Causal Effects of Multi-plant Coordination in the US Beef Packing Industry

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Causal Effects of Multi-plant Coordination in the U.S. Beef Packing Industry

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Abstract. Why have no economic studies utilized differences-in-differences to study price discovery and competition in the U.S. cattle and beef industry? Industry complexities make it difficult, if not impossible, to find untreated control groups necessary for differences-in-differences estimation. To overcome these challenges, we introduce novel theory and methods to demonstrate that a never-treated "device" can be used as a valid control group for identifying the average treatment effect on the treated group. Employing an industry wage rate series as our device, along with a panel of regional fed cattle to wholesale boxed beef price spreads, we estimate the cattle to beef price spread impacts of the industry-wide implementation of multi-plant coordination. Using the 2013 multi-plant coordination shutdown of a large beef packing plant as a marker for multi-plant coordination implementation, we estimate that cattle to beef price spreads were 13.5% wider in the post-shutdown period than they would have been in the absence of the business practice. This amounts to $\$9.42$/cwt that was captured by the beef packing industry from upstream cattle producers and/or downstream wholesale beef purchasers due to multi-plant coordination.

Keywords. Beef, Cattle, Causal Inference, Differences-in-Differences, Livestock Economics, Multi-plant Coordination

JEL Codes. L11, L13, L22, Q02, Q13, Q18

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1. Introduction

Differences-in-differences (DiD) is one of the most widely accepted and frequently applied econometric methodologies for estimating the causal effects of policies, events, and market interventions (Baker et al. 2025). The U.S. cattle and beef industry is one of the most-studied supply chains in the entire world (Sexton 2000), and several studies of the industry use methods conceptually similar to DiD (McKendree, Saitone, and Schaefer 2021; Pouliot and Sumner 2014; Pudenz and Schulz 2021; Schulz, Schroeder, and Ward 2011). Yet, we are not aware of any studies that have applied DiD *per se* to investigate price discovery and competition in the U.S. cattle and beef market. This begs the question, why has this ubiquitous tool not been applied in this setting?

Simply put, the U.S. cattle and beef supply chain "may well be the most complex set of markets in existence" (Peel 2021, p. 3). Cattle production and beef consumption are necessarily spread out throughout the country (Moschini and Smith 2025), and biological and logistical constraints result in unique, lagged, and sometimes counterintuitive responses to market signals (Lusk, Tonsor, and Schulz 2021; Rosen, Murphy, and Scheinkman 1994). The cattle and beef supply chain features a highly concentrated beef packing industry that is co-located and vertically-integrated with fed cattle production, and as Pudenz and Schulz (2024) demonstrate, in recent decades the largest companies have fully implemented multi-plant coordination, a form of intra-firm horizontal integration, among their multiple plants. Adding an additional layer of complexity are a wide variety of price discovery mechanisms for both cattle and beef, with prices for many transactions calculated using prices from other market segments or geographies (Xia and Sexton 2004; Anderson, Mitchell, and McKenzie 2022).

Such complexity and interconnectedness preclude the application of traditional DiD estimation to study price discovery and competition in the U.S. beef supply chain. With publicly-available cattle price data published at the regional level, there is surface-level use case appeal for the potential outcomes framework. However, there exist no plausibly untreated cattle or beef prices. A change in one region or market segment nearly universally influences pricing in another region or segment, directly or indirectly. Hence, in the language of Abadie (2005), there is no true "untreated comparison group" on which the identification of the conventional DiD framework relies. Therefore, DiD cannot be correctly applied, and researchers use other methods.

This research overcomes these challenges by introducing novel methodology for applying DiD

estimation. Specifically, we extend the classical potential outcomes framework with an innovation we call a "device." We apply our methods to estimate the fed cattle to wholesale boxed beef price spread impacts of multi-plant coordination implementation in the U.S. beef packing industry. Our innovative methods require very particular circumstances and data for proper application to the cattle and beef industry. These conditions are met by focusing on specific monthly Iowa/Minnesota regional cattle to beef price spreads, as well as relevant untreated industry wages in Iowa/Minnesota, from 2010 to 2015. The multi-plant coordination treatment is February 2013, which comes from a large beef packing company announcing the permanent closure of a large cattle slaughter plant and publicly acknowledging that company's multi-plant coordination activities. That company was not the first, nor the last, to implement multi-plant coordination, but its plant closure and concurrent acknowledgment of company-wide horizontal integration mark a watershed moment in the industry-wide implementation of the business practice.

Ultimately, our DiD estimation finds that full implementation of multi-plant coordination in the beef packing industry led to Iowa/Minnesota cattle to beef price spreads that were wider than they would have been in the absence of multi-plant coordination. In our baseline analysis, cattle to beef price spreads were 13.5% wider due to this business practice, amounting to $\$9.42$/hundredweight (cwt). Notably, our methods are agnostic as to which supply chain segment (fed cattle producers upstream, or beef procurers downstream) felt these effects more strongly. It is quite possible that most of the estimated price spread increase was passed downstream to wholesale beef purchasers, ultimately raising prices for consumers at retail.

This paper proceeds as follows. Section 2 lays out the details surrounding the 2013 beef packing plant closure of interest, explains how multi-plant coordination was at the core of the decision, and discusses how our research fits in the literature. Section 3 details the data utilized in the analysis and highlights how the data meets the requirements for DiD application. Section 4 establishes the novel identification methodology using our device innovation, while section 5 introduces a conceptual cattle to beef price spread model that supports identification. Section 6 presents DiD estimation results, and section 7 interprets those results. To conclude, section 8 formulates potential competition implications of our research, as well as potential extensions of the framework to other complex, concentrated industries.

2. U.S. Beef Supply Chain Background and Relevant Literature

On February 1, 2013, Cargill, Inc. permanently closed its 4,650 head/day fed cattle slaughter plant near Plainview, Texas (Fernandez 2013). Industry sources reported that the plant accounted for approximately 4% of national fed cattle slaughter capacity (Daily Livestock Report 2013). In their press release announcing the closure, Cargill, Inc. (Cargill) cited low cattle inventories as the determining factor, saying the shutdown resulted "primarily from the tight cattle supply brought about by years of drought in Texas and Southern Plains states" (Cargill 2013). Some studies have considered the economic impacts of the closure on the local Plainview economy using input-output models (Dudensing et al. 2013; Dudensing, Guerrero, and Amosson 2019), but few economic studies have discussed the motivations for—and beef supply chain implications of—the shutdown.

The Cargill plant closure took place during a prolonged trough in the U.S. cattle cycle. The cattle cycle is a well-documented phenomenon in the U.S. cattle industry (Rosen, Murphy, and Scheinkman 1994). Figure 1 shows the U.S. all cattle and calves inventory on January 1 of each year dating back to 1990 (USDA-NASS n.d.a). Cattle cycles are measured from one cyclical low in inventory numbers to the next. Three distinct cattle inventory cycles can clearly be seen in Figure 1: January 1, 1990 to December 31, 2003; January 1, 2004 to December 31, 2013; and January 1, 2014 to January 1, 2025 (present). The cycle beginning on January 1, 2004, saw cattle inventories peak on January 1, 2007, after which U.S. cattle inventories fell every year through 2014. As shown by the dashed lined in Figure 1, the Cargill plant closure occurred in the last year of that cycle. The January 1, 2013, inventory of all cattle and calves was the lowest on hand since 1952 (USDA-NASS 2013), and these cattle inventories were even lower to begin 2014 (USDA-NASS 2014).

At the time of the 2013 Cargill plant closure, the company had six other cattle slaughter plants throughout the country, several of which were operating at sub-optimal capacity utilization levels. Cargill's plants are shown as green squares in Figure 2, which depicts fed cattle slaughter plants in the United States in 2010 with at least 500 head-per-day capacity. Shutting down the plant in Plainview, TX, the company argued, "would allow Cargill to operate its other beef plants in Texas, Colorado and Kansas more consistently on a five-day-per-week basis to meet [their] customers' requirements, while helping [them] maintain [their] position in the U.S. beef sector" (Cargill 2013).[1] Cattle previously shipped to Plainview would instead be processed at plants in Friona, TX;

[1] See Appendix A for the complete text of Cargill's press release from January 17, 2013.

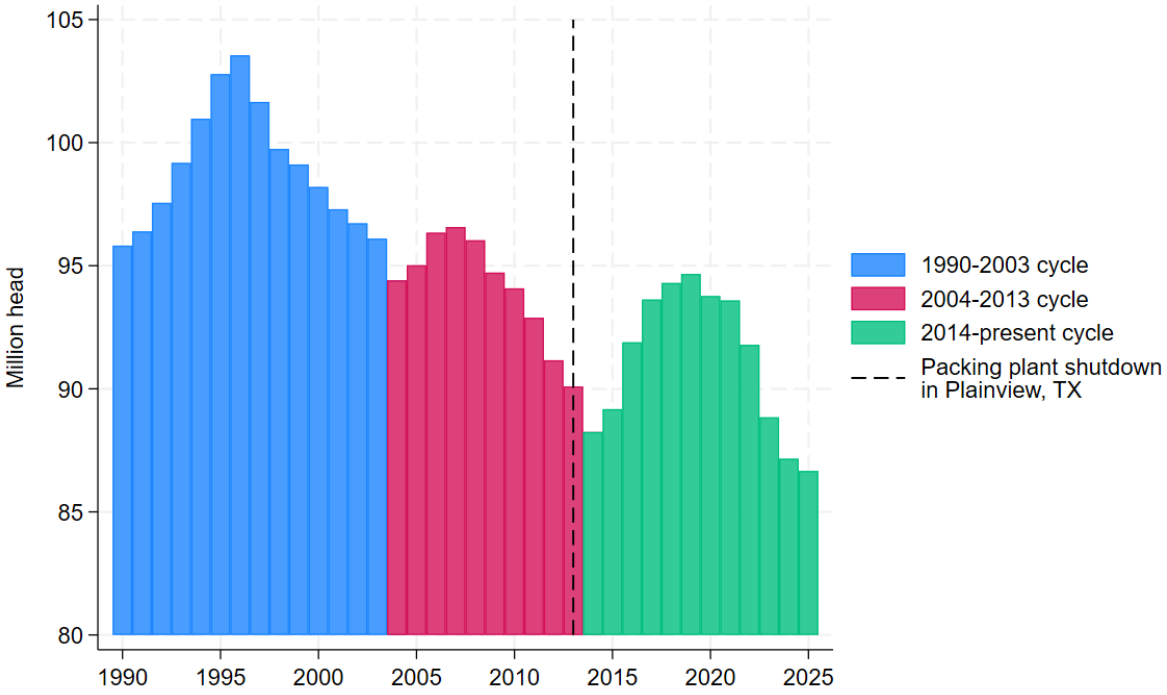

Figure 1: All cattle and calves inventory – United States: January 1

Dodge City, KS; and Fort Morgan, CO, the company said, all three of which are within 500 miles of Plainview, TX (see Figure 2).[2] This reshuffling brought company-wide packing capacity utilization closer in line with fed cattle supplies, and had broader beef packing sector impacts. According to the Livestock, Dairy, and Poultry Outlook published by the Economic Research Service (ERS) of the USDA shortly after the plant closure, "In the long run, closing of the Cargill meat packing plant in January of this year will likely be a positive thing for the meat packing industry" since it "immediately raised packer capacity utilization rates" (Johnson 2013, p. 4).

Cargill's press release is filled with language highlighting the company's use of multi-plant coordination (Pudenz and Schulz 2024). In the cattle and beef industry, multi-plant coordination is the firm-wide coordination of procurement, processing, and downstream beef marketing activities among the multiple plants operated by a multi-plant beef packer. The literature has identified three motivations for multi-plant coordination in the U.S. beef packing industry. First, multi-plant coordination allows for firm-wide optimization of packing capacity utilization

[2]Cattle feedlots and slaughter plants are typically regionally co-located, which allows for expedited delivery for slaughter, minimum transport time for cattle, and relatedly, minimum stress for cattle. In 2011, the average distance traveled for cattle shipments moving directly to slaughter facilities was 166 miles for cattle feedlots with a capacity of 1,000 or more head, and only 87 miles for feedlots with a capacity of fewer than 1,000 head (USDA-APHIS-VS 2013).

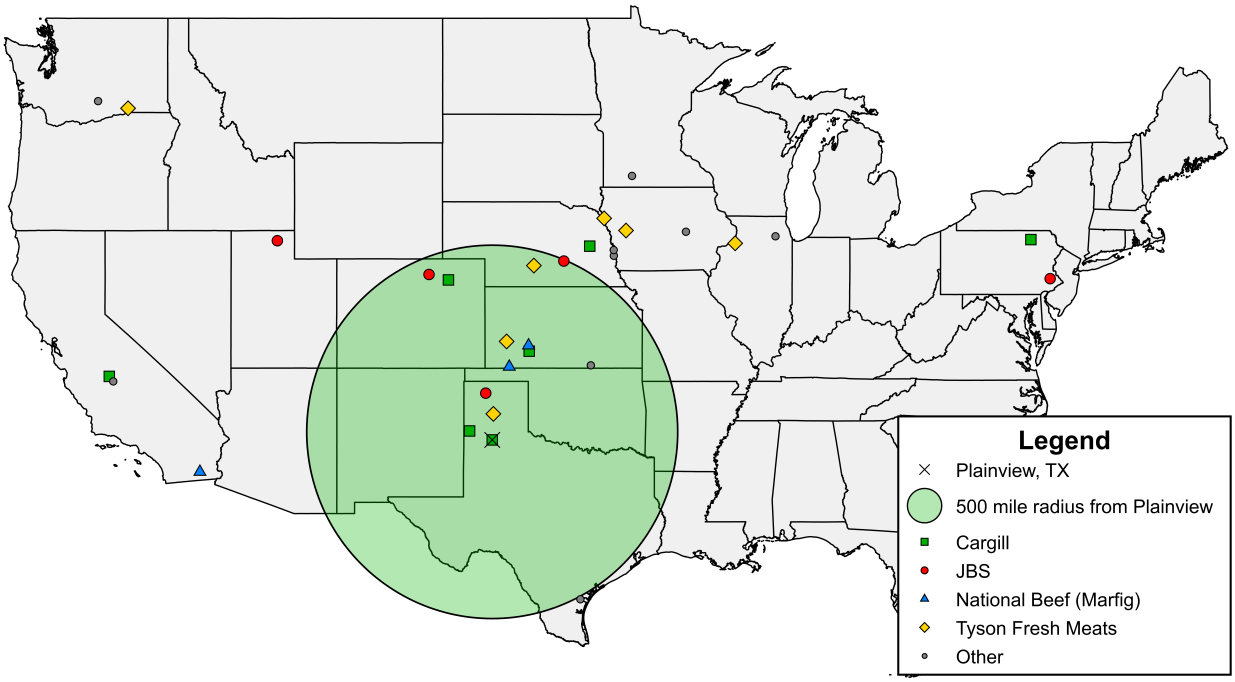

Figure 2: Fed cattle slaughter plants with at least 500 head-per-day capacity in 2010 by company. Data compiled from industry sources.

(MacDonald 2003). Second, multi-plant coordination could allow for economies of scale related to processes previously handled at the plant level, such as procurement. Third, multi-plant coordination reduces intra-firm competition among the several plants owned by multi-plant firms (Pudenz and Schulz 2024). Despite the evident potential benefits to beef packers, the complexity of the cattle and beef supply chain delayed implementation, likely until big data, cloud computing, machine learning, and artificial intelligence tools made firm-wide horizontal integration technically feasible (Scherer et al. 1975). Consequently, all available empirical evidence suggests that multi-plant coordination was not being effectively employed by the beef packing industry as late as 2005 (Morrison Paul 2000; Crespi and Sexton 2004; Koontz and Lawrence 2010).

The theoretical implications of multi-plant coordination for the cattle and beef supply chain flow directly from its motivations. First, efficiencies from multi-plant coordination economies of scale could get shared upstream to the cattle industry and/or downstream to wholesale beef purchasers in the form of higher or lower prices, respectively. Second, and conversely, the reduction in intra-firm competition could lead to lower fed cattle prices upstream and/or higher wholesale beef prices downstream. The net result of these two offsetting effects is uncertain theoretically, leaving it up to

empirical investigations to determine which effect outweighs the other (Pudenz and Schulz 2024).

Multi-plant coordination has a third theoretical implication for the U.S. cattle and beef supply chain, and it pertains to multi-plant coordination shutdowns. Compared to when plants are operated as individual entities, a multi-plant coordinating firm is more likely to shut down one of its facilities as cattle inventories decline, and such shutdowns lead to wider cattle to beef price spreads (Pudenz and Schulz 2024). While less immediately obvious, this implication is intuitive, as a horizontally integrated packing firm will be better positioned to capture the capacity utilization externalities from shutting down one of its plants. Multi-plant coordination clearly was operative in the Cargill plant closure in Plainview, TX, as well as for a slew of post-2005 packing plant closures. Tyson Fresh Meats (Tyson) used multi-plant coordination explanations when announcing the shutdowns of its packing plants in Emporia, KS, in 2008, and Denison, IA, in 2015; while National Beef Packing Company, LLC (National Beef) revealed the practice when announcing the 2014 shutdown of its Brawley, CA, packing plant (Pudenz and Schulz 2024). The cumulative impact of these shutdowns shifted supply chain leverage toward the packing industry, away from both upstream cattle producers and downstream wholesale beef purchasers. In fact, these multi-plant coordination shutdowns yielded a situation starting in 2016 in which national U.S. steer and heifer slaughter was greater than steer and heifer slaughter capacity for the first time in 35 years (Peel 2021).

Cargill's public acknowledgment of multi-plant coordination in their January 17, 2013, press release marks a watershed moment for the industry-wide implementation of multi-plant coordination. With Tyson's acknowledgment of the practice in 2008, Cargill's adoption brought more than half of U.S. fed cattle slaughter capacity at plants with more than 500 head per day capacity under the business practice (Pudenz and Schulz 2024). While the other multi-plant beef packers (JBS S.A. and National Beef) could have been utilizing the business practice in 2013 or earlier, there is no publicly-available evidence that this was taking place.

Despite industry-wide adoption and a clear trend of multi-plant coordination shutdowns, little economic research has been published regarding the business practice. Two recent studies, however, address multi-plant coordination and investigate its implications. Pudenz and Schulz (2024) develop a series of applied theoretical models based on Salop's Circular City to show that multi-plant coordination leads to wider spreads between downstream beef prices and upstream

fed cattle prices if multi-plant coordination markdowns outweigh multi-plant coordination efficiencies. Moschini and Smith (2025) develop and calibrate a spatial model in the U.S. beef packing industry utilizing 2022 data, and they attribute a small portion of the estimated fed cattle price markdown to multi-plant coordination.

This study is the first to apply DiD to estimate the causal effects of multi-plant coordination. Previous research has applied methods that are conceptually similar to DiD estimation in investigations of price discovery and competition in U.S. cattle and beef market (Pouliot and Sumner 2014; Schulz, Schroeder, and Ward 2011). None of this work, however, applies DiD *per se*. For example, two recent studies of the fed dairy cattle industry utilize econometric methods conceptually similar to DiD estimation (Pudenz and Schulz 2021; McKendree, Saitone, and Schaefer 2021). Neither of the articles actually uses DiD estimators, however, and instead rely on pre-treatment econometric relationships and forecasting methods to construct a post-treatment counterfactual. These post-treatment forecasts are then used to calculate forecasting errors, and thereby the effects of the change in procurement practices. While entirely valid, this methodology is rooted in the reality that it is very difficult to find untreated control groups in the U.S. cattle industry. As a result, the implicit counterfactual underpinning DiD results cannot be obtained. The same cattle and beef industry complexities that delayed implementation of multi-plant coordination also negated use of DiD to study the beef supply chain, until now. Further frustrating research efforts is the reality that, if such control groups can be found, the data may not exist at all, let alone publicly.

3. Data

Our analysis utilizes monthly data for March 2010 through July 2015. Regional fed cattle prices and national wholesale boxed beef values are used to calculate cattle to beef price spreads. Relevant industry wages serve as our device and are therefore critical for our novel DiD estimation. All data are publicly available.

3.1. Beef Values

Starting with beef values, we calculate monthly average national downstream boxed beef values, b_{kt}, from daily Choice 600-900 and Select 600-900 beef values in USDA Agricultural Marketing Service (USDA-AMS) report LM_XB403, which contains *National Daily Boxed Beef Cutout and Boxed Beef Cuts - Negotiated Sales* data. Notably, these beef values are free-on-board (FOB) values. Daily data from

this report is averaged for each calendar month t to create two monthly average values, indexed by k, one each for higher quality grade (Choice) and lower quality grade (Select) beef.

3.2. Cattle Prices

Regional monthly weighted average fed cattle prices, d_{jkt}, are liveweight-equivalent dressed delivered negotiated fed cattle prices. These prices are calculated from USDA-AMS report LM_CT137, which is a "Summary" of *IA-MN Daily Direct Slaughter Cattle - Negotiated Purchases* data that USDA-AMS began publishing in March 2010. USDA-AMS publishes this data in mutually-exclusive buckets defined according to combinations of various animal and transaction types, including by purchase method, class, percentage Choice quality grade, dressing basis, and delivery basis categories (Schroeder, Coffey, and Tonsor 2023). These buckets approximate panels, with each bucket reporting data over time for groups of cattle categorized according to certain standardized specifications. For our analysis, we are necessarily restricted to negotiated purchase data since that is the sole USDA-AMS purchase method category for which data are published separately by delivery basis (delivered and FOB).

We limit the analysis to *fed* (vs. non-fed) cattle classes, indexed by j (steers, heifers, mixed steers/heifers, and dairybred). By excluding cows from the analysis, we eliminate a factor that could impact identification. We also combine the USDA-AMS published "percentage Choice" categories into two categories indexed by k: one "high quality grade" (cattle that are greater than 80% Choice), and one "low quality grade" (cattle that are equal to or less than 80% Choice). In total, given our two quality grade categories and four fed cattle classes, eight total data buckets are available.

For the remaining eight data buckets, relevant data includes weighted average cattle prices and weighted average dressing percentages for months t. Before calculating monthly weighted averages using corresponding reported headcounts, data is downloaded in daily format since the daily report for the Iowa/Minnesota region provides dressing percentages whereas the relevant weekly and monthly reports do not provide dressing percentages during the period of study. These dressing percentages are not utilized explicitly in the analysis but are required for converting dressed delivered prices to liveweight-equivalent prices. This conversion allows for constructing cattle to beef price spreads that are non-negative over the entire time period of study. The conversion also makes price spreads comparable to those published by USDA-ERS and other academic studies (Lusk, Tonsor, and Schulz 2021; Schroeder et al. 2019; Martinez et al. 2023).

3.3. Cattle to Beef Price Spreads

The cattle to beef price spreads utilize a straightforward calculation in which, for each month, the four prices from "high quality grade" fed cattle buckets (cattle that are greater than 80% Choice) are subtracted from the single higher quality grade (Choice) boxed beef value, while the four prices from "low quality grade" fed cattle buckets (cattle that are equal to or less than 80% Choice) are subtracted from the single lower quality grade (Select) boxed beef value. Mathematically, this is represented as:

$$p_{jkt} = b_{kt} - d_{jkt},$$

where monthly boxed beef values and monthly weighted average dressed delivered fed cattle prices use the same notation as above. This calculation yields cattle to beef price spreads for eight panels for our DiD analysis.

We solely utilize dressed delivered fed cattle prices in the calculation of the cattle to beef price spreads for two reasons. First, price spreads between beef values and *live* (vs. dressed) cattle prices could embody information about the cost of slaughtering, dressing, and hanging animals. This process removes the head, hide, feet, blood, and internal organs in preparation of subsequent fabrication of the "dressed" carcass (Cauffman et al. 2020). Second and more problematic is that price spreads between beef values and *FOB* (vs. delivered) cattle prices likely incorporate transportation costs from farms to packing plants. Sexton, Kling, and Carman (1991), for example, use the difference between FOB and terminal market prices for celery as a measure of transaction costs. In our application, transportation costs implicitly embedded in FOB cattle prices jeopardize identification of the effects of multi-plant coordination by introducing a potentially confounding factor. Limiting the price spread calculation to delivered fed cattle prices, in combination with boxed beef values being FOB values, removes transportation costs from the cattle to beef price spreads entirely.

3.4. Relevant Industry Wages

To obtain relevant monthly weighted average industry wages, w_t, monthly average hourly earnings of production employees in nondurable goods manufacturing are obtained from the U.S. Bureau of Labor Statistics (BLS) for both Iowa and Minnesota. BLS collects this information as part of its Current Employment Statistics (CES) program. These wage rates are then converted into a single

Iowa/Minnesota monthly average, weighted by the number of nondurable goods manufacturing production employees in each respective state each month. While nondurable goods manufacturing is a broader category that, in addition to the slaughtering and meat packing sector, includes other sectors like paper manufacturing, this is the best data series available since wages for slaughterers and packers exclusively are not available from BLS at the state level at a monthly frequency.[3]

3.5. Summary Statistics

Table 1 reports data summary statistics for the time periods before and after the Cargill packing plant closure in February 2013. Average monthly cattle to beef price spreads were more than $\$15$/cwt wider after the Cargill plant closure than before, amounting to a 24% increase compared to the pre-shutdown period. This was due to, on average, beef values increasing relatively more after the closure than fed cattle prices. Notably, wages increased in the second period by $\$1.54$/hour, on average, representing an increase of less than 9%.

Table 1: Summary Statistics

	count (months)	mean	sd	min	max
Before 02/01/2013					
Fed Cattle Prices ($/cwt)	280	110.86	12.10	82.46	127.69
Head Count (head)	35	56,088	15,140	31,764	85,292
Dressed Weight (lbs)	35	847.63	13.48	826.81	871.73
Dressing Percentage (%)	35	62.75	0.36	61.81	63.36
Choice 600-900 Beef Values ($/cwt)	35	178.61	13.94	154.60	197.24
Select 600-900 Beef Values ($/cwt)	35	170.32	12.59	145.71	189.62
Price Spread ($/cwt)	280	63.61	6.78	48.84	81.94
Wage Rate ($/hour)	35	17.59	0.26	17.15	18.20
02/01/2013 and Later					
Fed Cattle Prices ($/cwt)	240	142.46	16.07	110.28	168.83
Head Count (head)	30	42,241	8,527	27,241	63,188
Dressed Weight (lbs)	30	866.16	15.15	841.97	891.42
Dressing Percentage (%)	30	62.97	0.32	62.44	63.50
Choice 600-900 Beef Values ($/cwt)	30	225.94	25.47	183.36	260.02
Select 600-900 Beef Values ($/cwt)	30	217.22	26.00	178.09	249.72
Price Spread ($/cwt)	240	79.13	13.07	53.54	112.35
Wage Rate ($/hour)	30	19.13	0.60	17.97	19.83

Figure 3 shows several of the key variables during the period of analysis. Graph (a) shows the monthly cattle to beef price spreads in $\$$/cwt from March 2010 to July 2015 for each of the eight data

[3]This data was downloaded using the Federal Reserve Economic Data (FRED) API and the following r package: https://cran.r-project.org/package=fredr

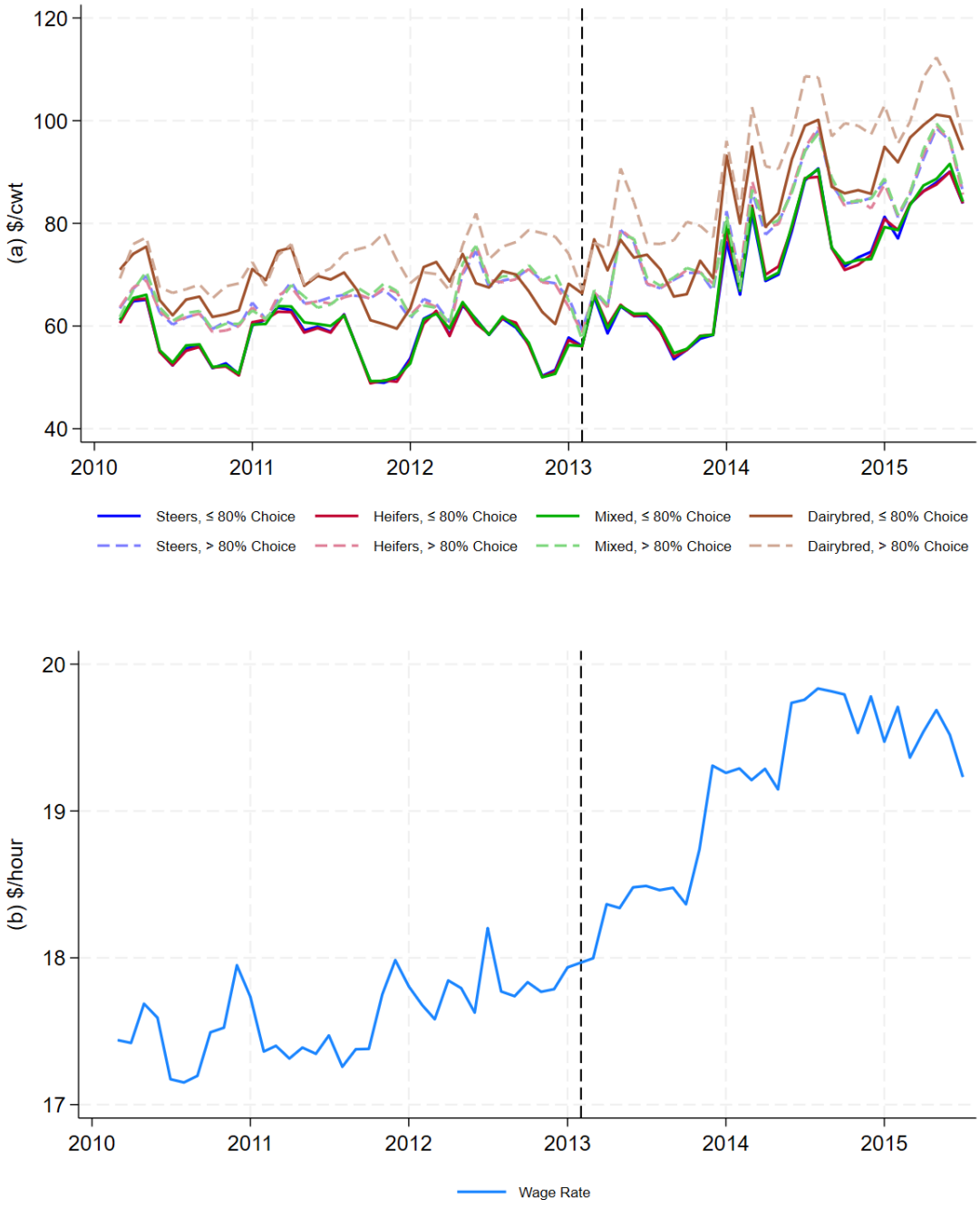

Figure 3: Line graphs of key variables over time. (a) Iowa/Minnesota Monthly Cattle to Beef Price Spreads ($/cwt), (b) Iowa/Minnesota Monthly Wage Rate ($/hour).

Note: The vertical dashed line represents the Cargill packing plant closure on February 1, 2013.

panels. As would be expected, each of the cattle to beef price spreads follows a similar pattern over time, though some variation across panels is apparent. For instance, the dairybred panels typically demonstrate the widest spreads, which is consistent with dairybred cattle often receiving dairy-type discounts relative to beef breed cattle. While cattle to beef price spreads are approximately flat before the Cargill shutdown in February 2013 (denoted by the vertical dashed line in the figure), there is an evident change in slope for all eight price spreads after the shutdown. The same is true for the Iowa/Minnesota nondurable goods manufacturing wage rates depicted in graph (b).

4. Methodology

In this section, we lay the theoretical foundations for our DiD analysis. Given the innovative DiD application, we begin by carefully demonstrating identification of the average treatment effect on the treated (ATT) through the introduction of a potential outcomes framework with a device.

4.1. Potential Outcomes Framework with a Device

We begin with a canonical potential outcomes model for the natural log of the price spread between national boxed beef values and regional fed cattle prices, which is as follows:

$$\tilde{p}_{it} = \begin{cases} \tilde{p}_{it}(0) & \text{if} \quad S_t = 0 \\ T_i\tilde{p}_{it}(1) + (1 - T_i)\tilde{p}_{it}(0) & \text{if} \quad S_t = 1 \end{cases},$$

where i is a panel index representing combinations of fed cattle class index j and quality grade index k; t is a month index for the time period of study; and S_t is the "shutdown" indicator representing the pre-shutdown and post-shutdown periods. In this application, the shutdown is the closure of the Cargill cattle slaughter plant in Plainview, TX, on February 1, 2013, which also marks industry-wide implementation of multi-plant coordination. We let $\tilde{p}_{it}$, henceforth "log spread," be the log of the cattle to beef price spread, which is national boxed beef value b_{it} less regional fed cattle price d_{it} in $\$/\text{cwt}$.[4] As shown, $\tilde{p}_{it}(1)$ and $\tilde{p}_{it}(0)$ are counterfactual log spreads with and without the treatment, respectively, if the binary treatment status T_i is exogenously set. The *no anticipatory effect* assumption is operative here because log spreads did not increase preemptively due to some expectation of the multi-plant coordination shutdown.[5]

Typically, if we were to proceed with a canonical DiD analysis, the parameter of interest would

[4] Mathematically, $\tilde{p}_{it} = ln(p_{it}) = ln(b_{it} - d_{it})$.

[5] The *no anticipatory effect* assumption yields $\tilde{p}_{it} = \tilde{p}_{it}(0)$ when $S_t = 0$ before the shutdown.

be the ATT of multi-plant coordination in the post-shutdown period:

$$\mathbb{E}\left[\tilde{p}_{it}(1) - \tilde{p}_{it}(0) | T_i = 1, S_t = 1\right].$$

The ATT would reveal the effects of the shutdown on regional log spreads impacted by multi-plant coordination by comparing the treated price spreads to hypothetical untreated price spreads in the post-shutdown period. In our application, however, we encounter a problem with identifying the ATT, which is that we do not have a control group in the data; all log spreads everywhere are treated by the implementation of multi-plant coordination in the post-shutdown period. Put succinctly, there is no way to identify the hypothetical untreated $\tilde{p}_{it}(0)$ observations in the post-shock period using DiD, because we have $T_i = 1$ for every unit.[6]

We overcome our lack of control group by introducing a novel feature called a *device*, which can be used to identify the ATT. To implement this device, we introduce a new potential outcomes model, with *observed* log outcome $\tilde{y}_{it}$ given by:

$$\tilde{y}_{it} = \begin{cases} \tilde{w}_t & \text{if} \quad D_i = 0 \\ \tilde{p}_{it} & \text{if} \quad D_i = 1 \end{cases}, \tag{1}$$

with D_i serving as the device indicator.[7] Hereafter "log wages," device $\tilde{w}_t$ is the natural log of a relevant hourly wage series for the region of study, which in our case is the Iowa/Minnesota region. While hourly wages are in \$/hour and price spreads are in \$/cwt, utilizing logarithmic values as shown in (1) normalizes units for analysis as percentage change. Equation (1) can be rewritten as:

$$\tilde{y}_{it} = D_i \tilde{p}_{it} + (1 - D_i)\tilde{w}_t.$$

It is worth mentioning here that the device $\tilde{w}_t$ could theoretically have its own potential outcomes model related to the treatment status, T_i, in the post-shutdown period. However, in our analysis, we maintain that the implementation of multi-plant coordination did not affect Iowa/Minnesota regional industry wages on average, nor did the multi-plant coordination shutdown in Plainview,

[6] In probability notation, $\mathbb{P}(T_i = 1 | S_t = 1) = 1$, which implies $\mathbb{E}[\tilde{p}_{it}(1) - \tilde{p}_{it}(0) | T_i = 1, S_t = 1] = \mathbb{E}[\tilde{p}_{it}(1) - \tilde{p}_{it}(0) | S_t = 1]$.

[7] To be precise, $\tilde{w}_t$ is defined only when $D_i = 0$ and $\tilde{p}_{it}$ is defined only when $D_i = 1$; equivalently, they are defined on disjoint events, so $(\tilde{w}_t, \tilde{p}_{it})$ is not well-defined as a pair of random variables (and a joint law for $(\tilde{w}_t, \tilde{p}_{it})$ is not defined). For notational convenience, we write $\mathbb{E}[\tilde{w}_t] \equiv \mathbb{E}[\tilde{w}_t | D_i = 0]$ and $\mathbb{E}[\tilde{p}_{it}] \equiv \mathbb{E}[\tilde{p}_{it} | D_i = 1]$. More generally, whenever the conditioning event is compatible with the variable's domain, we suppress D_i in conditional expectations; e.g., $\mathbb{E}[\tilde{w}_t | S_t = 1] \equiv \mathbb{E}[\tilde{w}_t | D_i = 0, S_t = 1]$.

TX. In the language of the potential outcomes framework, we argue that the device that we utilize is untreated, always.[8] This condition almost certainly holds in the Iowa/Minnesota region due to the geographical distance from Texas as well as the lack of a Cargill cattle slaughter plant in Iowa or Minnesota (see Figure 2). To summarize, while log spreads in Texas, log spreads in Iowa/Minnesota, and perhaps log industry wages in Texas are treated by multi-plant coordination due to high degrees of concentration and horizontal integration, log wages in Iowa/Minnesota are not treated by multi-plant coordination. Thus, the observed devices for both pre-shutdown and post-shutdown periods are given by:

$$\tilde{w}_t = \tilde{w}_t(0),$$

and thus, they serve as an effective control group.

Using equation (1), the observed outcome can be written as:

$$\tilde{y}_{it} = \begin{cases} D_i\tilde{p}_{it}(0) + (1 - D_i)\tilde{w}_t(0) & \text{if} \quad S_t = 0 \\ D_i\tilde{p}_{it}(1) + (1 - D_i)\tilde{w}_t(0) & \text{if} \quad S_t = 1 \end{cases}. \tag{2}$$

We note that treatment indicator, T_i, has fallen out of the model, and we are only dealing with the shutdown indicator, S_t, and the device indicator, D_i.

4.2. Identification

Moving forward with (2), consider the following canonical 2×2 DiD estimation equation for log outcomes:

$$\ln y_{it} \equiv \tilde{y}_{it} = \alpha_0 + \alpha_1 D_i + \alpha_2 S_t + \alpha_3 D_i S_t + \varepsilon_{it}, \tag{3}$$

Standard calculations show that the DiD coefficient, α_3, can be expressed as the following four terms:

$$\begin{aligned} \alpha_3 = {} & \mathbb{E}\left[\tilde{y}_{it} | D_i = 1, S_t = 1\right] - \mathbb{E}\left[\tilde{y}_{it} | D_i = 0, S_t = 1\right] \\ & - \left\{\mathbb{E}\left[\tilde{y}_{it} | D_i = 1, S_t = 0\right] - \mathbb{E}\left[\tilde{y}_{it} | D_i = 0, S_t = 0\right]\right\}. \end{aligned}$$

[8] To be precise, we here assume $\tilde{w}_t(1) = \tilde{w}_t(0)$ almost surely for all t, under the potential device specification. However, it can be shown that the identification of the ATT can also be achieved under a slightly weaker assumption on averages: $\mathbb{E}[\tilde{w}_t(1) - \tilde{w}_t(0) | S_t = 1] = 0$.

Combining (2) and (3), straightforward manipulations demonstrate:

$$
\begin{aligned}
\alpha_3 &= \mathbb{E}\left[\tilde{p}_{it}(1) - \tilde{w}_t(0) | S_t = 1\right] - \mathbb{E}\left[\tilde{p}_{it}(0) - \tilde{w}_t(0) | S_t = 0\right] \\
&= \mathbb{E}\left[\tilde{p}_{it}(1) - \tilde{w}_t(0) | S_t = 1\right] - \mathbb{E}\left[\tilde{p}_{it}(0) - \tilde{w}_t(0) | S_t = 0\right] \\
&\quad + \mathbb{E}\left[\tilde{p}_{it}(0) | S_t = 1\right] - \mathbb{E}\left[\tilde{p}_{it}(0) | S_t = 1\right] \\
&= \mathbb{E}\left[\tilde{p}_{it}(1) - \tilde{p}_{it}(0) | S_t = 1\right] \\
&\quad + \mathbb{E}\left[\tilde{p}_{it}(0) - \tilde{w}_t(0) | S_t = 1\right] - \mathbb{E}\left[\tilde{p}_{it}(0) - \tilde{w}_t(0) | S_t = 0\right], \qquad (4)
\end{aligned}
$$

The first term in (4) is the ATT of interest for log outcomes, but two additional terms remain. To address these terms, we now introduce the following version of the standard "parallel trends" assumption:

Assumption 1 (Parallel log trends)**.** *On average, the gap between the log spread and the log device would have been the same between pre-shutdown and post-shutdown periods had there been no treatment:*

$$\mathbb{E}[\tilde{p}_{it}(0) - \tilde{w}_t(0) | S_t = 1] = \mathbb{E}[\tilde{p}_{it}(0) - \tilde{w}_t(0) | S_t = 0].$$

This assumption is akin to saying that, in absence of the log spread being treated, on average, log spreads would have equaled log wages plus the same constant before and after the shutdown. Equivalently, the spread-device ratio would have been constant between pre-shutdown and post-shutdown periods had there been no treatment. Conversely, if there is an observed change in the gap between log wages and log spread in the post-shock period, then this is the result of treatment to cattle to beef price spreads. Note that this does not have to be satisfied period by period (t). Under Assumption 1, the second and third terms of equation (4) cancel out, so the following equality holds:

$$\alpha_3 = \mathbb{E}\left[\tilde{p}_{it}(1) - \tilde{p}_{it}(0) | S_t = 1\right]$$

Therefore, when Assumption 1 holds, the ATT is identified as the DiD coefficient, α_3, in estimation equation (3). Hence, use of the device is theoretically valid for identification purposes under Assumption 1.

5. Conceptual Cattle to Beef Price Spread Model

We turn to building a conceptual model of cattle to beef price spreads that further bolsters identification and justification of the ATT. This conceptual model is rooted in beef packing industry institutional details, and as will be carefully discussed in a later section, this model is also consistent with our data and pre-trend test results.

5.1. Model

Consider the following model of the functional relationship between cattle to beef price spread and hourly packing wages in levels for panel i and month t:

$$p_{it} = (b_{it} - d_{it}) = f(w_t) = w_t \cdot u_{it},$$

where p_{it} is the monthly spread between national boxed beef values and dressed delivered negotiated fed cattle prices for Iowa/Minnesota; b_{it} is a monthly national boxed beef value in $\$/\text{cwt}$; d_{it} is a monthly dressed-delivered Iowa/Minnesota fed cattle price in $\$/\text{cwt}$; and w_t is a monthly regional nondurable goods manufacturing wage in $\$/\text{hour}$. Observe that the cattle to beef price spread is a proportional function of wages in this specification. In particular, wages are multiplied by $u_{it} \geq 0$, which is a panel-month specific non-negative multiplier. This multiplier is in the units hours-per-hundredweight and is specified as follows:

$$u_{it} = e^{\tilde{\gamma}_i + \lambda_{it} \cdot S_t + \varepsilon_{it}},$$

where S_t is the shutdown indicator variable that is 0 before February 2013 and 1 starting in February 2013, λ_{it} is the panel-month specific effect of the shutdown on the multiplier, and ε_{it} is a mean-zero[9] unobserved idiosyncratic component with $\mathbb{E}[\varepsilon_{it} \mid S_t] = 0$. Letting $\gamma_i = e^{\tilde{\gamma}_i}$, we decompose the multiplier and rewrite the cattle to beef spread as follows:

$$p_{it} = \gamma_i \cdot w_t \cdot e^{\lambda_{it} \cdot S_t + \varepsilon_{it}} \tag{5}$$

This decomposition yields a conceptual interpretation for u_{it} by which the γ_i term can be viewed as a panel-specific "efficiency multiplier," i.e., what is the industry's baseline hours of labor required per hundredweight of beef produced for the cattle in that panel? Intuitively, for a given multiplier, the cattle to beef price spread increases as the wage rate goes up for the labor required to convert

[9] Note that without loss of generality we can assume $\mathbb{E}[\varepsilon_{it}] = 0$ due to $\tilde{\gamma}_i$.

dressed carcasses into boxed beef.

The remainder of the decomposed multiplier, which is $e^{\lambda_{it} \cdot S_t + \varepsilon_{it}}$, can be viewed as a "profit multiplier." For profit multipliers less than 1, the cattle to beef price spread is less than the product of the wage rate times the efficiency multiplier, which is not sustainable in the long run. For profit multipliers greater than 1, the cattle to beef price spread is greater than the product of the wage rate and the efficiency multiplier. For profit multipliers substantially larger than 1 (i.e., $\lambda_{it} \gg 0$), packers could be making excess profit.

Taking natural logs of equation (5), we obtain the following:

$$\ln p_{it} \equiv \tilde{p}_{it} = \tilde{\gamma}_i + \tilde{w}_t + \lambda_{it} \cdot S_t + \varepsilon_{it}. \tag{6}$$

Note that the effect of the shutdown on the log spread is captured by the term λ_{it}. Therefore, we define the ATT as the average of λ_{it} for those that experience the shutdown:

$$ATT = \mathbb{E}[\lambda_{it} | S_t = 1].$$

This ATT captures the approximate average change in log spreads caused by the shutdown. While the shutdown may impact the data panels differently, the ATT measures the average effect. Importantly, this ATT can be estimated by the classical 2×2 DiD estimation equation shown by (3).

Ultimately, our conceptual model accomplishes three primary goals. First, the model provides more insight into the functional relationships between key variables in the beef packing industry. Second, the model yields log spread equation (6) in which the ATT is able to be estimated by the classical 2×2 DiD estimation equation. Third, and critically, log spread model (6) is sufficient for Assumption 1.[10] Taken together, these three characteristics of our conceptual model support the identification and justification of the DiD estimate of the ATT when using a device.

5.2. Visualization

We find it useful to introduce a visualization to cement the interplay between Assumption 1 and the conceptual cattle to beef price spread model. Consider Figure 4, which utilizes the notation of DiD estimation equation (3). In Figure 4, the log spread (the outcome variable) is shown in solid red, while log wages (the device) is shown in solid blue. In dashed red is the counterfactual log price spread implied by log wages and Assumption 1. The counterfactual log spread demonstrates how, in

[10] Proof in Appendix B.

absence of the treatment, the gap between the log spread and log wages would have been constant, α_1. In our conceptual model, α_1 equals $\tilde{\gamma}_i$, the log of the efficiency multiplier. The difference between the dashed red line and the solid red line is, on average, the ATT, and it is measured by α_3. In our conceptual model, $\alpha_3 = \mathbb{E}[\lambda_{it}|S_t = 1]$. As demonstrated in Figure 4, log wages are allowed to increase in the post-treatment period as long as the wage increase was not influenced by the treatment.

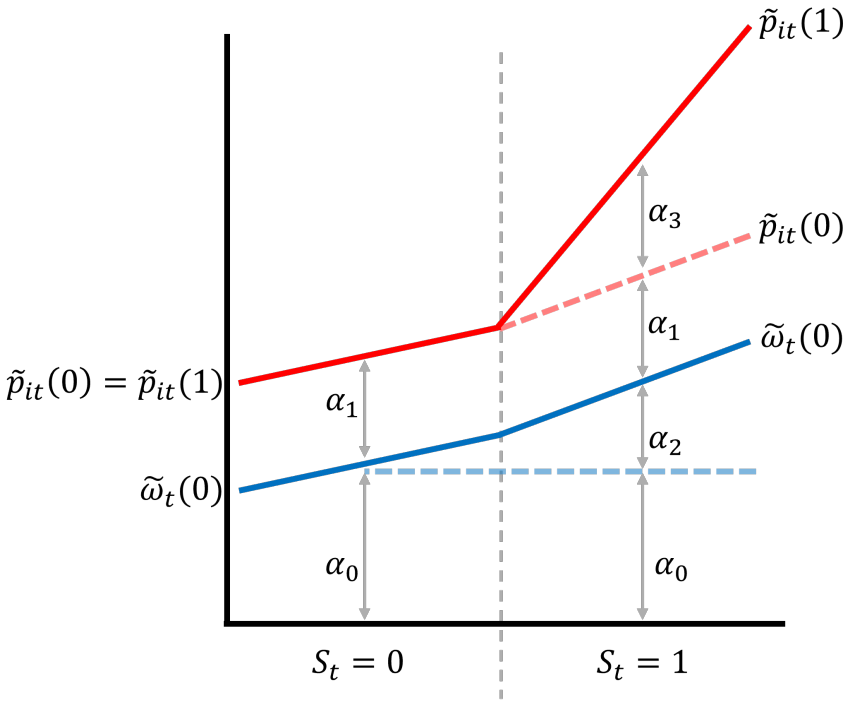

Figure 4: Visualization of Assumption 1

6. Estimation

Having established identification and conceptual justification for our estimation, we proceed with estimation utilizing monthly data for March 2010 through July 2015, with months indexed by t. The beginning of the period of study is when the relevant USDA-AMS published fed cattle data first becomes available, while the end of the period of study is the last full month before Tyson closed their cattle slaughter plant in Denison, IA, thereby introducing structural change into the Iowa/Minnesota fed cattle market (Pudenz and Schulz 2024).

Results from the DiD estimation are included in Table 2. Estimation was performed utilizing OLS with Driscoll-Kraay (1998) standard errors (see also Mullally and Lusk 2017) to address the

serial-correlation and cross-sectional-dependence issues documented by Bertrand, Duflo, and Mullainathan (2004). Estimation is reported for three specifications.[11] The basic specification (specification (I)) utilizes the standard two-by-two DiD estimation equation shown in equation (3). Specification (II) adds monthly fixed effects to account for the highly seasonal nature of fed cattle markets and wholesale beef demand. Finally, specification (III) (which is the preferred specification) adds a trend term to account for linear changes over time (e.g., inflation). As can be easily seen in Table 2, inclusion of the trend term impacts estimates for the Shutdown term and the Constant, but not the Efficiency Multiplier or the ATT.

Table 2: Regression Results

	(I) log spread	(II) log spread	(III) log spread
Shutdown	0.0835***	0.0810***	-0.121**
	(7.40)	(4.31)	(-2.28)
Efficiency Multiplier	1.280***	1.280***	1.280***
(device=1)	(96.86)	(95.94)	(95.86)
ATT	0.127***	0.127***	0.127***
(shutdown=1 $\times$ device=1)	(3.31)	(3.28)	(3.28)
Constant	2.867***	2.894***	2.760***
	(761.70)	(111.88)	(59.60)
Month FE	No	Yes	Yes
Time trend	No	No	Yes
R-squared	0.915	0.922	0.938
N	585	585	585

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Although all panel regressions post R-squared values exceeding 0.9, spurious regression concerns are unlikely as panel unit-root tests with a deterministic time trend (lags chosen by AIC) uniformly reject non-stationarity for the log spread series. The Im–Pesaran–Shin (2003) test where the alternative allows only some panels to be $I(0)$ produces test statistics with p-values less than 0.01 for the log spreads. The more stringent Levin–Lin–Chu (2002) test, whose alternative requires every panel to be stationary, also rejects the unit-root null with p-values less than 0.01. Rejection

[11] We additionally considered estimation specifications that excluded dairybred cattle. Previous work demonstrates beef packing companies have historically discounted fed dairy cattle relative to beef breeds for a variety of potential reasons (Pudenz and Schulz 2021; McKendree, Saitone, and Schaefer 2021). Results from these estimations were quantitatively similar, however, and though not presented for brevity, are available upon request.

by both tests, which need not coincide in finite samples, offers robust evidence that the log spreads are stationary ($I(0)$) and unit roots are not a concern.

Several additional comments regarding Table 2 are warranted. First, the results are remarkably consistent across specifications. This is because the monthly fixed effects and the linear time trend are not panel specific, so they do not change the point estimates of interest. Second, in each case, the Shutdown and Efficiency Multiplier estimates are highly statistically significant, as are the estimated Constants. Third, and most importantly, the estimates for the ATT (shutdown $= 1 \times$ device $= 1$) are statistically significant at $p < 0.01$ across all three specifications. Proceeding with specification (III), we highlight that the ATT is $\widehat{\alpha}_3 = 0.127$. This means that, due to multi-plant coordination, the log spread was 0.127 higher on average than what would have been observed in the post-shutdown period. Hence, any multi-plant coordination efficiencies are more than offset by the anti-competitive effects of the business practice and the effects of the plant shutdown.

Proceeding, we approximate the percentage change in cattle to beef price spread *levels* by exponentiating the ATT:

$$e^{\widehat{\alpha}_3} = 1.135$$

This tells us that cattle to beef price spreads were approximately 13.5% higher in the the post-shutdown period than they would have been in the absence of the shutdown.[12] Letting $\bar{p}_1$ be the observed average cattle to beef price spread in levels in the post-shutdown period (see Table 1), and additionally letting $\bar{p}_{1c}$ be the unobserved counterfactual cattle to beef price spread in the post-shutdown period, we deflate the observed cattle to beef price spread in the second period by $e^{\widehat{\alpha}_3}$ to calculate an unobserved counterfactual cattle to beef price spread $\bar{p}_{1c}$:

$$\overline{p}_{1c} = \frac{\overline{p}_1}{e^{\widehat{\alpha}_3}} = \frac{\$79.13/\text{cwt}}{1.135} = \$69.71/\text{cwt}.$$

With a counterfactual calculated, we obtain the difference between the observed cattle to beef price spread and the counterfactual:

$$\overline{p}_1 - \overline{p}_{1c} = \$79.13/\text{cwt} - \$69.71/\text{cwt} = \$9.42/\text{cwt}$$

[12] This percentage change approximation is accurate up to Jensen's Inequality, which tells us that the convex function of an expectation is less than or equal to the expectation of a convex function (see Chapter 6 of Wooldridge 2016, for further discussion). Since $e^{\widehat{\alpha}_3}$ is the exponential of an expectation (i.e., the ATT), it is less than or equal to the "true" value. Hence, 13.5% is actually a *conservative* estimate of the average percentage change in cattle to beef price spread levels due to the shutdown.

Thus, cattle to beef price spreads in the post-shutdown period were, on average, approximately $\$9.42$/cwt higher than they would have been in the absence of multi-plant coordination.[13]

This $\$9.42$/cwt average increase in cattle to beef price spread approximates the causal effect of the industry-wide implementation multi-plant coordination in U.S. beef packing, and it estimates the increase in packer margin due to the implementation of the business practice. This increase is substantial, accounting for 61% of the increase in the cattle to beef price spread from the pre-shutdown period to the post-shutdown period, with the remainder of the increase due to the trend term and increases in wages. For a $1,375$ pound animal (liveweight), $\$9.42$/cwt amounts to over $\$129$/head of price spread that was captured by beef packing plants in the second period instead of upstream fed cattle producers or downstream buyers of wholesale beef. For just the Iowa/Minnesota dressed delivered fed cattle in this sample, this totals to more than $\$164$ million during the 30 month post-shutdown period.

Our estimation is entirely agnostic as to which supply chain segment the increase in cattle to beef price spread was captured from. This is a notable differentiation compared to previous studies of the beef supply chain, many of which assume that beef is sold in competitive markets, and therefore take downstream beef values as given. It is possible that there was no additional markdown for fed cattle at all and that the entirety of the spread increase was due to higher boxed beef values. After all, beef values increased in the second period relatively more than fed cattle prices, suggesting that beef packers may have passed along more of the $\$9.42$/cwt multi-plant coordination effects to wholesale beef purchasers and ultimately beef consumers. We leave the separate identification of cattle to beef price spread components to future research.

7. Discussion

While subsections 4.1 and 4.2 have established identification of the ATT when utilizing the device, further discussion is warranted regarding the interpretation of DiD coefficient, $\widehat{\alpha}_3$, as the causal effect of the industry-wide implementation of multi-plant coordination. Clearly, this research proposes an innovative application of the DiD estimator. Even so, the causality of $\widehat{\alpha}_3$ as an estimate for the ATT relies on similar factors as are typically considered: the validity of Assumption 1, the details of the data, and the typical DiD pre-trend test.

[13] For precision, post-estimation calculations were performed using results with more decimal places than presented in Tables 1 and 2. More information regarding these calculations is available upon request.

Regarding Assumption 1, as has been demonstrated in Appendix B, the conceptual cattle to beef price spread model in section 5 is sufficient for the assumption. The question remains, in reality, was the relationship between log wages and log spread stable aside from the effects of multi-plant coordination during the time period of study? We assert, yes. While there have been some other structural changes in the industry besides multi-plant coordination that have likely altered the relationship between log wages and log spread, such as the introduction of boxed beef technology (Hall and McBride 1980), this assumption is believed to be reasonable in the relatively-short time period of study. Additionally, there were no major short-term disruptions such as COVID-19 shutdowns (Lusk, Tonsor, and Schulz 2021) or major packing plant fires (Bina et al. 2022) during the period of study.

The details of the data further support our claims of causality. First, our use of data carefully acknowledges and accordingly deals with the two biggest input costs to beef packers. Transportation costs are removed from our cattle to beef price spreads through the use of dressed delivered cattle prices and FOB boxed beef values, while wage cost changes are directly accounted for in estimation. Furthermore, as has been discussed, regional Iowa/Minnesota nondurable goods wages are not treated by multi-plant coordination. Changes in any other costs are insubstantial in the analysis of cattle to beef price spreads since according to National Beef's CEO Tim Klein in 2022, transportation and labor costs "are the two single biggest cost components that we have and the most that affect our business and has the biggest impact today" (U.S. Congress 2022).

These institutional realities are backed up by parallel trend test results demonstrating a stable relationship in the pre-treatment period. Results from this parallel trend test are included in Appendix C. To summarize, they demonstrate that treated group by year fixed effects in the pre-treatment period are not statistically significantly different from 0, individually or jointly. The shortcomings of such tests are well-documented (Kahn-Lang and Lang 2020; Callaway and Sant'Anna 2022), but in conjunction with aforementioned institutional knowledge and meticulous data usage, the pre-trend test results provide as good of evidence as possible for the causality of the DiD estimate.

As a final note, we come full circle to our conceptual cattle to beef price spread model by

reminding readers that $\overline{p}_1 \approx \overline{w}_1 \cdot e^{\widehat{\alpha}_1+\widehat{\alpha}_3}$. Applied in our context, that yields:

$$\overline{p}_1 - \overline{p}_{1c} = \overline{p}_1 - \frac{\overline{p}_1}{e^{\widehat{\alpha}_3}} \approx \overline{w}_1 \cdot e^{\widehat{\alpha}_1+\widehat{\alpha}_3} - \overline{w}_1 \cdot \frac{e^{\widehat{\alpha}_1+\widehat{\alpha}_3}}{e^{\widehat{\alpha}_3}} = \overline{w}_1 \cdot e^{\widehat{\alpha}_1+\widehat{\alpha}_3} - \overline{w}_1 \cdot e^{\widehat{\alpha}_1} = \$9.29/\text{cwt}$$

which is remarkably close to the $\$9.42$/cwt calculated above.[14] We further remind readers that, for specification (I) in Table 2 (OLS with no fixed effects or trend), we have that $\overline{w}_1 \approx e^{\widehat{\alpha}_0+\widehat{\alpha}_2} = \$19.12$/hour, which is within rounding error of the observed $\$19.13$/hour.

8. Conclusion

This study introduces novel methodology enabling application of DiD estimation to study the highly-complex U.S. cattle and beef industry. Using an innovation we call a device, we find that the implementation of multi-plant coordination led to cattle to beef price spreads that were significantly wider than they would have been in the absence of multi-plant coordination. Cattle to beef price spreads were 13.5% wider due to this business practice, amounting to $\$9.42$/cwt that would have gone upstream to fed cattle producers or downstream to wholesale beef purchasers had multi-plant coordination not been implemented.

The takeaways from this study are threefold. First, we have demonstrated that multi-plant coordination had net negative effects on cattle producers and/or procurers of wholesale beef during the time period of study. This is a meaningful contribution to the literature, with many previous studies demonstrating that efficiencies from various packer activities often offset anti-competitive effects from those packer activities (Azzam 1997; Wohlgenant 2013).

Second, and relatedly, this research verifies several key predictions in Pudenz and Schulz (2024) related to the effects of multi-plant coordination and multi-plant coordination shutdowns on the U.S. beef complex. These predictions appear especially prescient given Tyson Foods' November 21, 2025, announcement regarding the multi-plant coordination shutdown of its Lexington, NE, cattle slaughter plant, and the reduction in slaughter shifts at its Amarillo, TX, cattle slaughter plant. In Tyson's announcement, the company indicates that "production will be increased at other company beef facilities, optimizing volumes across [their] network" (Tyson 2025). In light of this multi-plant coordination shutdown, the results in this analysis will undoubtedly provide direction to economists, industry stakeholders, policymakers, and regulators for ongoing and future work on price discovery and competition in the U.S. cattle and beef market.

[14] In Appendix D, we include results from DiD estimations that incorporate monthly fed cattle slaughter volumes as a covariate. Results from these estimations were quantitatively similar to the baseline results.

Third, we have developed methods that allow application of differences-in-differences estimation when they might not have been possible before, namely in complex industries with high degrees of concentration. Institutional details matter immensely for the proper application of these methods, as do data characteristics and availability. Yet there remain potential applications of these methods for economists to explore, including perhaps applications to the fertilizer, oil refinery, and biofuels industries.

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A. Cargill Press Release Text

Cargill to idle Plainview, Texas, beef processing plant; dwindling cattle supply cited

Affected employees to receive support

PLAINVIEW, Texas – January 17, 2013 – Cargill today announced that it will idle its Plainview, Texas, beef processing facility effective at the close of business, Friday, Feb. 1, 2013, resulting primarily from the tight cattle supply brought about by years of drought in Texas and Southern Plains states. Approximately 2,000 people work at the Plainview facility, and they will receive company support. Federal, state, county and city government representatives, as well as Cargill customers, suppliers and other key stakeholders were informed today of Cargill's decision, concurrent with Cargill employees being notified.

"The decision to idle our Plainview beef processing plant was a difficult and painful one to make and was made only after we conducted an exhaustive analysis of the regional cattle supply and processing capacity situation in North America," said John Keating, president of Cargill Beef, based in Wichita, Kan. "While idling a major beef plant is unfortunate because of the resulting layoff of good people, which impacts their families and the community of Plainview, we were compelled to make a decision that would reduce the strain created on our beef business by the reduced cattle supply. The U.S. cattle herd is at its lowest level since 1952. Increased feed costs resulting from the prolonged drought, combined with herd liquidations by cattle ranchers, are severely and adversely contributing to the challenging business conditions we face as an industry. Our preference would have been not to idle a plant."

Cargill's Plainview employees affected by this decision will be provided support as well as assistance finding and filling open positions at other Cargill locations or with other employers. Cargill will continue to honor its community support commitments at Plainview for 2013. The company's remaining beef cattle processing plants in the region, at Friona, Texas; Dodge City, Kan. and Fort Morgan, Colo., will receive cattle that were previously destined for processing at Plainview. The company's regional beef facilities at Fresno, Calif.; Milwaukee, Wis.; and Wyalusing, Pa., as well as its beef plant in Schuyler, Neb., and two beef plants in Canada, are unaffected.

"Given the over-capacity that exists with four major beef plants in the Texas Panhandle and a dwindling supply of cattle in the region, idling Plainview will allow Cargill to operate its other beef plants in Texas, Colorado and Kansas more consistently on a five-day-per-week basis to meet our

customers' requirements, while helping us maintain our position in the U.S. beef sector," explained Keating. "Our long-term commitment to U.S. beef production is unwavering. Over the past 10 years we've invested more than $766 million in our U.S. beef plants to ensure they remain best in class in the industry."

The plan to idle Cargill's Plainview facility includes measures for preserving its infrastructure for potential reopening if the U.S. cattle herd rebounds and requires additional processing capacity. However, Cargill does not expect the U.S. cattle herd to significantly increase in size for a number of years.

"We delayed the decision to idle Plainview as long as possible, due in part to our outstanding team and ongoing excellent support from the community. We were also hoping the drought would break, pasturelands would be restored, cattle ranchers would retain heifers and the national herd trend of declining numbers over the past few years would be reversed," stated Keating. "Unfortunately, the drought has not broken, feed costs remain higher than historical averages and the herd continues to shrink. The industry has experienced this cycle in the past, although this one is longer and more severe than most. Nevertheless, we are optimistic about the long-term prospects for U.S. beef demand from American and international consumers, and that the drought in Texas and the Southern Plains will become a memory."

B. Proof of Sufficiency of the Conceptual Cattle to Beef Price Spread Model for Assumption 1

Note that (6) implies:

$$\tilde{p}_{it}(1) = \tilde{\gamma}_i + \tilde{w}_t(0) + \lambda_{it} \cdot S_t + \varepsilon_{it},$$
$$\tilde{p}_{it}(0) = \tilde{\gamma}_i + \tilde{w}_t(0) + \varepsilon_{it},$$

because the bucket-specific baseline efficiency multiplier (and thus its natural log, $\tilde{\gamma}_i$) and the idiosyncratic component ε_{it} are assumed to be unaffected by multi-plant coordination. While multi-plant coordination could lead to efficiencies, these are captured by λ_{it} with the other multi-plant coordination effects. Hence, we have:

$$\tilde{p}_{it}(0) - \tilde{w}_t(0) = \tilde{\gamma}_i + \varepsilon_{it},$$

and:

$$\begin{aligned}\mathbb{E}[\tilde{p}_{it}(0) - \tilde{w}_t(0)|S_t = s] &= \mathbb{E}[\tilde{\gamma}_i + \varepsilon_{it}|S_t = s] \\ &= \tilde{\gamma}_i + \mathbb{E}[\varepsilon_{it}|S_t = s] \\ &= \tilde{\gamma}_i,\end{aligned}$$

for all $s = 0, 1$ because the efficiency multiplier is assumed to be constant over time and $\mathbb{E}[\varepsilon_{it}|S_t] = 0$. $\square$

C. Pre-trend Test Results

Table 3: Pre-trend Test Results

	(I) log spread	(II) log spread	(III) log spread
yfe=1 × device=1	-0.0342	-0.0342	-0.0342
	(-1.17)	(-1.16)	(-1.16)
yfe=2 × device=1	-0.0139	-0.0139	-0.0139
	(-0.49)	(-0.49)	(-0.49)
yfe=4 × device=1	0.000730	0.000730	0.000730
	(0.03)	(0.03)	(0.03)
yfe=5 × device=1	0.157***	0.157***	0.157***
	(6.16)	(6.11)	(6.11)
yfe=6 × device=1	0.240***	0.240***	0.240***
	(9.05)	(8.97)	(8.97)
Pre-test p-value	0.4947	0.5013	0.5013
Month FE	No	Yes	Yes
Time trend	No	No	Yes
R-squared	0.946	0.951	0.951
N	585	585	585

t statistics in parentheses

The pre-test p-value is calculated from a statistical test on a null hypothesis that pre-trends are parallel between the spreads and wages.

Year fixed effects (yfe) are defined as treatment-year bins aligned to the February treatment start date (i.e., "year" runs Feb–Jan rather than Jan–Dec): $yfe = 1$ for months before Feb 2011, $yfe = 2$ for Feb 2011–Jan 2012, and so on.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

D. Incorporating Covariates: Theory and Estimation Results

In this appendix, we introduce methodology that incorporates time-varying covariates when utilizing a device. Note that the conditional parallel trend utilizing a set of time-constant covariates (Abadie 2005; Sant'Anna and Zhao 2020) is not applicable for our framework as we do not have common unit-specific covariate data for both spreads (outcome) and wages (device).

For a vector of time-varying covariates or factors, $\boldsymbol{x}_t$, that are held common for all panels i, consider the following factor-augmented model (e.g., Gobillon and Magnac (2016), Callaway and Karami (2023)) for the log of the price spread between national boxed beef values and regional fed cattle prices and the log of regional industry wages:

$$\tilde{p}_{it}(d) = \boldsymbol{x}_t'\boldsymbol{\mu}_i + \overline{p}_{it}(d)$$
$$\tilde{w}_t(0) = \boldsymbol{x}_t'\boldsymbol{\mu}_i + \overline{w}_t(0),$$

for $d = 0, 1$ where $\boldsymbol{x}_t$ is a common time-varying factor and $\boldsymbol{\mu}_i$ is a unit-specific loading vector.

Then, it can be shown that β_3 from the following regression model

$$\tilde{y}_{it} = \beta_0 + \beta_1 D_i + \beta_2 S_t + \beta_3 D_i S_t + \boldsymbol{x}_t'\boldsymbol{\mu}_i + e_{it},$$

identifies the ATT under the parallel trends on $\overline{p}_{it}(0)$ and $\overline{w}_t(0)$, the factor-adjusted (residual) potential outcome net of the common factor $\boldsymbol{x}_t'\boldsymbol{\mu}_i$:[15]

$$\mathbb{E}[\overline{p}_{it}(0) - \overline{w}_t(0)|S_t = 1] = \mathbb{E}[\overline{p}_{it}(0) - \overline{w}_t(0)|S_t = 0].$$

For the factor, we use monthly U.S. federally inspected cattle slaughter published by USDA's National Agricultural Statistical Service (NASS) (USDA-NASS n.d.b). To construct this variable, we add steer and heifer slaughter data together to create a total fed cattle slaughter headcount variable ($fed\_slaughter$). Previous research shows cattle inventories influence packer procurement decisions (Pudenz and Schulz 2021; McKendree, Saitone, and Schaefer 2021) and cattle pricing (Crespi, Xia, and Jones 2010). Interacting $fed\_slaughter$ with unit specific loading vectors could control for variation in cattle to beef price spreads that results from differential packer behavior

[15] Although this assumption and Assumption 1 are not ordered in a set-theoretic sense, it is arguably more natural to assume the former under the factor-augmented model. At the same time, our specification belongs to the broader class of regression implementations that impose additional parametric structure (e.g., two-way fixed effects with covariates (Caetano and Callaway 2024)), which are known to be more fragile to misspecification than the canonical DiD estimator under standard parallel trends.

toward different class-quality grade combinations. For example, some beef packing plants that do not specialize in processing fed dairybred cattle may still procure animals of this type. These plants tend to increase (decrease) fed dairy cattle procurement when the supply of beef-breed cattle is low (high) and fed cattle prices are high (low) (Boetel and Geiser 2019).

We perform estimation for the same fixed effects and linear trend specifications used in Table 2 in the main text. Table 4 demonstrates how the models pass the joint pre-trend test (i.e., the joint pre-trend test p-value is not statistically significant).

Table 4: Pre-trend Test Results with Covariates

	(IV) log spread	(V) log spread	(VI) log spread
yfe=1 × device=1	-0.0539*	-0.0539*	-0.0539*
	(-1.93)	(-1.92)	(-1.92)
yfe=2 × device=1	-0.0237	-0.0237	-0.0237
	(-1.01)	(-1.00)	(-1.00)
yfe=4 × device=1	0.00826	0.00826	0.00826
	(0.39)	(0.39)	(0.39)
yfe=5 × device=1	0.186***	0.186***	0.186***
	(8.42)	(8.34)	(8.34)
yfe=6 × device=1	0.282***	0.282***	0.282***
	(13.14)	(13.01)	(13.01)
Pre-test p-value	0.1456	0.1510	0.1510
Fed_slaughter	Yes	Yes	Yes
Month FE	No	Yes	Yes
Time trend	No	No	Yes
R-squared	585	585	585

t statistics in parentheses
The pre-test p-value is calculated from a statistical test on a null hypothesis that pre-trends are parallel between the spreads and wages.
Year fixed effects (yfe) are defined as treatment-year bins aligned to the February treatment start date (i.e., "year" runs Feb–Jan rather than Jan–Dec): $yfe = 1$ for months before Feb 2011, $yfe = 2$ for Feb 2011–Jan 2012, and so on.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5 reports results from the DiD estimation with covariates. The primary takeaway from the models incorporating covariates is that the ATT estimate of 0.117 is statistically significant and is very similar to 0.127 reported in Table 2. Using the methods from Section 6 yields that cattle to beef price spreads in the post-shutdown period were, on average, approximately $\$8.76$/cwt higher

than they would have been in the absence of multi-plant coordination. Therefore, incorporating monthly U.S. steer and heifer slaughter volumes does not materially change the results of the estimation.

Table 5: Regression Results with Covariates

	(IV) log spread	(V) log spread	(VI) log spread
Shutdown	0.0718***	-0.00527	-0.108**
	(6.47)	(-0.20)	(-2.53)
Efficiency Multiplier (device=1)	1.388***	1.388***	1.388***
	(6.54)	(6.48)	(6.47)
ATT (shutdown=1 × device=1)	0.117***	0.117***	0.117***
	(2.77)	(2.74)	(2.74)
Constant	3.004***	3.897***	3.198***
	(61.99)	(19.13)	(16.06)
Fed_slaughter	Yes	Yes	Yes
Month FE	No	Yes	Yes
Time trend	No	No	Yes
R-squared	0.945	0.963	0.968
N	585	585	585

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$