-large wholesale inventories leading to lower wholesale prices. Finally, our measure of CATTLE on FEED captures expected future supplies of beef on the market. If wholesale markets are efficient, and current prices capture expected future supplies, we expect price-based resilience to be positively associated with live-cattle inventories. Our results in table 7 also support this hypothesis.

[Table 7 in here]

In summary, we find that both supplier and retailer concentration have economically-important effects on the resilience of retail food supply chains. Consistent with our theoretical expectations, greater supplier concentration tends to exacerbate the initial shock from a disruption, but also speeds the recovery to pre-disruption conditions. In this sense, our findings with respect to supplier concentration are opposite to that of [**?**], who find that supplier concentration reduces the initial shock of a disruption, but slows the recovery. Although our definition of downstream concentration differs from theirs (buyer concentration is not the same as rival concentration), our findings are consistent in that they find that buyer concentration worsens the impact of a disruption, but aids in recovery. Both sets of results suggest that the answer to which type of market is more resilient lies in the nature of the vertical relationships between entities, and how their relative bargaining power affects their incentives to either absorb or accentuate the effect of disruptions. We suggest future research ideas along these lines below, but finish our results presentation by examining the sensitivity of our findings to our underlying identification assumptions.

5.3 Robustness Checks

We conduct a number of robustness checks in order to examine the sensitivity of our base-model results to how our maintained counterfactual definition, and a number of other assumptions underlying our core model. First, we examine how price spreads in the beef category compare to price spreads in four other product categories during the Holcomb-fire event-study window. We estimate four models that estimate the change in price spreads

in the beef category relative to spreads in the milk, eggs, potato, and apple categories, respectively. In each case, the dependent variable represents the week-to-week change price spreads in the beef category relative to spreads in each of the other categories. In essence, therefore, we use these other categories as control categories relative to prices in the affected beef category.

We show our estimates of this alternative model in table 8 below. In this table, based on our findings above, we expect price-spreads to narrow in the beef category relative to other, presumably non-affected categories. The estimates in table 8 show that this is indeed the case with respect to every category, to varying degrees. The impact relative to milk is small relative to the other categories (8.1% relative to 38.1% initial shock), but this is perhaps due to the nature of milk pricing. In general, milk prices in the U.S. are highly regulated, and it is often used by retailers as a loss-leader so it may be the case that retailers seek to use milk pricing to offset the effect of higher retail prices in other categories on consumers. For the other categories, including eggs (Model 2), potatoes (Model 3), and apples (Model 4), relative price-spreads in beef took from 2 weeks (eggs) to 7 weeks (apples) to recover and return to pre-disruption levels. Regardless, our conclusions regarding the effect of the Holcomb fire on beef-price spreads holds when we use spreads in other categories as control – the disruption appeared to cause a significant widening of spreads, which slowly returned to normal over time.

[Table 8 in here]

Next, we re-estimate the models in table 8 with the event-study terms on the right-side of the model in (2) interacted with supplier concentration, as in equation (3), but with our alternative identification assumption. In table 9, the estimates show a slightly different pattern to those presented in table 7 above. Namely, price spreads in retailers with more concentrated supplier bases are less affected in the intitial period, but still return to their previous levels more quickly than in the base model. In short, when we define our counterfactual as other categories, rather than simply prior values of spreads in the beef category, we see the same qualitative effect of concentration hastening the process of recovery relative to less concentrated supply chains.

[Table 9 in here]

6 Conclusions

In this paper, we examine the resilience of food supply chains from an empirical lens, and consider prices as a sufficient statistic for supply chain resilience. Prices reflect the balance of buying and selling pressure in the market, and are more readily available than actual product flows, so represent an ideal way to study supply chain risk, and supply chain resilience. We focus on a disruption to the fresh beef retail supply chain that removed 6% of the U.S. supply of fresh beef in 2019 to examine the change in price spreads, defined as retail prices less wholesale prices, among a large set of retail grocery chains in five metropolitan markets. We examine the influence of concentration both among beef suppliers and rivals in the retail market in an event-study econometric framework.

Controlling for week, store, and store-by-week fixed effects, and a range of control variables, we find that beef price spreads narrowed significantly during the disruption period as retailers maintained relatively constant prices in the consumer market and absorbed much higher wholesale prices. Retailers with more highly concentrated supply chains, however, narrowed their price spreads by nearly 100% (98.9%) relative to their non-concentrated competitors, but recovered some 13.3% faster (3.01 weeks versus 3.52 weeks). Although suppliers who provide a large share of an individual retailer's beef output may be able to exercise a greater degree of market power, and hold wholesale prices higher for longer, it appears that the value of stronger supply relationships dominates, and supplier concentration improves resilience. We also examine the impact of downstream concentration, or rival concentration in the consumer market on price-based resilience. In this case, we find that the initial shock is again larger for retailers in more concentrated markets, but not as large as concentrated supply markets, and spreads also return to their pre-disruption levels much faster than otherwise. When retail markets are more highly concentrated, it is likely that retailers are simply better able to pass along wholesale price increases to consumers, and re-establish retail price spreads after a disruption.

Our findings are important because there is a clear policy debate regarding the impact of concentration on supply chain resilience. In the wake of the COVID-19 pandemic, federal policy initiatives in the U.S. targeted highly concentrated food supply chains under an assumption that large suppliers imply equally large failures. Policy assumptions like this are understandable given that Cournot (quantity-based) conduct implies greater volatility and margins that are inversely related to the number of firms in the industry. However, research in the operations and supply chain management literatures suggests the opposite – that large, sophisticated buyers and sellers are better able to maintain supply relationships through disruptions and manage through crises like the Holcomb plant fire. Our findings support the latter perspective, that concentrated supply chains tend to promote resilience rather than detract from it. Instead of subsidizing smaller, local food suppliers, therefore, our policy recommendations instead support a more "hands off" or market-based approach to maintaining resilience.

Future research in this area would benefit from more granular data on retailer wholesale markets. With retailer-specific inventory and purchasing data we would be able to see clearer supply-chain paths between suppliers and retailers, and connect events to ordering behavior. Second, and similarly, with data on shipments from individual processing plants we would be able to see exactly how suppliers sought to make up for shortfalls, either in their own production or from rivals, in the event of a disruption like the wholesale fire. Because supply has to equal demand for highly perishable categories like beef, we can infer shipments from retail sales, but the connection is not perfect. Finally, our event-study approach assumes that the pre-disruption period represents a time of relatively "normal" sales activity and pricing. However, in many perishable product categories, periods of normalcy are rare and business-as-usual tends to consist of a series of "normal disruptions." Future research may want to consider quantifying exactly what constitutes a true disruption in highly volatile consumer markets.

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Table 1. Retail, Wholesale and Covariate Data Summary

Variable	Units	Mean	Std. Dev.	Min.	Max.
Beef Spread	$ / lb.	$0.0921	$0.0913	-$0.2247	$0.9782
Milk Spread	$ / lb.	$0.3233	$0.0927	$0.0784	$0.8812
Egg Spread	$ / lb.	-$0.0360	$0.0532	-$0.3114	$0.1378
Potato Spread	$ / lb.	$0.0263	$0.0176	-$0.0248	$0.2645
Apple Spread	$ / lb.	$0.0640	$0.0218	-$0.0383	$0.1463
Beef Supplier HHI	Index	0.6473	0.2646	0.1041	1.0000
Milk Supplier HHI	Index	0.3958	0.1828	0.0863	1.0000
Egg Supplier HHI	Index	0.5296	0.2109	0.0589	1.0000
Potato Supplier HHI	Index	0.5491	0.2166	0.1005	1.0000
Apple Supplier HHI	Index	0.6465	0.2371	0.1082	1.0000
Retail HHI	Index	0.3179	0.1971	0.1621	0.8374
Variety	#	13.1782	7.6543	1.0000	45.0000
Feature	%	0.58%	3.70%	0.00%	100.00%
Display	%	0.04%	0.75%	0.00%	66.67%
Interpurchase Time	Days	25.8801	5.0090	10.2727	42.4872
Retail Inventory	$ billion	50.5212	1.9305	47.4940	55.1630
Wholesale Inventory	$ billion	40.1332	1.3296	38.1470	42.7890
Cattle on Feed	million	3.6099	0.9256	1.8000	5.4000

Note: All retail data from NielsenIQ RMS data, wholesale data from USDA-AMS Market News Service, inventory data from Bureau of Census, Surveys of Retail and Wholesale Trade, respectively, and cattle on feed from USDA-NASS.

Table 2. Price Spreads, by Category, Before and After Disruption

	Before		During		After	
	Spread	Std. Dev.	Spread	Std. Dev.	Spread	Std. Dev.
Beef	0.0813***	0.0643	0.0747	0.0623	0.0916***	0.0619
Milk	0.3240	0.0864	0.3265	0.0872	0.3280	0.0843
Eggs	-0.0301	0.0376	-0.0310	0.0267	-0.0306	0.0275
Potatoes	0.0306	0.0184	0.0308	0.0186	0.0320***	0.0198
Apples	0.0651***	0.0288	0.0675	0.0202	0.0690***	0.0237

Note: All estimates from the combined NielsenIQ RMS and USDA AMS data. “Before" is defined as the 5 weeks prior to the Holcomb Fire, “During" is the week of the fire, and “After" is the 5 weeks subsequent to the fire. *** ($p < 0.01$), ** ($p < 0.05$), * ($p < 0.10$), where null hypothesis maintains spread in Before / After period is the same as During.

Table 7. Control Variables in Resilience Model

Variable	Estimate	Std. Err.
Variety	-0.0116***	0.0049
Feature	-0.0735***	0.0131
Display	-0.1544***	0.0644
Interpurchase Time	-0.0012***	0.0001
Retail Inventory	1.2220***	0.0266
Wholesale Inventory	-1.3069***	0.0259
Cattle on Feed	0.0010***	0.0003
Constant	-0.0604***	0.0065

Note: Model is Base Model in Table 4 with controls. Variety simple assortment county by store and week, Feature and Display are promotion variables in NielsenIQ RMS data, Interpurchase Time calculated from NielsenIQ Consumer Panel data for beef category, and represents days between purchase, on average, for each market, Retail and Wholesale Inventory from Bureau of Census, Cattle on Feed from USDA, NASS. Standard errors clustered at the store level. *** ($p<0.01$), ** ($p<0.05$), * ($p<0.10$).

Table 3. Reduced-Form Estimates of Recovery Rates

	Model 1		Model 2		Model 3		Model 4		Model 5	
Variable	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.
gspread	-0.1700	0.0042	-0.1664	0.0048	-0.4224	0.0093	-0.5449	0.0099	-0.5636	0.0111
gspread*fire	0.0586	0.0060	0.1387	0.0135	0.0545	0.0124	0.0303	0.0026	0.0228	0.0119
Assortment	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	0.0030	0.0002
Supplier HHI	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	-0.2435	0.0154
Retail HHI	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	-1.5831	0.0705
Feature	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	-0.0797	0.0115
Display	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	-0.1172	0.0404
ITT	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	N.A.	-0.0013	0.0001
Week FE	No		Yes		Yes		Yes		Yes	
Store FE	No		No		Yes		Yes		Yes	
Week*Store FE	No		No		No		Yes		Yes	
Controls	No		No		No		No		Yes	
R^2	0.0844		0.2667		0.3691		0.4184		0.4549	
RMSE	0.1398		0.1252		0.1165		0.1122		0.1087	

Note: Models estimated with Kilts / NielsenIQ RMS data for retail prices in the beef category, and wholesale prices from the Livestock Information Center (choice cuts) on a weekly basis, 2018 - 2021. The “fire" variable refers to the Tyson beefpacking plant fire in Holcomb, KS in week 84 of the data. Model 1 estimates the rate of price-spread reversion with no fixed effects or controls, Model 2 adds week fixed effects, Model 3 adds store-level fixed effects, Model 4 adds store-by-week fixed effects, and Model 5 adds controls. All standard errors are clustered at the store level.
Model 4 adds store-by-week fixed effects, and Model 5 adds controls. All standard errors are clustered at the store
*** ($p < 0.01$), ** ($p < 0.05$), * ($p < 0.10$).

Table 4. Event-Study Models of Fire Recovery

	Model 1		Model 2		Model 3		Model 4		Model 5	
Variable	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.
Spread (t-5)	0.1968	0.0128	0.1959	0.0128	0.3042	0.018	0.3044	0.018	0.3082	0.0181
Spread (t-4)	-0.0915	0.0085	-0.0925	0.0085	-0.1146	0.0122	-0.1144	0.0123	-0.1121	0.0123
Spread (t-3)	-0.0566	0.0112	-0.0576	0.0113	-0.0649	0.0168	-0.0648	0.0168	-0.0592	0.0163
Spread (t-2)	-0.1159	0.0084	-0.1168	0.0084	-0.1048	0.0119	-0.1047	0.0119	-0.1121	0.0122
Spread (t-1)	0.2508	0.0065	0.2498	0.0065	0.0301	0.0091	0.0301	0.0092	0.0256	0.0093
Spread (t=0)	-0.1259	0.0076	-0.1268	0.0076	-0.1932	0.0115	-0.1931	0.0116	-0.1948	0.0117
Spread (t+1)	0.0456	0.0056	0.0447	0.0056	0.1107	0.0086	0.1108	0.0086	0.1109	0.0085
Spread (t+2)	0.0256	0.0062	0.0247	0.0062	0.0105	0.0146	0.0105	0.0146	0.0100	0.0146
Spread (t+3)	0.0398	0.0061	0.0388	0.0061	0.0358	0.0164	0.0358	0.0164	0.0313	0.0165
Spread (t+4)	-0.1536	0.0063	-0.1545	0.0064	0.0852	0.01	0.0852	0.0101	0.0885	0.0101
Spread (t+5)	-0.1025	0.0064	-0.1034	0.0065	-0.0964	0.0101	-0.0964	0.0101	-0.1052	0.0105
Store Effects?	No		Yes		Yes		Yes		Yes	
Week Effects?	No		No		Yes		Yes		Yes	
Store-by-Week Effects?	No		No		No		Yes		Yes	
Controls	No		No		No		No		Yes	
R^2	0.0094		0.0095		0.2145		0.2147		0.2183	
RMSE	0.1522		0.1528		0.1361		0.1367		0.1366	

Note: Dependent variable is the change in the log-price spread from previous period to the current period, while explanatory variables are the lag of the log-price price at periods from t-5 to t+5. Coefficients therefore represent rates of rates of change back to the pre-shock level during each time period in the table. Models estimated with Kilts / NielsenIQ RMS data for retail prices in the beef category, and wholesale prices from Livestock Information Center (choice prices from the Livestock Information Center (choice cuts) on a weekly basis, 2018 - 2021. The “fire" variable refers to the Tyson beefpacking plant fire in Holcomb, KS in week 84 of the data. Model 1 estimates the rate of price-spread reversion with no fixed effects or controls, Model 2 adds week fixed effects reversion with no fixed effects or controls, Model 2 adds week fixed effects, Model 3 adds store-level fixed effects, Model 4 adds store-by-week fixed effects, and Model 5 adds controls. All standard errors are clustered at the storemlevel. Event study model estimated with window of +/- 10 periods, only 5 periods shown for clarity. Control variables include aggregate retail and wholesale inventories, retail assortment depth, mean featuring and display probabilities by store and display probabilities by store for the beef category, interpurchase time for households in the market around the store for the beef category, and the number of cattle on feed. *** ($p < 0.01$), ** ($p < 0.05$), * ($p < 0.10$).

Table 5. Event-Study Models of Recovery and Supplier Concentration

	Model 1		Model 2		Model 3		Model 4		Model 5	
Variable	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.
Spread (t-5)	0.2068	0.0154	0.2046	0.0155	0.1483	0.0171	0.148	0.0172	0.1521	0.0174
Spread (t-4)	-0.2219	0.0116	-0.2241	0.0116	-0.2908	0.0169	-0.2911	0.017	-0.2981	0.0173
Spread (t-3)	0.0326	0.0133	0.0304	0.0133	0.1728	0.0155	0.1725	0.0155	0.1634	0.0149
Spread (t-2)	-0.1671	0.0107	-0.1693	0.0108	-0.0831	0.0134	-0.0833	0.0134	-0.0894	0.0139
Spread (t-1)	0.4762	0.0117	0.4741	0.0118	0.1477	0.0148	0.1475	0.0149	0.1329	0.0152
Spread (t=0)	-0.2658	0.0121	-0.2681	0.0121	-0.3667	0.0165	-0.3668	0.0166	-0.3876	0.0170
Spread (t+1)	0.1114	0.0098	0.1092	0.0098	0.2158	0.0141	0.2157	0.0142	0.2031	0.0143
Spread (t+2)	0.0672	0.0102	0.0651	0.0102	0.0613	0.0213	0.0612	0.0211	0.0581	0.0210
Spread (t+3)	0.0723	0.0096	0.0712	0.0096	0.0568	0.0212	0.0567	0.0211	0.0342	0.0213
Spread (t+4)	-0.2606	0.0103	-0.2629	0.0104	0.1079	0.0151	0.1078	0.0151	0.0973	0.0149
Spread (t+5)	-0.1961	0.0109	-0.1982	0.0111	-0.1767	0.0156	-0.1767	0.0157	-0.1831	0.0163
Store Effects?	No		Yes		Yes		Yes		Yes	
Week Effects?	No		No		Yes		Yes		Yes	
Store-by-Week Effects?	No		No		No		Yes		Yes	
Controls	No		No		No		No		Yes	
R^2	0.0083		0.0084		0.2139		0.2142		0.2177	
RMSE	0.1523		0.1529		0.1362		0.1367		0.1366	

Note: Dependent variable is the change in the log-price spread from previous period to the current period, while explanatory variables are the lag of the log-price price at periods from t-5 to t+5. Coefficients therefore represent rates of rates of change back to the pre-shock level during each time period in the table. Models estimated with Kilts / NielsenIQ RMS data for retail prices in the beef category, and wholesale prices from Livestock Information Center (choice prices from the Livestock Information Center (choice cuts) on a weekly basis, 2018 - 2021. The "fire" variable refers to the Tyson beefpacking plant fire in Holcomb, KS in week 84 of the data. Model 1 estimates the rate of price-spread reversion with no fixed effects or controls, Model 2 adds week fixed effects reversion with no fixed effects or controls, Model 2 adds week fixed effects, Model 3 adds store-level fixed effects, Model 4 adds store-by-week fixed effects, and Model 5 adds controls. All standard errors are clustered at the storemlevel. Event study model estimated with window of +/- 10 periods, only 5 periods shown for clarity. Control variables include aggregate retail and wholesale inventories, retail assortment depth, mean featuring and display probabilities by store and display probabilities by store for the beef category, interpurchase time for households in the market around the store for the beef category, and the number of cattle on feed. *** ($p < 0.01$), ** ($p < 0.05$), * ($p < 0.10$).

Table 6. Event-Study Models of Recovery and Retailer Concentration

	Model 1		Model 2		Model 3		Model 4		Model 5	
Variable	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.
Spread (t-5)	0.6197	0.0450	0.6151	0.0451	0.7537	0.0579	0.7539	0.0582	0.7406	0.0580
Spread (t-4)	-0.2193	0.0275	-0.2239	0.0275	-0.1777	0.0334	-0.1775	0.0335	-0.1785	0.0337
Spread (t-3)	-0.2093	0.0391	-0.2139	0.0393	-0.2363	0.0496	-0.2361	0.0498	-0.2317	0.0479
Spread (t-2)	-0.4384	0.0271	-0.4430	0.0271	-0.4445	0.0349	-0.4444	0.0351	-0.4685	0.0361
Spread (t-1)	0.6588	0.0248	0.6542	0.0249	0.0390	0.0242	0.0391	0.0243	0.0408	0.0247
Spread (t=0)	-0.2801	0.0224	-0.2847	0.0226	-0.2712	0.0295	-0.2711	0.0296	-0.2618	0.0298
Spread (t+1)	0.1308	0.0172	0.1262	0.0173	0.2247	0.0240	0.2248	0.0241	0.2178	0.0240
Spread (t+2)	0.0524	0.0192	0.0478	0.0193	-0.0131	0.0344	-0.0131	0.0345	-0.0293	0.0338
Spread (t+3)	0.1081	0.0200	0.1035	0.0201	0.0685	0.0391	0.0685	0.0392	0.0818	0.0394
Spread (t+4)	-0.3503	0.0228	-0.3549	0.0228	0.2653	0.0272	0.2653	0.0273	0.2595	0.0273
Spread (t+5)	-0.3621	0.0199	-0.3667	0.0200	-0.3536	0.0275	-0.3536	0.0276	-0.3788	0.0288
Store Effects?	No		Yes		Yes		Yes		Yes	
Week Effects?	No		No		Yes		Yes		Yes	
Store-by-Week Effects?	No		No		No		Yes		Yes	
Controls	No		No		No		No		Yes	
R^2	0.0081		0.0082		0.2143		0.2146		0.2180	
RMSE	0.1523		0.1529		0.1362		0.1367		0.1366	

Note: Dependent variable is the change in the log-price spread from previous period to the current period, while explanatory variables are the lag of the log-price price at periods from t-5 to t+5. Coefficients therefore represent rates of rates of change back to the pre-shock level during each time period in the table. Models estimated with Kilts / NielsenIQ RMS data for retail prices in the beef category, and wholesale prices from Livestock Information Center (choice prices from the Livestock Information Center (choice cuts) on a weekly basis, 2018 - 2021. The “fire" variable refers to the Tyson beefpacking plant fire in Holcomb, KS in week 84 of the data. Model 1 estimates the rate of price-spread reversion with no fixed effects or controls, Model 2 adds week fixed effects reversion with no fixed effects or controls, Model 2 adds week fixed effects, Model 3 adds store-level fixed effects, Model 4 adds store-by-week fixed effects, and Model 5 adds controls. All standard errors are clustered at the storemlevel. Event study model estimated with window of +/- 10 periods, only 5 periods shown for clarity. Control variables include aggregate retail and wholesale inventories, retail assortment depth, mean featuring and display probabilities by store and display probabilities by store for the beef category, interpurchase time for households in the market around the store for the beef category, and the number of cattle on feed. *** ($p < 0.01$), ** ($p < 0.05$), * ($p < 0.10$).

Table 8. Event-Study Models of Beef Relative to Other Commodities

	Model 1		Model 2		Model 3		Model 4	
Variable	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.
Spread (t-5)	0.1838	0.0221	-0.1070	0.0171	-0.0162	0.0203	0.2484	0.0199
Spread (t-4)	-0.1263	0.0154	-0.0308	0.0128	0.0767	0.0265	-0.1231	0.0148
Spread (t-3)	-0.1049	0.0211	0.0670	0.0158	-0.1162	0.0197	0.0396	0.0251
Spread (t-2)	-0.1223	0.0111	-0.1925	0.0113	-0.0226	0.0129	-0.1157	0.0233
Spread (t-1)	0.0717	0.0105	0.2548	0.0265	0.0537	0.0177	-0.2600	0.0204
Spread (t=0)	-0.0809	0.0117	-0.4895	0.0195	-0.1848	0.0159	-0.4707	0.0278
Spread (t+1)	0.0500	0.0111	0.3096	0.0164	0.1256	0.0161	0.2042	0.0303
Spread (t+2)	0.0418	0.0140	0.1909	0.0221	-0.0110	0.0139	0.1771	0.0266
Spread (t+3)	-0.0159	0.0177	-0.0984	0.0213	0.0309	0.0150	0.0900	0.0163
Spread (t+4)	0.1426	0.0111	-0.1475	0.0220	-0.0090	0.0109	0.0387	0.0103
Spread (t+5)	-0.1317	0.0127	-0.1842	0.0154	-0.0018	0.0147	-0.0858	0.0263
Store Effects?	Yes		Yes		Yes		Yes	
Week Effects?	Yes		Yes		Yes		Yes	
Store-by-Week Effects?	Yes		Yes		Yes		Yes	
Controls	Yes		Yes		Yes		Yes	
R^2	0.2464		0.4156		0.1349		0.1616	
RMSE	0.1470		0.1952		0.2209		0.2085	

Note: Dependent variable is the change in the log-price spread from previous period to the current period, while explanatory variables are the lag of the log-price spread at periods from t-5 to t+5. Coefficients represent rates of change back to the pre-shock level during each time period. Spreads in this table are defined as the difference between retail beef prices, and retail prices of items in other non-disrupted categories: Milk, eggs, potatoes, and apples for each of our five sample retail markets. Models estimated with Kilts / NielsenIQ RMS data for retail prices in each category, weekly, 2018 - 2019. The "fire" variable refers to the Tyson beefpacking plant fire in Holcomb, KS in week 87 of the data. Model 1 estimates the rate of price-spread reversion between beef and milk prices, Model 2 between beef and egg prices, Model 3 between beef and potato prices, and Model 4 between beef and apple prices. All standard errors are clustered at the store level. Event study model estimated with window of +/- 10 periods, only 5 shown for clarity. *** ($p < 0.01$), ** ($p < 0.05$), * ($p < 0.10$). Control variables include aggregate retail and wholesale inventories, retail assortment depth, mean featuring and display probabilities by store for the beef category, interpurchase time for households in the market around the store for the beef category, and the number of cattle on feed.

Table 9. Event-Study Models of Beef Relative to Other Commodities with Supplier Concentration

	Model 1		Model 2		Model 3		Model 4	
Variable	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.
Spread*SHHI(t-5)	0.1096	0.0065	-0.2016	0.0153	-0.0783	0.0236	0.3022	0.0169
Spread*SHHI(t-4)	0.0227	0.004	-0.0128	0.0109	0.2858	0.0324	0.003	0.0129
Spread*SHHI(t-3)	-0.0684	0.0046	0.1232	0.0123	-0.1032	0.0205	-0.1066	0.0211
Spread*SHHI(t-2)	-0.0073	0.0035	-0.1598	0.0101	-0.0668	0.0159	0.0406	0.0188
Spread*SHHI(t-1)	-0.0386	0.0032	0.1988	0.0204	-0.1633	0.0193	-0.3148	0.0124
Spread*SHHI (t=0)	0.0241	0.0032	-0.3658	0.0166	-0.1395	0.0171	-0.2809	0.0172
Spread*SHHI(t+1)	-0.0042	0.0030	0.2412	0.0122	0.1535	0.0167	0.1082	0.0127
Spread*SHHI(t+2)	-0.0149	0.0030	0.1530	0.0152	-0.0272	0.0146	0.0458	0.0181
Spread*SHHI(t+3)	-0.0059	0.0030	-0.0683	0.0159	0.0230	0.0138	0.0519	0.0102
Spread*SHHI(t+4)	0.0205	0.0038	-0.1113	0.0177	-0.0056	0.0130	0.0484	0.0084
Spread*SHHI(t+5)	-0.0324	0.0042	-0.1015	0.0135	0.0266	0.0157	-0.2087	0.0226
Store Effects?			Yes		Yes		Yes	
Week Effects?			Yes		Yes		Yes	
Store-by-Week Effects?			Yes		Yes		Yes	
Controls			Yes		Yes		Yes	
R^2	0.2480		0.4153		0.1357		0.1619	
RMSE	0.1469		0.1952		0.2208		0.2084	

Note: Dependent variable is the change in the log-price spread from previous period to the current period, while explanatory variables are the lag of the log-price spread at periods from t-5 to t+5, interacted with the fire indicatore and SHHI. Coefficients represent rates of change back to the pre-shock level during each time period. Spreads in this table are defined as the difference between retail beef prices, and retail prices of items in other non-disrupted categories: Milk, eggs, potatoes, and apples for each of our sample retail markets. Models estimated with Kilts / NielsenIQ RMS data for retail prices in each category, weekly, 2018 - 2019. The “fire" variable refers to the Tyson beefpacking plant fire in Holcomb, KS in week 87 of the data. Model 1estimates the rate of price-spread reversion between beef and milk prices, Model 2 between beef and egg prices, Model 3 between beef and potato prices, and Model 4 between beef and apple prices. Standard errors are clustered at the store level. Event study model estimated with window of +/- 10 periods, only 5 shown for clarity. *** ($p < 0.01$), ** ($p < 0.05$), * ($p < 0.10$). Control variables include aggregate retail and wholesale inventories, retail assortment depth, mean featuring and display probabilities by store for the beef category, interpurchase time for households in the market around the store for the beef category, and the number of cattle on feed.