ESSAYS ON SPATIAL DIFFERENTIATION AND IMPERFECT COMPETITION IN AGRICULTURAL PROCUREMENT MARKETS

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ABSTRACT

Jung, Jinho, Ph.D., Purdue University, August 2020. Essays on Spatial Differentiation and Imperfect Competition in Agricultural Procurement Markets. Major Professor: Juan P. Sesmero.

First Essay: We study the effect of entry of ethanol plants on the spatial pattern of corn prices. We use pre- and post-entry data from corn elevators to implement a clean identification strategy that allows us to quantify how price effects vary with the size of the entrant (relative to local corn production) and with distance from the elevator to the entrant. We estimate Difference-In-Difference (DID) and DID-matching models with linear and non-linear distance specifications. We find that the average-sized entrant causes an increase in corn price that ranges from 10 to 15 cents per bushel at the plant's location, depending on the model specification. We also find that, on average, the price effect dissipates 60 miles away from the plant. Our results indicate that the magnitude of the price effect as well as its spatial pattern vary substantially with the size of the entrant relative to local corn supply. Under our preferred model, the largest entrant in our sample causes an estimated price increase of 15 cents per bushel at the plant's site and the price effect propagates over 100 miles away. In contrast, the smallest entrant causes a price increase of only 2 cents per bushel at the plant's site and the price effect dissipates within 15 miles of the plant. Our results are qualitatively robust to the pre-treatment matching strategy, to whether spatial effects are assumed to be linear or nonlinear, and to placebo tests that falsify alternative explanations.

Second Essay: We estimate the cost of transporting corn and the resulting degree of spatial differentiation among downstream firms that buy corn from upstream farmers and examine whether such differentiation softens competition enabling buyers to exert market power (defined as the ability to pay a price for corn that is below its marginal value product net of processing cost). We estimate a structural model of spatial competition using corn procurement data from the US state of Indiana from 2004 to 2014. We adopt a strategy that allows us to estimate firm-level structural parameters while using aggregate data. Our results return a transportation cost of 0.12 cents per bushel per mile (3% of the corn price under average conditions), which provides evidence of spatial differentiation among buyers. The estimated average markdown is $0.80 per bushel (16% of the average corn price in the sample), of which $0.34 is explained by spatial differentiation and the rest by the fact that firms operated under binding capacity constraints. We also find that corn prices paid to farmers at the mill gate are independent of distance between the plant and the farm, providing evidence that firms do not engage in spatial price discrimination. Finally, we evaluate the effect of hypothetical mergers on input markets and farm surplus. A merger between nearby ethanol producers eases competition, increases markdowns by 20%, and triggers a sizable reduction in farm surplus. In contrast, a merger between distant buyers has little effect on competition and markdowns.

Third Essay: We study the dynamic response of local corn prices to entry of ethanol plants. We use spatially explicit panel data on elevator-level corn prices and ethanol plant entry and capacity to estimate an autoregressive distributed lag model with instrumental variables. We find that the average-sized entrant has no impact on local corn prices the year of entry. However, the price subsequently rises and stabilizes after two years at a level that is about 10 cents per bushel higher than the pre-entry level. This price effect dissipates as the distance between elevators and plants increase. Our results imply that long-run (2 years) supply elasticity is smaller than short-run (year of entry) supply elasticity. This may be due to rotation benefits that induce farmers to revert back to soybeans, after switching to corn due to price signals the year the plant enters. Furthermore, our results, in combination with findings in essay 2 of this dissertation, indicate that ethanol plants are likely to use pricing strategies consistent with a static rather than dynamic oligopsony competition.

1. INTRODUCTION

In this dissertation I study whether buyers of farm products are spatially differentiated; whether spatial differentiation confers market power on them; the pricing strategy buyers use if they exert market power; and the market and efficiency implications of such pricing strategies. My dissertation is motivated by a growing concern among stakeholders, regulators, and researchers regarding features of agricultural procurement markets that can cause deviations from a frictionless benchmark. Agricultural procurement markets are typically characterized by large buyers that are spatially dispersed and by products that are costly to transport from the farm to the buyer. These features have led many to assert that spatial differentiation among buyers can confer market power on them, inducing inefficiencies typically associated with imperfect competition (e.g. Durham, Sexton, and Song 1996; Alvarez et al. 2000; Fousekis 2011; Graubner, Balmann, and Sexton 2011). However, empirical evidence on this is remarkably scarce. This dissertation is intended to fill the empirical gap in the body of knowledge.

Measuring market power and its welfare implications requires estimation of structural parameters; in particular we need to estimate firm-level parameters characterizing the residual supply faced by oligopsonists and the resulting marginal factor cost. Without knowledge of these curves, we cannot compute markdown (i.e., the difference between the price the buyer pays for the input and the input's value of marginal product (VMP) which is the price the buyers would pay in a competitive market). But the validity of empirical structural models hinges upon correct specification of the trading environment. And any test of the performance of the model is conducted on the assumption that the model is correctly specified. This is perhaps one of structural models' main weakness. Reduced form empirical analyses impose less structure but cannot deliver an estimate of market power, nor can they generate market and policy counterfactuals conditional on parameter estimates. The strategy I follow in this dissertation is to combine these reduced form and structural approaches to leverage their relative strengths.

I examine the corn market because it displays all the features of agricultural procurement markets that motivate concerns about deviation from the competitive benchmark. Corn is costly to transport and there are large spatially scattered processors that buy from small uniformly distributed farmers. We focus on the corn procurement market in the State of Indiana because large processors in Indiana are relatively insulated from other large processors in neighboring states, though they are likely to compete among themselves.

In the first essay I examine whether reduced-form evidence in the corn procurement markets is consistent with deviation from the competitive benchmark. I do so by exploiting spatially explicit data on ethanol plant entry and corn prices. My premise is simple. If plants have market power, then they must face an upward sloping corn supply. If they face an upward sloping corn supply, then plant entry must raise corn prices at the plant site. Moreover, if plants are spatially differentiated then farm products are costly to transport, which implies that the price effect of entrants should dissipate as we move away from the plant.

I collect temporal and spatially explicit data on elevator-level prices and plants entry and, in combination with other data collected from multiple sources, estimate the impact of plant entry on the spatial pattern of local corn prices. We do so by employing difference-in-difference (DID) and DID-matching strategies that allow for varying intensity of treatment (the size of entrants relative to local corn supply) and heterogeneous treatment effects (effects vary with distance between elevator and the entrant). I find strong and robust evidence that entry raises corn prices at the plant's site (plants face an upward sloping supply) and that the price-effect dissipates with distance (plants are spatially differentiated).

Motivated by findings in the first essay, I develop in the second essay a structural model designed to test whether processors exert buying power. I adopt a recently developed structural approach that allows us to estimate firm-level structural parameters while using aggregate data. I extend this approach to accommodate the possibility of plants operating under binding capacity constraints, a common feature among large corn processors. I estimate the cost of transporting corn and the resulting degree of spatial differentiation among downstream firms that buy corn from upstream farmers and examine whether such differentiation softens competition enabling buyers to exert market power (defined as the ability to pay a price for corn that is below its marginal value product net of processing cost, VMP).

I find strong evidence of spatial differentiation among large corn buyers. This allows buyers to exert market power and pay a price for corn well below its VMP. The markdown increases even further when plants operate at capacity, which I find they did often in the 2004-2014 period. Finally, I use estimated parameters to evaluate the effect of hypothetical mergers–a common trend in agricultural procurement markets–on input markets and farm surplus. A merger between nearby ethanol producers eases competition, increases markdowns by 20%, and triggers a sizable reduction in farm surplus. In contrast, a merger between distant buyers has little effect on competition and markdowns.

A common argument in the literature on the “modern agricultural markets” (MAM) paradigm (Sexton 2013) is that the supply of farm products is inherently dynamic. If large processors suppress the price considerably following a myopic oligopsony procurement strategy, then they may find themselves facing a very limited supply the following year. This is because by suppressing the price today they cause farmers to exit production of that specific farm product which results in reduced future supply. Proponents of MAM further elucidate that, if firms internalize these intertemporal effects, they would have incentive to pay a higher price so as to keep a stock of farmer producers supplying to them in the future. Essays 1 and 2 do not consider a dynamic supply and model situations in which either buyers do not internalize the intertemporal price externalities or long-run farm supply elasticity with respect to price is not different from its short-run supply elasticity. In the third essay, I examine whether the reduced-form evidence is consistent with a dynamic supply response in the sense of a higher long-run supply elasticity. I exploit temporally and spatially disaggregated data on corn prices and ethanol plant entry and implement an autoregressive distributed lag model to examine the dynamic response of prices to a demand shock; i.e., ethanol plant entry. In other words, while essay 1 focuses on the spatial pattern of price response to entry, essay 3 focuses on the temporal pattern of price response to entry.

We find that prices are barely affected by entry the year of entry but do increase afterwards. While we do not explicitly estimate a short- and long-run elasticity of corn supply with respect to its price, our results suggest a high short-term supply elasticity and a smaller long-term supply elasticity. These results are consistent with previous estimates of corn supply elasticity (Chavas and Holt, 1996; Hendricks, Smith, and Sumner, 2014). This may be due to benefits of crop rotation, which limit the willingness of farmers to switch to corn indefinitely. Therefore, farmers initially switch to corn in response to price signals, but then revert back to soybeans due to agronomic effects. A direct corollary of these findings is that the mechanism of market discipline advanced by proponents of MAM is likely of limited effectiveness in the corn procurement market. If firms do suppress prices severely, farmers will not switch to soybeans indefinitely as rotational benefits will induce them to eventually switch back to corn, limiting the reduction in corn supply induced by price suppression.

In sum, this dissertation constitutes an investigation into the existence of buying power in agricultural procurement markets, enabled by spatial differentiation due to transportation costs. We conduct our investigation in the market for corn in Indiana, a market that, due to its features, is particularly suitable for our investigation. The collection of three essays strongly indicates that buyers are spatially differentiated due to transportation cost and locational configuration; that spatial differentiation does confer market power on buyers; that buyers set a Bertrand price (with differentiated inputs) when conditions are not favorable enough to operate at capacity, and they set an Edgeworth-

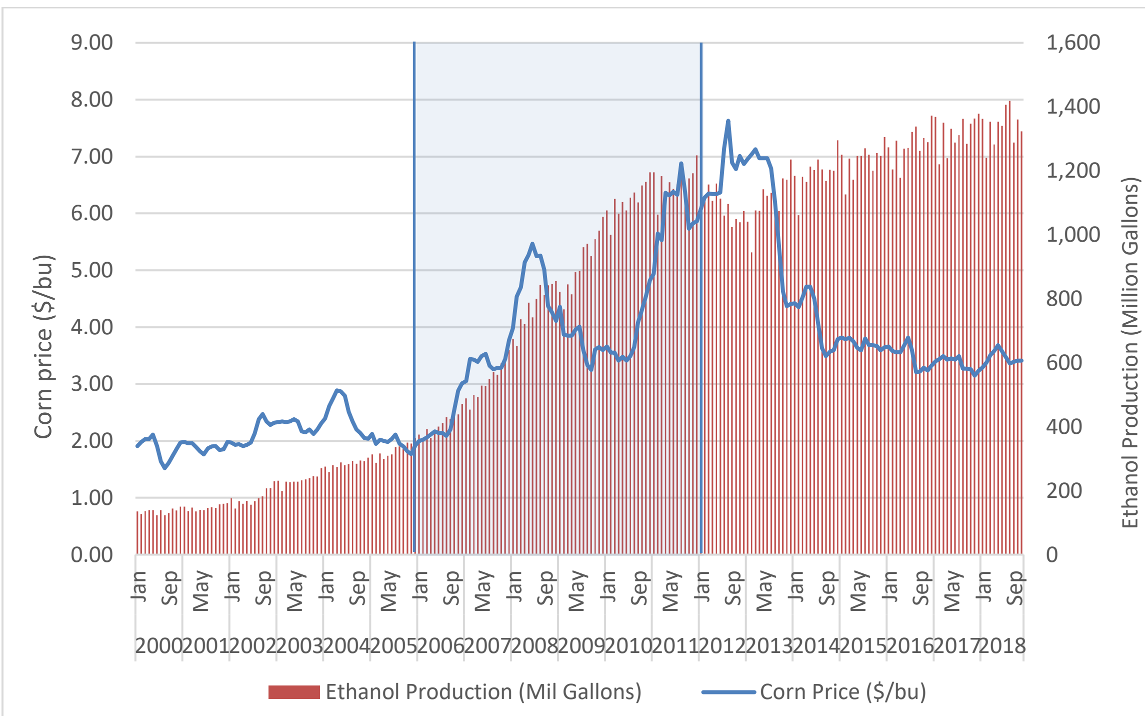
Bertrand price when conditions are very favorable and they operate at capacity; and, finally, that this deviation from the competitive benchmark has a limited effect on efficiency but a large effect on distribution shifting rents away from farmers and towards buyers of farm products.

2. USING PRE- AND POST-ENTRY DATA TO IDENTIFY THE EFFECT OF ETAHNOL EXPANSION ON THE SPATIAL PATTERN OF CORN PRICES: A STUDY IN INDIANA

2.1 Introduction

Ethanol production in the US has increased from 0.2 billion gallons in 1980 to 15.9 billion gallons in the 2018 (RFA, 2018). As a result, the ethanol industry became a major disruption in corn markets, moving from being an unimportant destination of corn to being one of its largest destinations absorbing about one third of corn produced in the US (USDA). Additionally, this drastic transformation took place very rapidly from 2005 (production capacity was 4 billion gallons) to 2011 (production capacity had expanded to 14 billion gallons). Public policies (e.g. tax credits and Renewable Fuel Standards,RFS;, Energy Policy Act of 2005 prompting transition from MTBE to ethanol as an additive) and market conditions (e.g. high petroleum prices) were among key factor underlying this remarkable expansion. The expansion of the ethanol industry and, consequently, corn demand, coincided with a rapid increase in corn prices (shaded area in Figure 2.1). This prompted economists and stakeholders to commonly assert that ethanol expansion was behind the increase in corn prices.

The effect of ethanol expansion on corn prices has been extensively scrutinized by a number of studies. Most of these studies focus on price effects at the national or global levels (Zilberman 2013). But this focus on aggregate markets conceals substantial heterogeneity at the local level. Transportation costs lead ethanol firms to procure most of their corn within a geographically confined area around the plant (Wang et al. 2020). In turn, this suggests that entry is likely to have a higher price impact for suppliers located in close proximity to the plant. Moreover, larger plants are likely to have a larger impact on local corn prices, and this impact is also likely to expand over a larger area. In this study we quantify the effect of ethanol plant entry on the spatial pattern of local corn prices and examine how this effect varies with the size of the entrant.



* Sources: NASS, USDA (2019) for price of annual corn price; ERS, USDA (2019) for ethanol production

Figure 2.1. History of monthly average price of corn and ethanol production in the US

A key challenge to econometric identification of price effects from ethanol plant entry is the fact that entry is not random; ethanol plants are likely to locate in areas with relatively plentiful supply of corn and relatively limited competition from other buyers. Therefore, an OLS estimate of the price effect would suffer from downward bias. We use elevator-level data on prices before and after entry of ethanol plants in the State of Indiana. We use these data to employ difference-in-difference (DID) and DID-matching approaches to construct valid control observations. We find that plant entry raises local corn prices; on average entry of an ethanol plant raises corn price at the plant's site by 8 cents per bushel. We also find that the price effect grows in magnitude with the size of the entrant; the largest plant in the sample raises corn price at the plant's site by 15 cents per bushel while the smallest raises it by only 3 cents per bushel. Finally, the price effect dissipates with distance. The effect dissipates at 20 miles for the smallest plant (relative to local supply) in the sample, 50 miles for the average plant in the sample, and 80 miles for the largest plant in the sample.

Our results have important implications for local market structure. The fact that entry rises price implies that individual plants face an upward sloping corn supply; i.e. they are sufficiently large relative to supply that procurement results in higher prices. The fact that price effects dissipate with distance indicates that procurement markets are geographically localized. These facts are intimately related. Plants face an upward sloping supply because procurement markets are geographically localized. The combination of these features suggest that plants may exert buying power onto local corn suppliers, thereby possibly paying a corn price that is below its marginal value product. Furthermore, our model suggests farm-gate prices decrease linearly with distance suggesting that plants do not engage in spatial price discrimination.

Our paper is closely related to the literature on *local*, i.e. in proximity to the plant, effects of ethanol production expansion.[1] Two separate strands of this literature have examined the effects of ethanol expansion on local land use and local corn prices respectively. The former strand of this literature (Miao, 2013; Brown et al., 2014; Fatal and Thurman, 2014; Motamed, McPhail, and Williams, 2016; Li, Miao, and Khanna, 2018; Wang et al. 2020) finds that expansion of ethanol production, either through entry or increased capacity, induces conversion of land to corn in the area located in close proximity to the expansion, suggesting a positive price effect. But our study is most closely related to the second strand of this literature. Studies in this strand find positive price effects from ethanol plants' siting (Urbanchuk and Kapell, 2002; FAPRI, 2005; McNew and Griffith 2005; Fatal 2007; Grashuis 2019), no effect (Blomendahl et al. 2011; Lewis and Tonsor 2011; Katchova 2010; Katchova 2019), or even negative effects (Lewis 2010). The ambiguity of results may be partly explained by differences in time periods and study areas considered. But it is also, likely, the result of a lack of adequate control groups against which areas with an ethanol plant can be compared.

We address this issue by exploiting pre- and post-entry price data in the State of Indiana. We exploit these data to implement a difference-in-difference estimation strategy. Katchova and Sant'Anna (2019) also used a DID estimation strategy where plant entry is the treatment and corn price is the outcome of interest. Our study differentiates from

[1] There is a vast literature on the effects of the expansion of the ethanol industry on national and global markets as reviewed by Zilberman (2013).

Katchova and Sant'Anna (2019) in two important ways. First, we quantify price effects from plant entry allowing the magnitude of the treatment to vary according to the capacity of the entrant relative to local supply. Second, we exploit spatially explicit data to examine the *spatial pattern* of price effects. McNew and Griffith (2005) also looked at spatial patterns of price effects but did not let the magnitude of the treatment to vary with plant size relative to local supply. More importantly, they did not have an adequate control group as they used cross-sectional data, which may explain why estimates of how the price effect decreases with distance are statistically insignificant; i.e. this study was perhaps picking up global, instead of local effects. We choose a study area (Indiana) and a time period (2004-2014) that deliver clean identification through DID and DID-matching models. This is because we have data on prices received by elevators before any of them were treated, and data on prices received by elevators well after some of them were treated. Moreover, plants are sufficiently scattered so that treatment spillovers are limited. Finally, our identification strategy benefits from the fact that selection in this context is likely to be on well-known observables that we have detailed data on.

The remainder of the essay is structured as follows. The next section describes institutional details of the corn procurement market and the spatial pattern and nature of ethanol plant entry in Indiana. We then describe the data and econometric identification strategy. We subsequently discuss results and their robustness and, finally, introduce concluding remarks.

2.2 The Corn Ethanol Market in Indiana and Empirical Strategy

We study the effect of ethanol expansion on corn prices received by elevators in the State of Indiana. We focus on this geographical area because it displays features that greatly facilitate identification of the effect of ethanol expansion on corn prices. The ethanol industry has undergone substantial growth in Indiana, not unlike growth in other areas of the Corn Belt. A total of 13 ethanol plants entered over a 5-year period. The ethanol industry consumed 4% of corn supplied in 2005 (due to one old wet-mill plant that had been in operation for over two decades) and grew spectacularly to consume 38% in 2011 (Table 2.1, Figure 2.2)[2], becoming the main destination of Indiana corn (NASS, USDA). On the other hand, corn consumption by other sectors have stayed relatively constant, suggesting that the increase in corn price over this period may be attributed to plants' entry as also suggested by temporal evolutions depicted in Figure 2.2.

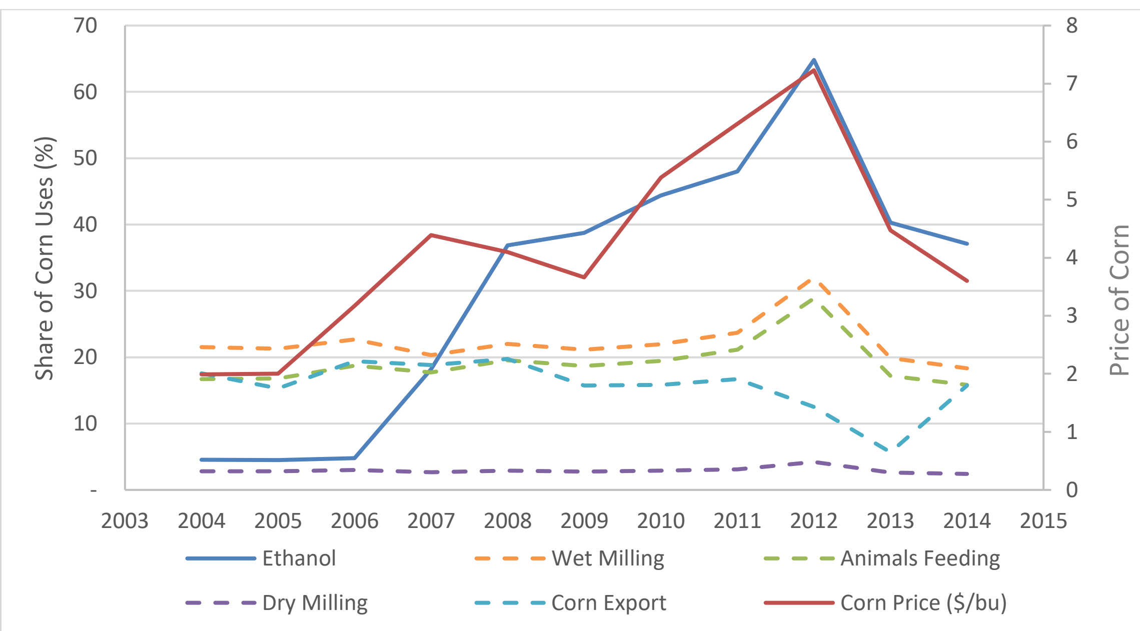
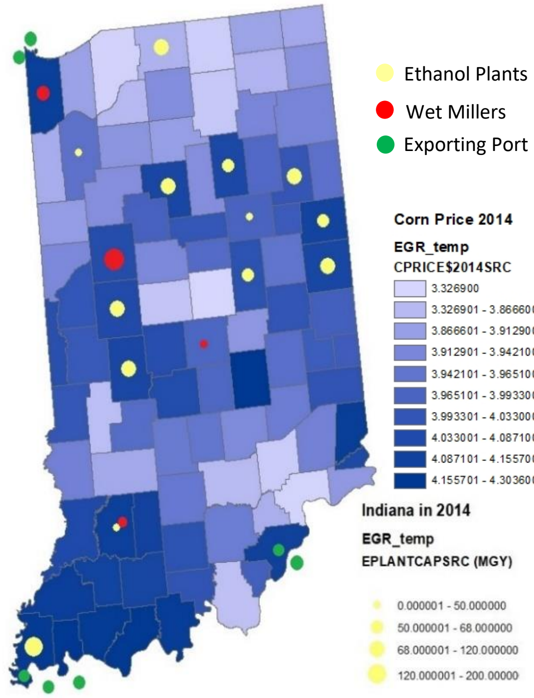


Figure 2.2. Estimated Share of Corn Uses and Price of Corn in Indiana

[2] The share of corn consumed by ethanol plants in 2012 climbed to around 65% but this was an outlier explained by an unusually small corn supply due to a major drought in 2012.

Information in Table 2.1 and Figure 2.2 portrays only an aggregate picture of ethanol expansion and changes in corn prices. A closer look at entry patterns directly informs our empirical strategy. A total of 13 plants entered at different points in time in the State of Indiana. In regard to the *spatial pattern of entries*, plants are relatively spatially scattered as indicated in Figure 2.3. Previous studies found that ethanol plants affect corn prices in close proximity to the plant but tend to dissipate with distance (McNew and Griffith, 2005; Grashuis, 2019) which is expected due to the fact that corn is costly to transport (Denicoff et al., 2014). This implies that ethanol expansion will likely affect prices received by some elevators (those located in close proximity to entrants), but not all. In regard to the *temporal pattern of entries*, as portrayed in Figure 2.4, expansion of ethanol capacity takes place through discrete jumps. These discrete jumps do represent entry and not spatial relocation as high relocation costs preclude plants from moving (Official Nebraska Government, 2019).



* Note: Yellow dots represent ethanol plants, red dots locate wet-milling corn processors, green dots are exporting ports.
* Source: Renewable Fuel Association (2017) and Official Nebraska Government (2017) provide ethanol plant location and capacities. Authors purchase corn price data from Geo Grain at elevator level and aggregate it up to individual county average corn price.

Figure 2.3. Ethanol Plants Locations and Corn Prices in Indiana in 2014

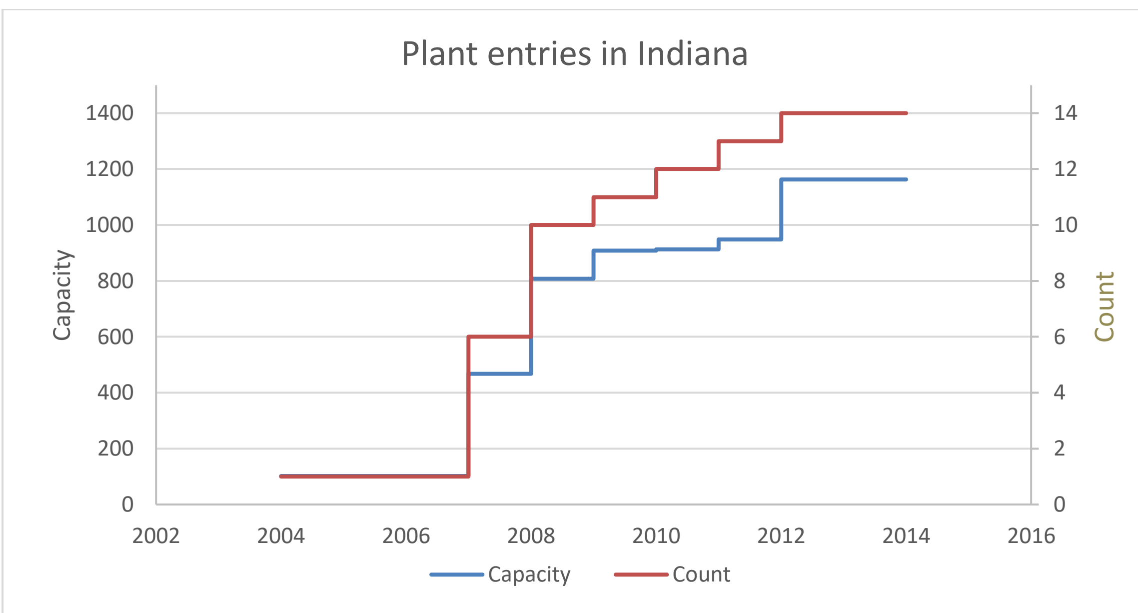


Figure 2.4. Entry Pattern of Ethanol Plants
Figure 2.4. a. Entry Pattern at State Level

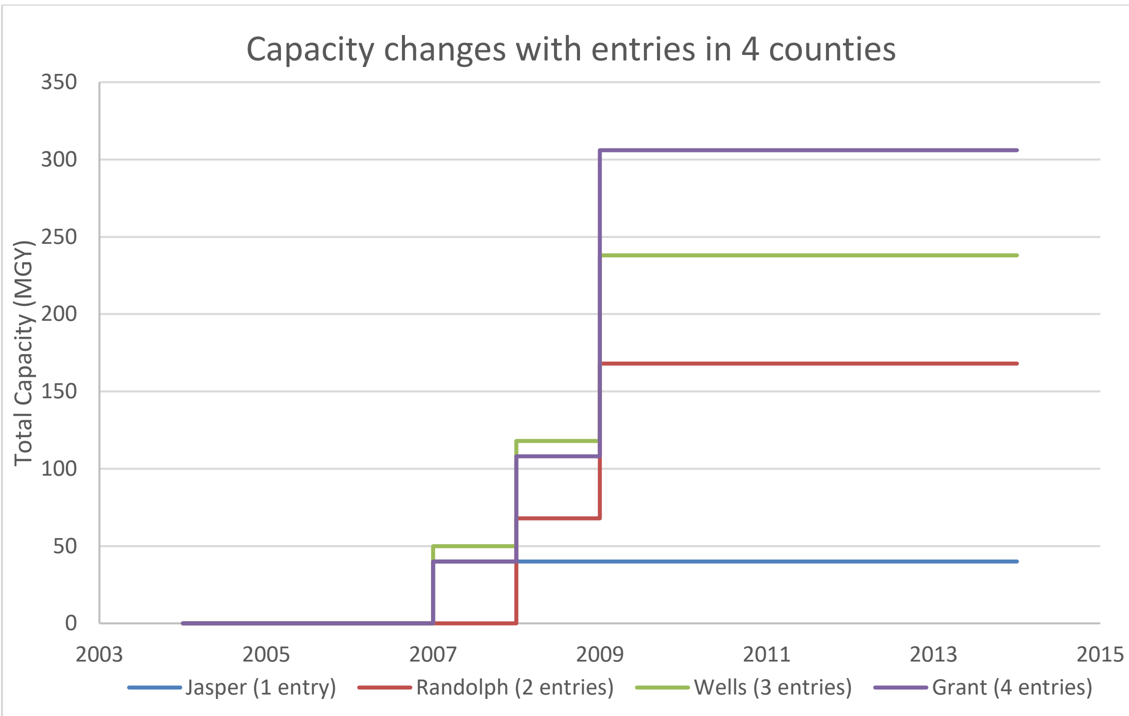


Figure 2.4. b. Entry Pattern at County Level

Table 2.1. Estimated Share of Corn Use by Processing Sector in Indiana (% of total supply)

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Ethanol[1]	3.85	4.00	3.97	10.06	21.15	32.71	34.82	38.46	65.48	38.65	37.86
Wet Milling	21.58	22.44	22.26	19.81	22.61	20.72	21.94	23.33	32.52	19.36[2]	18.97[2]
Animals Feeding[3]	16.72	17.70	18.39	17.30	20.06	18.29	19.46	20.81	29.31	16.73	16.38
Dry Milling	2.84	2.95	2.93	2.60	2.97	2.72	2.88	3.07	4.27	2.55	2.49
Corn Export[4]	17.63	16.12	19.02	18.35	20.29	15.43	15.84	16.41	12.70	5.52	16.26
Others (Storage, ship outside IN)	37.39	36.78	33.44	31.87	12.91	10.13	5.06	-2.08	-44.28	17.19	8.03
Total Corn Supply[5]	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Annual Production[6]	94.12	93.68	88.30	91.26	92.78	90.86	92.48	92.00	91.15	93.82	96.62
Corn Stock from the previous year[7]	5.88	6.32	11.70	8.74	7.22	9.14	7.52	8.00	8.85	6.18	3.38

* Data source: Hurt (2012) for the period from 2007 to 2012, Author's estimation (NASS Quick Stats, USDA; ERS, USDA) for the period from 2013 to 2014.

1. Estimated based on the information of ethanol plants capacities
2. Assume to stay constant from 2012 (Hurt, 2012)
3. Estimated based on the livestock inventory data (NASS, USDA). This is converted to the annual amount fed based on the assumption of 11.6 bushels of corn per head of a hog over its lifespan (4 months), 50 bushels of corn per head of a cattle over its lifespan (18 months), 0.62 bushels of corn per head of poultry over its lifespan (10 weeks).
4. State Export Data (ERS, USDA) and Survey Data for global price of corn (FRED, Federal Reserve Bank of St. Louis).
5. Total corn supply in Indiana is the sum of the corn production harvested in the crop year and the corn stock from the previous crop year.
6. Extremely low due to drought in absolute number
7. This is the corn stock from the previous *crop year of corn*.

As a result of their spatial and temporal patterns, ethanol plant entries are likely to result in two well-defined groups: a treatment group (elevators whose prices are influenced by plant entry) and a control group (elevators whose prices are not influenced by plant entry). Moreover, most elevators in the treatment group will experience one single discrete jump (one entry) over the entire sample period precluding empirical strategies that require within-elevator variability over time in ethanol capacity. These features favor a *difference-in-difference* (DID) strategy over other strategies that exploit repeated observations such as fixed-effects, dynamic panel, and IV strategies. Our estimating equation is as follows:

$$Corn\ \ Price_{eit} = \alpha_0 + \gamma_e + \lambda_t + \delta_1(Entry_{it} * Post_t * RATIO_{it}) + \delta_2(Entry_{it} * Post * RATIO_{it} * DIST_{eit}) + \delta_3(Entry_{it} * Post * RATIO_{it} * DIST_{eit}^2) + \eta\, X_{it} + \varepsilon_{eit} \qquad (2.1)$$

where the outcome variable $Corn\ \ Price_{eit}$ is the real price paid for corn by elevator e located in county i ($i \in \{1, \dots, 92\}$) in period t ($t \in \{pre-treatment, post-treatment\}$); α_0 is a common intercept; γ_e is an elevator-level fixed effect; λ_t is a time effect; $Entry_{it}$ is a binary variable indicating whether the elevator is treated or not ($Entry_{it}$ is equal to 1 if a plant enters county i or a surrounding county and it is equal to 0 otherwise); $Post_t$ is also a binary variable that takes a value of 1 if the observation belongs to the post-treatment period and 0 if it belongs to the pre-treatment period; $RATIO_{it}$ denotes the ratio between the plant's capacity and corn production in period t in the county where the plant is located; $DIST_{eit}$ is the distance between elevator e located in county i in period t and the nearest ethanol plant; X_{it} is a vector of county-level control variables; ε_{eit} is the error term; and the rest are parameters to be estimated.

The variable $RATIO_{it}$ is intended to capture variation in the intensity of treatment. Alternatively, we could use capacity, which varies from plant to plant, to capture intensity of treatment. All else constant, capacity represents demand pressure for corn; but all else is not constant. If a plant located in county i is 10% larger than another located in county j, but county j produces 20% more corn, using capacity would be misleading. What intensity of treatment should capture is the size of demand from the plant *relative to local corn supply*; the ratio is precisely intended to capture this relative measure of size. Notice that intensity of treatment varies over time as corn supply fluctuates from period to period, even though plant capacity does not. Of course, other variables that affect excess demand for corn such as livestock inventory may not remain constant across observations. Such variables would be captured in the vector of county-specific controls X_{it}.

The variable $DIST_{eit}$ is intended to capture heterogeneous treatment effects, conditional on the intensity of treatment. We include both a linear and a quadratic term for distance to allow for a non-linear price-distance gradient for reasons previously discussed. In contrast to McNew and Griffith (2005), we do not allow for heterogeneous quadrant effects; i.e. a situation in which a mile away from the plant in the north-east direction has a different impact on price that a mile away in the north-west direction. The benefits of this additional flexibility are likely to be small in Indiana due to homogeneity in land use. Moreover, adding this flexibility comes at a price–a loss in parsimony and degrees of freedom that is costly in our context as we want to add flexibility through intensity of treatment and non-linearity of the price-distance gradient.

Based on findings from previous studies we advance several hypotheses that can be tested after estimation of equation (1). First, we hypothesize that entry of an ethanol plant raises corn price at the plant's site and that such effect grows with the intensity of treatment; i.e. $\delta_1 > 0$. Due to our specification in (1) the parameter δ_1 indicates the price effect (or treatment effect) associated with an entrant with a ratio of 1; i.e. the capacity of the plant is equal to total corn production in the county where the plant is located. Note from Table 2.2 that a ratio of 1 is well below the average across plants during our study period. Another way to interpret this parameter is to think of it as the effect on price from increasing the ratio by one unit which, in short, means an expansion in processing capacity equivalent to total corn production in the county where the expansion occurs.

We also hypothesize that the price effect should dissipate as the distance between an elevator and the entrant increases and that the price effect diminishes linearly with distance; i.e. $\delta_2 < 0$ and $\delta_3 = 0$. The relationship between the price-effect of entry and distance, henceforth the price-distance gradient, may be non-linear for at least two prominent reasons. First, as the plant is forced to source corn from larger distances railroads can be used instead of trucks. Since transportation by railroad is generally less costly for larger distances, the price-distance gradient may be convex (the price received by the elevator at the elevator's gate may decrease at a decreasing rate with distance from the ethanol plant). On the other hand, a positive price effect if one exists implies that a plant faces an upward sloping supply. If plants recognize this fact and exert buying power, they may also engage in spatial price discrimination; i.e. they may pay lower elevator-gate prices to elevators located in close proximity. This would result in a concave price-distance gradient. Therefore, the shape of the price-distance gradient is an empirical question which we examine here.

Table 2.2. Ratio of ethanol plants' corn processing capacity to county corn production

Firm	County	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
The Andersons Clymers Ethanol, LLC	Cass	-	-	-	2.06	2.10	2.44	2.70	2.72	3.77	2.04	2.12
Grain Processing Corp.[1]	Daviess	-	-	-	-	-	-	-	0.53	1.04	0.46	0.40
Central Indiana Ethanol, LLC	Grant	-	-	-	1.31	1.22	1.17	1.30	1.78	2.00	1.31	1.27
Iroquois Bio–Energy Company, LLC	Jasper	-	-	-	0.54	0.54	0.65	0.57	0.59	0.62	0.47	0.51
POET Bio-refining	Jay	-	-	-	-	2.56	2.43	2.44	2.53	3.00	1.96	1.96
POET Bio-refining	Madison	-	-	-	-	1.79	1.73	1.68	1.77	2.20	1.55	1.38
Valero Renewable Fuels Company, LLC	Montgomery	-	-	-	-	2.08	1.84	1.94	1.94	3.38	1.72	1.66
Abengoa Bioenergy Corp.	Posey[2]	-	-	-	-	-	-	-	-	4.54	2.04	4.18
POET Bio-refining	Putnam	-	-	-	-	-	3.14	3.06	3.50	7.92	2.70	2.43
Cardinal Ethanol	Randolph	-	-	-	-	-	2.37	2.47	2.72	3.83	2.14	2.10
Noble Americas South Bend Ethanol LLC	St. Joseph	3.33	3.69	3.53	3.24	3.72	3.20	3.25	3.14	3.62	3.15	3.29
POET Bio-refining	Wabash	-	-	-	-	-	1.97	2.05	2.45	2.84	1.76	1.66
Green Plains Renewable Energy	Wells	-	-	-	-	-	3.21	2.63	4.34	4.50	2.88	2.94
Below 1[3]		0	0	0	1	1	1	1	2	1	2	2
Above 1[4]		1	1	1	3	6	10	10	10	12	11	11

* Note: All counties have 1 ethanol plant but Posey county with 2 ethanol plants.

* Source: Official Nebraska Government (2017), Renewable Fuel Association (2017) and The Biofuel Atlas, NREL

1. Grain Processing Corp. (GPC) operates as both of ethanol plants and wet-milling processor.
2. Posey county has two ethanol plants.
3. The number of counties that ethanol plants demand less corn than produced among counties where at least one ethanol plant is located.
4. The number of counties that ethanol plants demand more corn than produced among counties where at least one ethanol plant is located.

2.3 Identification Strategy

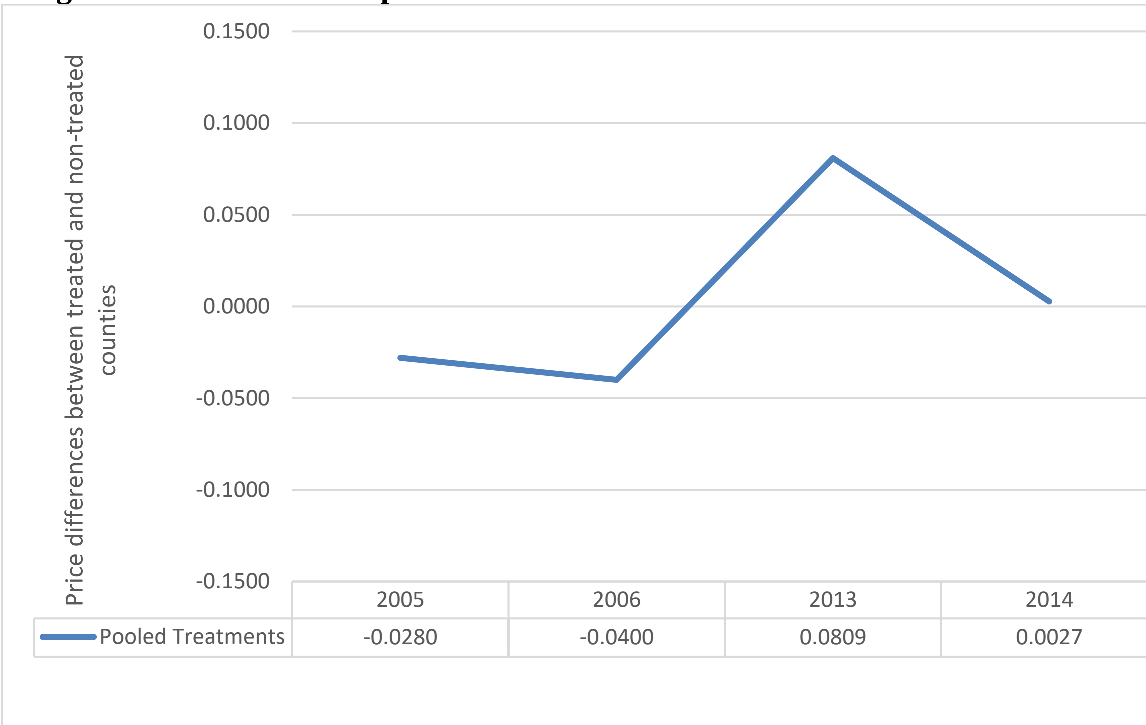
Causal identification in a DID framework is not without challenges. In our context, selection is an obvious potential source of bias as ethanol plants may choose to locate in a certain area due to unobservable and observable characteristics displayed by that location that make entry more attractive for a potential ethanol investor.

To control for unobservable characteristics the DID strategy requires fulfillment of the parallel trend assumption. In our context, this assumption requires that prices paid by treated and control elevators follow a sufficiently similar trend over the pre-treatment period. We test this assumption by looking at unconditional (average) prices for treatment and control elevators in Indiana and using a placebo test. Figure 1.5 shows the average price differences between treated and control elevators ($P_{Treated} - P_{Non-Treated}$) for the pre- and post- treatment periods. First, the relatively flat pre-treatment trend is consistent with the parallel trend qualification underpinning the DID model. In addition, following Jakiela (2019) and Yamamoto (2016), a placebo test that runs the main DID model in equation (2.1) with a "fake" treatment group detects no treatment effect (Table 2.3). Therefore, visual inspection and results from a placebo test validate the parallel trend assumption suggesting that the DID model is an adequate empirical strategy in our context.

Table 2.3. Impact of ethanol plant on local corn prices (Placebo test)

Estimator	Effect of a new plant with 100 MGY
DID	-0.0002 (0.0011)
DID-matching	
NNM (2N)	-0.0003 (0.0011)
NNM (4N)	-0.0004 (0.0011)
PSM (2N)	-0.0003 (0.0011)
PSM (4N)	-0.0004 (0.0011)
OLS	
OLS	0.0112 (0.0114)
OLS (PSM, 2N)	0.0118 (0.0111)

Figure 2.5. Trend in corn price differences between treated and control elevators



As revealed by Figure 2.5 prices in treated elevators tend to be lower than those in controlled elevators, before treatment. This is not surprising given that plants tend to locate where corn is cheap. But this observation strongly suggests selection on observables; i.e. characteristics that make certain locations more likely to host an ethanol plant. Selection on observables is not controlled for by the parallel trend assumption; a condition that is intended to circumvent selection on unobservables. Fortunately, observable characteristics that tend to influence location of ethanol plants are limited in number and well-identified in the literature, particularly the literature looking at the effects of entry on land use around the new plant (Motamed et al. 2016; Wang et al. 2020). We use this information to control for possible selection on observables by estimating DID-matching models. This strategy consists of two steps. First, we match elevators based on pre-treatment characteristics that have been found to influence plant location in previous studies to remove selection bias (Imbens, 2004). Then, we compare the change in treated elevators' price between pre- and post-treatment periods with the change in control elevators' price between pre- and post-treatment periods.

For the first step of the DID-matching estimation we use Nearest Neighbors Matching (NNM) and Propensity Score Matching (PSM) strategies to match each treated county to the one, two and four closest untreated counties based on pre-treatment characteristics. A key condition for valid implementation of DID-matching is that observables that drive selection into treatment are not themselves affected by the treatment, which is why we match observations based on pre-treatment characteristics. The observables based on which we match elevators include corn production in the county where the elevator is located, corn demand from livestock operators in the county where the elevator is located, distance between the elevator and the closest exporting port, railroad density around the elevator, and population in the county where the elevator is located. Table 2.4 presents some descriptive statistics on pre-treatment characteristics.

Table 2.4. Descriptive Statistics for Main Characteristics of Counties (with Posey county)

# of observation	Treatment Group		Matched Group		Control Group
	n=420	Normalized Difference	n=1680	Normalized Difference	n=116
Corn Price (Post-Treatment)	5.054 (0.132)	-0.022	-	-	5.029 (0.991)
Corn Price (Pre-Treatment)	2.693 (0.104)	0.033	2.708 (0.070)	0.023	2.743 (0.093)
Corn Production (Post-Treatment)	14.662 (6.000)	-0.141	-	-	7.015 (5.272)
Corn Production (Pre-Treatment)	12.405 (4.948)	-0.073	9.955 (4.331)	-0.050	5.726 (4.505)
Livestock Demand (Post-Treatment)	2.591 (3.318)	-0.046	-	-	1.324 (2.091)
Livestock Demand (Pre-Treatment)	2.527 (2.883)	-0.037	1.710 (1.704)	-0.014	1.259 (1.599)
Distance to Port (Post-Treatment)	77.310 (38.777)	-0.053	-	-	59.699 (28.416)
Distance to Port (Pre-Treatment)	77.310 (38.777)	-0.037	72.746 (22.377)	-0.027	59.699 (28.416)
Railroad Density (Post-Treatment)	83.758 (68.803)	-0.034	-	-	62.953 (56.881)
Railroad Density (Pre-Treatment)	83.758 (68.803)	-0.021	65.816 (43.643)	-0.003	62.9523 (56.881)
Population (Post-Treatment)	71,812 (92,175)	-0.004	-	-	70,822 (151,539)
Population (Pre-Treatment)	69,832 (87,807)	-0.006	48,088 (72,757)	0.009	68,502 (143,448)

* Note: Treatment Group refers to counties which has either of direct- or indirect- plant entries. Both Entries means that entries happen both in its own county and any neighboring county. Direct Entries accounts for counties that have entries only in itself while Indirect Entries includes counties with entries only in any neighboring county. Control Group refers to counties that has no entry at all neither in itself and neighboring counties. Matched Group presents the same information on Treatment Group, but the information is based on counites in comparison group that are selected in the matching process of using 4 Nearest Neighbors Matching (NNM (4)). ND abbreviates Normalized Difference in means between the treated and control groups. ND in one of the Treatment Group columns is the one before the matching procedure. ND in one of the Matched Group is the one after the matching procedure.

We start by computing propensity scores as functions of all the characteristics in Table 2.4. Figure A1 in the Appendix A illustrates the kernel distribution of propensity scores for treated and control elevators. This figure indicates that our matching strategy seems to perform well based on overlap of kernel densities. We calculate the normalized difference in pre-treatment characteristics between treatment and control groups (Table

2.4) to examine the extent of balancing between the two groups before and after the matching procedure. As suggested by Rosenbaum and Rubin (1985) and Stuart (2010), the normalized difference is the difference in means between treatment and control groups divided by the square root of the sum of variances for both groups. When the normalized difference is below 0.25, the rule of thumb suggested by Rubin (2001) and Imbens and Wooldridge (2009), groups are sufficiently balanced. Table 2.4 shows that the normalized differences are already lower than 0.25 before matching, indicating that *random selection* seems an adequate assumption in our context. Nevertheless, normalized differences are reduced by matching suggesting that application of the matching procedure may improve selection of an appropriate control group.[3]

Finally, we have two additional challenges to identification: spillover effects and dynamic evolution of corn prices. The corn ethanol market in Indiana displays two key features that facilitate identification with a DID model against the backdrop of these identification challenges. First, the ethanol market in Indiana is characterized by relatively few and spatially dispersed plants (Figure 2.3). Since transporting corn is costly, plants tend to procure corn locally. Therefore, price effects of different plants may be relatively insulated from each other ameliorating spillover effects of entry. This seems further supported by considerable spatial variability of corn prices across space and positive, albeit weak, unconditional correlation between local prices and ethanol plants' locations (Figure 2.3). *This feature facilitates identification* because it reduces the risk of violation of the

[3] We examined the robustness of our findings to elimination of Posey county from the sample. This is because Posey is a treated county that also happens to be located in close proximity to an exporting port. As a result, Posey has a very high pre-treatment price which increases the average pre-treatment price of treated elevators. Nevertheless, our analysis indicates that our conclusions regarding normalized differences and balancing improvement still stand after elimination of Posey from the sample.

Stable Unit Treatment Value Assumption (SUTVA), also called the Individualistic Treatment Response (ITR), a condition requiring that the treatment status of any one unit must not affect the outcomes of any other unit (Rubin 1980; Manski 2013). Second, all modern ethanol plants[4] operating in Indiana entered within a limited time window comprising the years 2007-2011 which allows us to cleanly define a pre- and post-treatment period. *This feature also facilitates identification* because corn prices (the outcome variable) can have complicated dynamics in response to permanent shocks (such as plant entry) due to its storable nature (Carter et al. 2017). We allow for a reasonable period of time after entry to examine prices so that observed prices likely correspond to the new (after full adjustment) equilibrium.

2.4 Data

The data come from multiple sources. We collected county-level data on corn production and livestock inventory, as well as State-level data on corn storage from the National Agricultural Statistics Service of the United States Department of Agriculture (NASS, USDA). We purchased elevator-level corn cash bids data from Geo Grain. Geo Grain records commodity cash bids at multiple elevator locations across the state. These data provide full coverage of the Indiana territory. We also know exact locations of these elevators and can then calculate elevator-level distances to ethanol plants and exporting ports. Corn export data and international price of corn are from Economic Research Service

[4] One older, wet-milling plants had been in operation in Indiana for over two decades. Modern plants use a different technology called dry-milling. The main difference is that wet-milling plants are designed to produce a diversified set of outputs while modern dry-milling plants specialize in the production of ethanol are, consequently, more efficiency.

(ERS), USDA and Federal Reserve Bank of St. Louis (FRED), respectively. The information on ethanol plants such as locations, year built, ownership, name plate and operating capacity comes from the Official Nebraska Government (ONG), the Renewable Fuel Association (RFA), US Environmental Information Administration (EIA), and the Biofuel Atlas published by the National Renewable Energy Laboratory (NREL). Information on food milling plants' capacities and locations is based on Hurt (2012) and personal communications with the author of that publication. Historical diesel prices and electricity rates are obtained from the US EIA.

Given the seasonality of corn supply, we conduct a temporal aggregation over the crop year, the period between one harvest to the next which starts on Sep 1st and ends on Aug 31st of the next year. Total supply of corn in counties of Indiana in a given year is the sum of the stock from the last crop year and the harvest at the beginning of the current crop year. Monthly data on operational capacities of ethanol plants are available from ONG. We use this information and assume that, if a plant is in operation before September 1st, the plant participates in price bidding in that crop year starting on September 1st.

In total, our data consist of a balanced panel data with 268 elevators over 11 years (2004-2014). We determine that an elevator is treated when an ethanol plant locates in the county where the elevator is located or a surrounding county. Another alternative commonly used is to define the boundaries of the plant's procurement region based on a circle of a certain radius around the plant. Behnke and Fortenbery (2011) compare different measurement of spatial weight matrices and suggest that using contiguous counties out-performs a circle with a 50 mile-radius based on likelihood function values. Because of this, and because it makes the analysis and data management simpler, we use contiguous counties to define treatment as opposed to a circle. This definition results in 210 treated elevators and 58 control elevators as a result of 13 ethanol plant entries.

All 13 entries of ethanol plants in Indiana took place between 2007 and 2012. We define a pre-treatment period consisting of the years 2004 and 2006 and a post-treatment period consisting of years 2013 and 2014. As previously discussed, we chose these periods to minimize biases from short-term dynamic adjustments in prices. To minimize the effect of seasonal and other short-term variations of corn prices the pre-treatment price for each elevator is the average of corn prices during the entire pre-treatment period (2004-2006). Similarly, the post-treatment price for each elevator is the average of corn prices during the entire post-treatment period (2013-2014).

We use two different levels of data. Corn price, our outcome variable, is measured at the elevator level, and so are distance from the elevator to the nearest ethanol plant (explanatory variable in the outcome equation) and to the nearest exporting port (used as a pre-treatment matching characteristic). All other variables are measured at the county level since this is the smallest level of aggregation available to us. We control for time-constant unobservables at the elevator level by including elevator fixed effects in estimation.

2.5 Results

We present results from a range of models in Tables 2.5-2.7. Table 2.5 presents models that allow for a non-linear price-distance gradient. Table 2.6 presents models that assume a linear price-distance gradient. And, finally, Table 2.7 presents results from models that ignore potentially heterogeneous treatment effects due to distance. In each Table we report results from estimation with different matching strategies. Comparison across Tables conditional on the matching strategy reveals the implications for estimation and inference regarding price effects of ethanol plant entry of allowing for more flexible spatial patterns of such price effects. Comparison across models conditional on the price-distance gradient reveals the importance of adequate matching on estimated results and hypothesis testing.

Results across models in Tables 2.5 and 2.6 and across matching strategies conditional on those models show that entry of an ethanol plant does raise the price of corn at the plant's site. The increase under a ratio of 1 (the entrant's capacity is equal to corn production in the county where the plant located) is about 8 cents per bushel (about 2% of average corn price in our sample) according to the model that allows for a non-linear price-distance gradient (Table 2.5). The same effect is about 5 cents per bushel in the model that assumes a linear price-distance gradient (Table 2.6). The average ratio in our sample (Table 2.2) is about 2. Therefore, on average, plant entry seems to have raised local corn prices by an amount that ranges from 10 to 15 cents per bushel. These estimates are substantially larger than those of McNew and Griffith (2005) and Grashuis (2019) who found an average impact of 6 cents per bushel. The smallest ratio in our sample is about 0.6 and the largest is 4. Therefore, price effects at the plant's site could have fluctuated between 3 cents and 30 cents depending on corn supply conditions. Consequently, we fail to reject the null hypothesis that ethanol plant entry increases local corn prices.

It is interesting to note that when we estimate the price effect ignoring the effect of distance, results suggest that entry of an ethanol plant has no discernible effect on corn prices. This is likely the result of averaging price effects across elevators, many of which are located far from the entrant. This result underscores the importance of explicitly accounting for a price-distance gradient in estimation.

Table 2.5. Impact of Entries of Dominant (Ethanol) Plants on Local Corn Prices (Linear and Quadratic Distance)

	$Corn\ \ Price_{ect}$	Main model	Eliminating county-fixed effect	Eliminating year-fixed effect	Eliminating both fixed-effect
DID	$Ratio_{ect} * Treat_{et}$	0.0733**	0.0929***	1.4677***	1.1002***
		(0.0294)	(0.0227)	(0.1747)	(0.1089)
	$Ratio_{ect} * DIST_{et} * Treat_{et}$	-0.0040**	-0.0062***	-0.0142	-0.0123
		(0.0020)	(0.0015)	(0.0130)	(0.0079)
	$Ratio_{ect} * DIST_{it}^2 * Treat_{et}$	4.93E-05	7.97E-05***	0.0001	0.0001
		(3.52E-05)	(2.73E-05)	(0.0002)	(0.0001)
	$LSTOCK_{ct}$	0.0022	-0.0063**	-0.1014*	-0.0433***
		(0.0087)	(0.0030)	(0.0574)	(0.0153)
	$Intercept$	2.6739***	2.6939***	3.3875***	3.4640***
		(0.0229)	(0.0132)	(0.1453)	(0.0590)
	R-Square	0.9787	0.9792	0.4365	0.4411
NNM (1)	$Ratio_{ect} * Treat_{et}$	0.0677**	0.0934***	1.3719***	1.0856***
		(0.0293)	(0.0228)	(0.1782)	(0.1102)
	$Ratio_{ect} * DIST_{et} * Treat_{et}$	-0.0038**	-0.0062***	-0.0105	-0.0121
		(0.0020)	(0.0015)	(0.0131)	(0.0079)
	$Ratio_{ect} * DIST_{it}^2 * Treat_{et}$	4.72E-05	7.97E-05***	5.98E-05	9.75E-05
		(3.51E-05)	(2.73E-05)	(0.0002)	(0.0001)
	$LSTOCK_{ct}$	0.0090	-0.0067**	0.0515	-0.0214
		(0.0074)	(0.0032)	(0.0491)	(0.0169)
	$Intercept$	2.6623***	2.6915***	3.0570***	3.4091***
		(0.0170)	(0.0126)	(0.1105)	(0.0577)
	R-Square	0.9780	0.9792	0.4218	0.4345
	Year-fixed effect	Yes	Yes	No	No
	County-fixed effect	Yes	No	Yes	No

Table 2.5 Continued

	$Corn\ Price_{ect}$	Main model	Eliminating county-fixed effect	Eliminating year-fixed effect	Eliminating both fixed-effect
NNM (2)	$Ratio_{ect} * Treat_{et}$	0.0724***	0.0947***	1.4346***	1.0967***
		(0.0168)	(0.0160)	(0.1012)	(0.0774)
	$Ratio_{ect} * DIST_{et} * Treat_{et}$	-0.0040***	-0.0063***	-0.0123*	-0.0122**
		(0.0011)	(0.0011)	(0.0075)	(0.0056)
	$Ratio_{ect} * DIST_{it}^2 * Treat_{et}$	4.96E-05**	7.96E-05***	8.15E-05	9.59E-05
		(2.01E-05)	(1.92E-05)	(1.35E-04)	(1.00E-04)
	$LSTOCK_{ct}$	0.0029	-0.0079***	-0.0233	-0.0344***
		(0.0037)	(0.0023)	(0.0246)	(0.0120)
	$Intercept$	2.6731***	2.6951***	3.2012***	3.4372***
		(0.0095)	(0.0091)	(0.0606)	(0.0416)
	R-Square	0.9786	0.9793	0.4357	0.4371
NNM (4)	$Ratio_{ect} * Treat_{et}$	0.0726***	0.0938***	1.4365***	1.0911***
		(0.0010)	(0.0113)	(0.0660)	(0.0548)
	$Ratio_{ect} * DIST_{et} * Treat_{et}$	-0.0040***	-0.0062***	-0.0122**	-0.0121***
		(0.0007)	(0.0008)	(0.0049)	(0.0039)
	$Ratio_{ect} * DIST_{it}^2 * Treat_{et}$	4.98E-05***	7.96E-05***	8.07E-05	9.67E-05
		(1.31E-05)	(1.36E-05)	(8.79E-05)	(7.08E-05)
	$LSTOCK_{ct}$	0.0022	-0.0072***	-0.0228*	-0.0275***
		(0.0020)	(0.0016)	(0.0131)	(0.0085)
	$Intercept$	2.6747***	2.6929***	3.1975***	3.4217***
		(0.0054)	(0.0064)	(0.0337)	(0.0291)
	R-Square	0.9787	0.9792	0.4348	0.4355
	Year-fixed effect	Yes	Yes	No	No
	County-fixed effect	Yes	No	Yes	No

Table 2.5 Continued

	$Corn\ \ Price_{ect}$	Main model	Eliminating county-fixed effect	Eliminating year-fixed effect	Eliminating both fixed-effect
PSM (1)	$Ratio_{ect} * Treat_{et}$	0.0761***	0.0942***	1.5285***	1.0969***
		(0.0301)	(0.0228)	(0.1769)	(0.1099)
	$Ratio_{ect} * DIST_{et} * Treat_{et}$	-0.0041***	-0.0063***	-0.0151	-0.0122
		(0.0020)	(0.0015)	(0.0129)	(0.0079)
	$Ratio_{ect} * DIST_{it}^2 * Treat_{et}$	5.04E-05**	7.96E-05***	0.0001	9.59E-05
		(3.51E-05)	(2.73E-05)	(0.0002)	(1.42E-04)
	$LSTOCK_{ct}$	-0.0007	-0.0074**	-0.0782**	-0.0344**
		(0.0048)	(0.0034)	(0.0310)	(0.0175)
	$Intercept$	2.6805***	2.6941***	3.3016***	3.4367***
		(0.0140)	(0.0130)	(0.0837)	(0.0594)
	R-Square	0.9789	0.9792	0.4352	0.4369
PSM (2)	$Ratio_{ect} * Treat_{et}$	0.0765***	0.0930***	1.4274***	1.0898***
		(0.0167)	(0.0161)	(0.1007)	(0.0777)
	$Ratio_{ect} * DIST_{et} * Treat_{et}$	-0.0041***	-0.0062***	-0.0120*	-0.0121**
		(0.0011)	(0.0011)	(0.0075)	(0.0056)
	$Ratio_{ect} * DIST_{it}^2 * Treat_{et}$	5.02E-05**	7.97E-05***	7.69E-05	9.69E-05
		(2.01E-05)	(1.93E-05)	(0.0001)	(0.0001)
	$LSTOCK_{ct}$	-0.0018	-0.0064***	-0.011	-0.0260**
		(0.0025)	(0.0024)	(0.0164)	(0.0.123)
	$Intercept$	2.6824***	2.6913***	3.1758***	3.4185***
		(0.0075)	(0.0091)	(0.0467)	(0.0414)
	R-Square	0.9787	0.9792	0.4348	0.4355
	Year-fixed effect	Yes	Yes	No	No
	County-fixed effect	Yes	No	Yes	No

Table 2.5 Continued

	$Corn\ \ Price_{ect}$	Main model	Eliminating county-fixed effect	Eliminating year-fixed effect	Eliminating both fixed-effect
PSM (4)	$Ratio_{ect} * Treat_{et}$	0.0750***	0.0921***	1.4329***	1.0922***
		(0.0109)	(0.0114)	(0.0657)	(0.0548)
	$Ratio_{ect} * DIST_{et} * Treat_{et}$	-0.0041***	-0.0062***	-0.0121**	-0.0122***
		(0.0007)	(0.0008)	(0.0049)	(0.0039)
	$Ratio_{ect} * DIST_{it}^2 * Treat_{et}$	5.01E-05***	7.98E-05***	7.63E-05	9.65E-05
		(1.31E-05)	(1.36E-05)	(8.78E-05)	(7.09E-05)
	$LSTOCK_{ct}$	-0.0003	-0.0057***	-0.0171*	-0.0293***
		(0.0015)	(0.0016)	(0.0099)	(0.0084)
	$Intercept$	2.6795***	2.6904***	3.1876***	3.4265***
		(0.0048)	(0.0064)	(0.0298)	(0.0292)
	R-Square	0.9788	0.9792	0.4346	0.4360
	Year-fixed effect	Yes	Yes	No	No
	County-fixed effect	Yes	No	Yes	No

Table 2.6. Impact of Entries of Dominant (Ethanol) Plants on Local Corn Prices (Linear Distance only)

	$Corn\ \ Price_{ect}$	Main model	Eliminating county-fixed effect	Eliminating year-fixed effect	Eliminating both fixed-effect
DID	$Ratio_{ect} * Treat_{et}$	0.0475**	0.0522***	1.4068***	1.0519***
		(0.0229)	(0.0180)	(0.1259)	(0.0816)
	$Ratio_{ect} * DIST_{et} * Treat_{et}$	-0.0014**	-0.0020***	-0.0080*	-0.0073***
		(0.0006)	(0.0005)	(0.0042)	(0.0026)
	$LSTOCK_{ct}$	0.0034	-0.0064**	-0.0986*	-0.0435***
		(0.0087)	(0.0030)	(0.0571)	(0.0153)
	$Intercept$	2.6710***	2.6942***	3.3810***	3.4644***
		(0.0228)	(0.0132)	(0.1445)	(0.0589)
	R-Square	0.9783	0.9789	0.4366	0.4407
NNM (1)	$Ratio_{ect} * Treat_{et}$	0.0431*	0.0526***	1.3408***	1.0359***
		(0.0229)	(0.0212)	(0.1298)	(0.0830)
	$Ratio_{ect} * DIST_{et} * Treat_{et}$	-0.0013**	-0.0021***	-0.0073*	-0.0069***
		(0.0006)	(0.0005)	(0.0043)	(0.0026)
	$LSTOCK_{ct}$	0.0097	-0.0069**	0.0523	-0.0216
		(0.0074)	(0.0033)	(0.0488)	(0.0168)
	$Intercept$	2.6610***	2.6917***	3.0554***	3.4095***
		(0.0169)	(0.0127)	(0.1102)	(0.0576)
	R-Square	0.9777	0.9789	0.4211	0.4340
NNM (2)	$Ratio_{ect} * Treat_{et}$	0.0497***	0.0541***	1.3927***	1.0478***
		(0.0132)	(0.0128)	(0.0739)	(0.0523)
	$Ratio_{ect} * DIST_{et} * Treat_{et}$	-0.0014***	-0.0021***	-0.0080***	-0.0072***
		(0.0004)	(0.0004)	(0.0025)	(0.0018)
	$LSTOCK_{ct}$	0.0032	-0.0080***	-0.0228	-0.0345***
		(0.0037)	(0.0023)	(0.0245)	(0.0119)
	$Intercept$	2.6724***	2.6954***	3.2002***	3.4376***
		(0.0095)	(0.0092)	(0.0606)	(0.0416)
	R-Square	0.9783	0.9789	0.4352	0.4366
	Year-fixed effect	Yes	Yes	No	No
	County-fixed effect	Yes	No	Yes	No

Table 2.6 Continued

	$Corn\ \ Price_{ect}$	Main model	Eliminating county-fixed effect	Eliminating year-fixed effect	Eliminating both fixed-effect
NNM (4)	$Ratio_{ect} * Treat_{et}$	0.0469***	0.0532***	1.3951***	1.0419***
		(0.0087)	(0.0090)	(0.0482)	(0.0413)
	$Ratio_{ect} * DIST_{et} * Treat_{et}$	-0.0014***	-0.0021***	-0.0080***	-0.0071***
		(0.0002)	(0.0003)	(0.0016)	(0.0013)
	$LSTOCK_{ct}$	0.0024	-0.0073***	-0.0225*	-0.0277***
		(0.0019)	(0.0016)	(0.0131)	(0.0085)
	Intercept	2.6944***	2.6931***	3.1970***	3.4222***
		(0.0054)	(0.0064)	(0.0337)	(0.0291)
	R-Square	0.9784	0.9789	0.4343	0.4350
	Year-fixed effect	Yes	Yes	No	No
	County-fixed effect	Yes	No	Yes	No

Table 2.6 Continued

	$Corn\ \ Price_{ect}$	Main model	Eliminating county-fixed effect	Eliminating year-fixed effect	Eliminating both fixed-effect
PSM (1)	$Ratio_{ect} * Treat_{et}$	0.0498**	0.0535***	1.4761***	1.0481***
		(0.0239)	(0.0181)	(0.1300)	(0.0827)
	$Ratio_{ect} * DIST_{et} * Treat_{et}$	-0.0014**	-0.0021***	-0.0097**	-0.0072***
		(0.0007)	(0.0005)	(0.0043)	(0.0026)
	$LSTOCK_{ct}$	-0.0004	-0.0076**	-0.0776**	-0.0346**
		(0.0047)	(0.0034)	(0.0309)	(0.0174)
	Intercept	2.6799***	2.6944***	3.3006***	3.4371***
		(0.0140)	(0.0131)	(0.0834)	(0.0594)
	R-Square	0.9786	0.9789	0.4348	0.4364
PSM (2)	$Ratio_{ect} * Treat_{et}$	0.0507***	0.0523***	1.3882***	1.0405***
		(0.0132)	(0.0128)	(0.0737)	(0.0586)
	$Ratio_{ect} * DIST_{et} * Treat_{et}$	-0.0015***	-0.0021***	-0.0079***	-0.0070***
		(0.0003)	(0.0004)	(0.0024)	(0.0018)
	$LSTOCK_{ct}$	-0.0018	-0.0065***	-0.0115	-0.0262**
		(0.0025)	(0.0023)	(0.0164)	(0.0123)
	Intercept	2.6824***	2.6916***	3.1759***	3.4189***
		(0.0075)	(0.0091)	(0.0466)	(0.0413)
	R-Square	0.9786	0.9788	0.4333	0.4346
PSM (4)	$Ratio_{ect} * Treat_{et}$	0.0493***	0.0513***	1.3940***	1.0431***
		(0.0087)	(0.0090)	(0.0481)	(0.0412)
	$Ratio_{ect} * DIST_{et} * Treat_{et}$	-0.0014***	-0.0020***	-0.0091***	-0.0071***
		(0.0002)	(0.0002)	(0.0016)	(0.0013)
	$LSTOCK_{ct}$	-0.0003	-0.0058***	-0.0171*	-0.0295***
		(0.0015)	(0.0016)	(0.0098)	(0.0084)
	Intercept	2.6979***	2.6906***	3.1877***	3.4269***
		(0.0048)	(0.0065)	(0.0298)	(0.0292)
	R-Square	0.9786	0.9788	0.4342	0.4355
	Year-fixed effect	Yes	Yes	No	No
	County-fixed effect	Yes	No	Yes	No

Table 2.7. Impact of Entries of Dominant (Ethanol) Plants on Local Corn Prices (No Distance Addressed)

	$Corn\ \ Price_{ect}$	Main model	Eliminating county-fixed effect	Eliminating year-fixed effect	Eliminating both fixed-effect
DID	$Ratio_{ect} * Treat_{et}$	0.0079	-0.0053	1.1969***	0.8560***
		(0.0232)	(0.0112)	(0.0588)	(0.0425)
	$LSTOCK_{ct}$	0.0042	-0.0050*	-0.0948*	-0.0389**
		(0.0087)	(0.0030)	(0.0574)	(0.0154)
	Intercept	2.6690***	2.6909***	3.3774***	3.4612***
		(0.0229)	(0.0134)	(0.1452)	(0.0593)
	R-Square	0.9777	0.9782	0.4285	0.4324
NNM (1)	$Ratio_{ect} * Treat_{et}$	0.0052	-0.0052	1.1467***	0.8487***
		(0.0142)	(0.0112)	(0.0619)	(0.0434)
	$LSTOCK_{ct}$	0.0112	-0.0052	0.0607	-0.0161
		(0.0074)	(0.0033)	(0.0488)	(0.0168)
	Intercept	2.6582***	2.6887***	3.0441***	3.1060***
		(0.0170)	(0.0129)	(0.1103)	(0.0579)
	R-Square	0.9770	0.9782	0.4135	0.4265
NNM (2)	$Ratio_{ect} * Treat_{et}$	0.0074	-0.0045	1.1817***	0.8547***
		(0.0082)	(0.0079)	(0.0347)	(0.0304)
	$LSTOCK_{ct}$	0.0045	-0.0063***	-0.0154	-0.0289**
		(0.0037)	(0.0023)	(0.0246)	(0.0019)
	Intercept	2.6698***	2.6919***	3.1903***	3.4332***
		(0.0096)	(0.0093)	(0.0608)	(0.0418)
	R-Square	0.9777	0.9783	0.4275	0.4287
	Year-fixed effect	Yes	Yes	No	No
	County-fixed effect	Yes	No	Yes	No

Table 2.7 Continued

	$Corn\ \ Price_{ect}$	Main model	Eliminating county-fixed effect	Eliminating year-fixed effect	Eliminating both fixed-effect
NNM (4)	$Ratio_{ect} * Treat_{et}$	0.0075	-0.0050	1.1842***	0.8517***
		(0.0054)	(0.0056)	(0.0227)	(0.0216)
	$LSTOCK_{ct}$	0.0033*	-0.0056***	-0.0173	-0.0221**
		(0.0020)	(0.0017)	(0.0131)	(0.0085)
	Intercept	2.6725***	2.6898***	3.1921***	3.4181***
		(0.0054)	(0.0065)	(0.0339)	(0.0293)
	R-Square	0.9778	0.9782	0.4270	0.4274
PSM (1)	$Ratio_{ect} * Treat_{et}$	0.0080	-0.0048	1.2137***	0.8546***
		(0.0146)	(0.0112)	(0.0600)	(0.0432)
	$LSTOCK_{ct}$	0.0016	-0.0058*	-0.0656**	-0.0286
		(0.0047)	(0.0034)	(0.0306)	(0.0174)
	Intercept	2.6756***	2.6907***	3.2819***	3.4322***
		(0.0139)	(0.0133)	(0.0837)	0.0597)
	R-Square	0.9779	0.9782	0.4274	0.4284
PSM (2)	$Ratio_{ect} * Treat_{et}$	0.0098	-0.0055	1.1784***	0.8509***
		(0.0082)	(0.0079)	(0.0342)	(0.0306)
	$LSTOCK_{ct}$	-0.0007	-0.0048**	-0.0060	-0.0203*
		(0.0025)	(0.0024)	(0.0164)	(0.0122)
	Intercept	2.6804****	3.6882***	3.1705***	3.1416***
		(0.0075)	(0.0092)	(0.0469)	(0.0416)
	R-Square	0.9780	0.9782	0.4261	0.4270
	Year-fixed effect	Yes	Yes	No	No
	County-fixed effect	Yes	No	Yes	No

Table 2.7 Continued

	$Corn\ Price_{ect}$	Main model	Eliminating county-fixed effect	Eliminating year-fixed effect	Eliminating both fixed-effect
PSM (4)	$Ratio_{ect} * Treat_{et}$	0.0090*	-0.0059	1.1808***	0.8523***
		(0.0053)	(0.0056)	(0.0222)	(0.0215)
	$LSTOCK_{ct}$	0.0007	-0.0041**	-0.0115	-0.0240***
		(0.0015)	(0.0016)	(0.0099)	(0.0084)
	Intercept	3.6775***	2.6873***	3.1818***	3.4228***
		(0.0049)	(0.0066)	(0.0300)	(0.0294)
	R-Square	0.9780	0.9782	0.4268	0.4277
	Year-fixed effect	Yes	Yes	No	No
	County-fixed effect	Yes	No	Yes	No

Both non-linear and linear models in Tables 2.5 and 2.6 also clearly indicate that the price effect dissipates with distance. While both linear and quadratic terms are statistically significant for many matching strategies in Table 2.5, improvements in the goodness of fit from the non-linear price-distance gradient specification relative to the linear specification (Table 2.6) are negligible. As a result, both the Akaike and Bayesian Information Criteria favor the linear price-distance gradient model. Consequently, we fail to reject the null that price effects dissipate with distance in a linear fashion. This result implies that transportation by trucks prevails in corn procurement even when corn is sourced from relatively larger distances. It also implies that, if plants exert buying power, they are not engaging in spatial price discrimination.

Coefficients δ_1, δ_2, and δ_3 combine to determine the spatial pattern of price effects from an ethanol plant's entry. Estimated coefficients under a linear price-distance gradient indicate that, on average, the price effect dissipates at around 65 miles away from the plant. However, for the largest plant in the sample (ratio of around 4) the price-effect may propagate over 100 miles. And for the smallest, the price effect may dissipate after only 20 miles.

2.6 Robustness Tests

In this section, we test whether our results are robust across alternative specifications with and without matching strategies. We conduct robustness tests along two dimensions: 1) different model specifications and 2) removing Posey county, which may distort our original estimation due to its unusually high price pre-treatment. The local price effect from different model specifications falls on the range of the estimates from the main model. We do present only unmatched data for robustness tests because individual matching strategies generate highly consistent effects due to the fact that matching does not improve our data quality much because treatment is already random enough.

2.6.1 Different Model Specifications

Our main specification identifies heterogeneity of the plant entry effect conditioning on the ratio and distance by using interaction term. However, it is also desirable to examine different model specifications such as Ordinary Least Square (OLS), Fixed Effect (FE) model with panel data, and a regular saturated DID, for reference which enables to examine robustness of earlier results. A FE model and a regular saturated DID will be of a particular interest because of the occasional entry pattern over the period. Meanwhile, OLS and FE models may still suffer from endogeneity problem stemming from reverse causality.

We begin with the OLS by regressing local corn prices on distance to the nearest ethanol plant, the ratio as is defined, and corn demand from livestock operators. Results from the OLS specification appear in Appendix Table A2. Parameter estimates show that plant entry seems to increase corn price by 19 cents and this decays with distance by 1 cent per bushel-mile. OLS does not provide consistent results and small R-square values suggest that, due to occasion and sporadic entries, variability of the independent variables is limited in explaining variability of local corn prices. In addition, the OLS model may be suffering from endogeneity problem stemming from reverse causality and unobservability for the ratio.

For a regular saturated DID, we follow the typical approach by introducing post-treatment period indicator, treatment indicator, interaction of the two indicators, and shifters. We are interested in the parameter estimate for the interaction term. Table A3 shows that an ethanol plant entry increases local corn price on average by 8 cents and this estimated price impact of the entry falls on the range of the results from the original model specification, 5 to 8 cents. Negative sign of the $Treat_e$ variable albeit being statistically insignificant or weakly significant suggests that a lower value of corn price around treated counties in the pre-treatment period may dominate increases in corn prices in the post-treatment period due possibly to spillover effect of plant effect on corn price around non-treated counties. Even after DID approach controls other factors driving changes in corn prices such as international corn prices, the spillover effect may increase corn prices in non-treated counties as well, keeping its corn prices close to the one in treated counties. Therefore, even though corn prices are higher in treated counties after the plant entry, the spillover effect keep the increase relatively weak so as not to outweigh its lower value in pre-treatment period. However, the DID model is limited because it does not account for the distance effect.

FE presents robustness results with a 3 cents-increase at the plant site and declines by 0.23 cents (Table A4). This reassures the importance of transportation cost from the main model. Results seem highly consistent with the estimates from the original model, but this may also suffer from endogeneity from reverse causality and/or serial correlation even after including elevator- and year- fixed effects. In order to conduct a careful analysis of the marginal impact of plant entry on local corn prices, it is important to consider other factors that potentially influence corn prices and more advanced investigation of the model will be a nice future research topic.

2.6.2 Removing Posey County

Since corn prices in Posey county in pre-treatment period are high due to the nearby exporting port nearby (one in the same county and two in its neighboring counties), removing Posey county will eliminates the exceptionally high price in the pre-treatment period which may weaken the overall average treatment effect of ethanol plant entries. Besides, neighboring counties surrounding Posey are now classified into the control group because they are not treated either directly or indirectly.

Appendix Table A1 describes descriptive statistics after Posey county is removed. Corn prices in pre-treatment period in the treatment group becomes smaller. Before being matched, the absence of Posey county reduces average corn prices from $2.693 to $2.680 in the treatment group. On the other hand, matching the treatment group without Posey county results in an increase in average price and approach to the control group (from $2.708 to $2.711).

Price impact of ethanol without Posey is presented in Appendix Tables A5 and A6 for the case both with linear and quadratic distance and the other case only with linear distance. Corresponding to the fact that removing Posey reduces average price of the treatment group, the price impact of the ethanol plant entry is stronger.

2.7 Plant Entry and the Spatial Pattern of Corn Prices

We employ our estimated parameters to examine, within our sample, the relationship between corn price effects (price increase due to entry relative to a counterfactual without plant entry) and distance, and corn price effects and size of the entrant. These relationships depict the range of the spatial pattern of price effects associated with entry of ethanol plants.

This is an informative analysis as previous studies on the effect of ethanol expansion on local corn prices estimated averages that can hide substantial heterogeneity. A clear demonstration of the limitations of estimating average effects comes from our estimation of a model without distance (Table 2.7). This model fails to detect a price effect from plant entry while other models that allow for heterogeneous treatment effects along the distance spectrum (and that also display a much better goodness of fit) detect a strong and statistically significant effect.

We start by plotting the price-distance gradient for treated elevators in our sample. Figure 2.6 plots each elevator's distance and the elevator-specific predicted price effect. We use predictions from the linear model given its superiority (based on Akaike and Bayesian Information Criteria) over the non-linear model. We evaluate the predicted price effect at the sample mean ratio of plant's capacity to county corn supply. Therefore, in Figure 2.6 we isolate the effect of distance on the price effect by conditioning the prediction on average ratio. Figure 2.6 reveals that the price effect, for the average plant capacity to county supply ratio, dissipates 67 miles away from the plant. It also shows that the majority of treated elevators are located sufficiently close to a plant that they would benefit from the price increase. However, 40 out of 210 elevators or 20% of elevators defined as treated (those that are located in a county hosting an ethanol plant or a surrounding county) would not benefit from an average-sized entry because transportation cost would offset price gains.

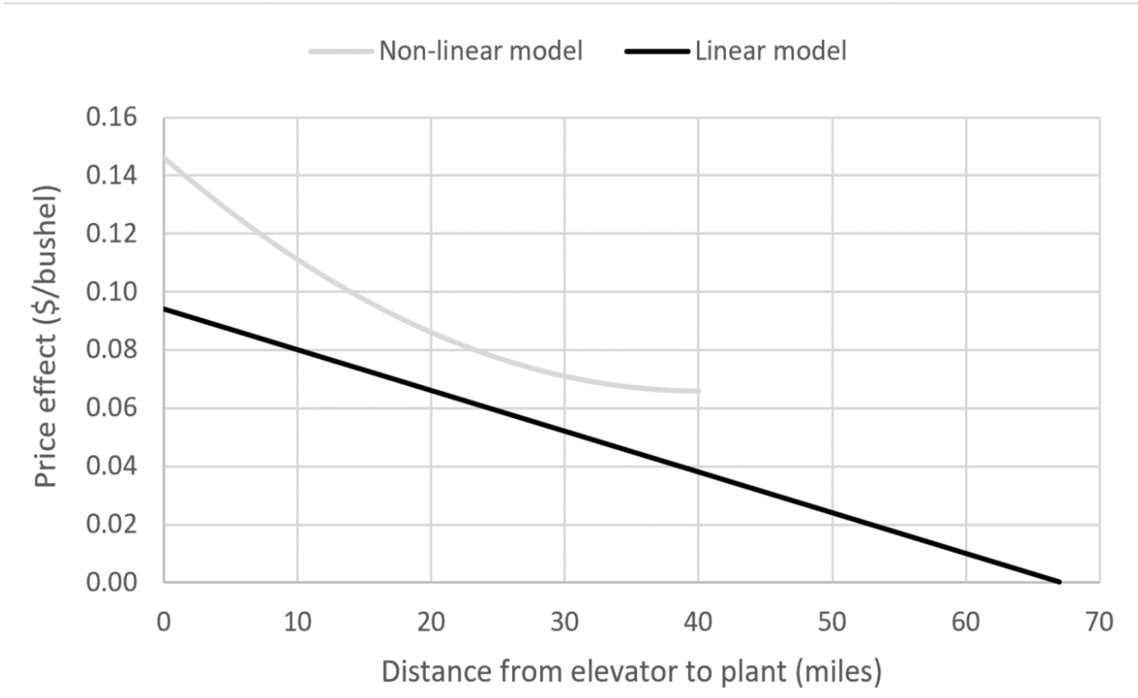


Figure 2.6. Distance and price effect of entry

Figure 2.7 plots each elevator's treatment intensity and the elevator-specific predicted price effect. We use our preferred model which is the one with a linear price-distance gradient and evaluate the predicted price effect at the sample mean distance between elevators and plants. Therefore, in Figure 2.7 we isolate the effect of treatment intensity (the size of the plant relative to corn supply in the county where the plant located) by conditioning the prediction on average distance. Figure 2.7 reveals that the price effect at the plant site in our sample ranges from 2 cents per bushel to 15 cents per bushel. It also shows that there is a considerable number of elevators treated by plants that are twice as large as corn supplied in the county where the plant is located. For these elevators the price effect at the plant site is around 10 cents per bushel.

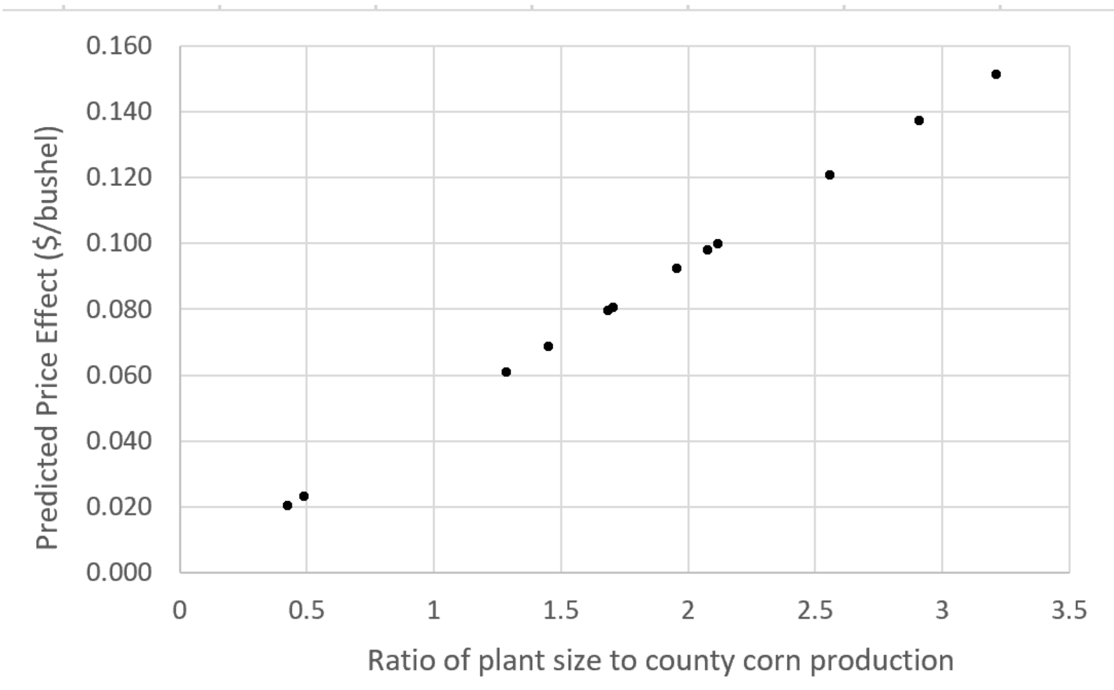


Figure 2.7. Size of entrant and price effect of entry

Conditional on a linear price-distance gradient the size of the entrant relative to local supply and the distance at which the price effect fully dissipates are jointly determined. Figure 2.8 portrays the price-distance gradient for the largest, the average, and the smallest entrant in our sample. The distance at which the price-effect dissipates is 14 miles for the smallest plant, 56 miles for the average plant, and 110 miles for the largest plant. This illustrates the wide variability in the size of the procurement region (determined by the distance at which the price effect dissipates) depending on the size of the plant relative to local corn supply. Recall that local corn supply can vary widely due to weather and other conditions likely prompting large changes in the size of the procurement region of a given plant over time.

2.8 Conclusion

Driven by government policies, ethanol production in the US expanded substantially over the past 15 years. The price of corn, the main input of ethanol production, has increased over the ethanol boom period (2006-2011). Several previous studies examined the link between ethanol plant expansion and local (in the area around the plant) corn prices. This study revisited this issue by using an improved identification strategy (DID and DID - matching) that controls for selection on both observables and unobservables that may bias estimates of the effect of plant entry on the spatial pattern of local corn prices. Moreover, expanding on previous analyses, we allow the intensity of treatment to vary and also allow for heterogeneous treatment effects based on the distance between corn elevators and ethanol plants.

We find that entry of an ethanol plant raises local prices and that the price effects dissipates with distance. The effect at the plant's site and, consequently, the distance at which the price effect dissipates vary widely depending on the size of the entrant relative to local corn supply. This heterogeneity underscores the importance of flexibility provided in our framework. Assuming away heterogeneous treatment effects greatly underestimates price-effects associated with plant entry; and so does the use of a simple OLS estimation strategy which strongly suggests presence of selection bias.

The importance of the size of the entrant relative to local supply (treatment intensity) in determining the magnitude of the price-effect reveals that fluctuations in corn supply due to weather or other conditions can drastically change the effect of an ethanol plant on the spatial pattern of local prices. This is because changes in local corn supply affect the magnitude of the price-effect at the plant's gate and the distance at which the price-effect dissipates.

Our results raise many questions. First, the fact that plants trigger positive price effects directly implies that individual plants are large enough to face an upward sloping supply of corn. In turn, this creates a wedge between supply and marginal factor cost, perhaps prompting plants to exert buying power by reducing procurement and suppressing the price paid to farmers. Second, if initial price-effects generate a dynamic supply response (as the land use literature seems to suggest), then the price-effect associated with entry may vary over time until it stabilizes. This is important because our study tries to quantify the price-effect allowing for sufficient time for full adjustment to take place. However, we do not know how long it takes to get to full adjustment and what is the path (price trajectory) to get there. These seem like interesting areas of future research.

3 SPATIAL DIFFERENTIATION AND MARKET POWER IN INPUT PROCUREMENT: EVIDENCE FROM A STRUCTURAL MODEL OF THE CORN MARKET

3.1 Introduction

Economists and regulators are paying increasing attention to spatial competition in agricultural procurement markets, or markets in which downstream firms purchase products from upstream farmers to use as inputs in their production processes. These markets are typically characterized by buyers that are spatially dispersed and by products that are costly to transport from the farm to the buyer. These features have led researchers to routinely assert, despite scant empirical evidence, that spatial differentiation among agricultural processors may soften competition, possibly allowing firms to price inputs below their marginal value product net of processing costs (that is, allowing input buyers to engage in input price markdown) (e.g. Durham, Sexton, and Song 1996; Alvarez et al. 2000; Fousekis 2011; Graubner, Balmann, and Sexton 2011). The extent to which transportation cost and the resulting spatial differentiation among buyers of farm products affects prices, markdowns, and surpluses is the empirical question we address in this study.

When a farmer is located at a certain distance from the buyer, the price received by the farmer at the farm gate is lower than the price paid by the buyer at the plant gate. The difference between these prices is equal to transportation cost. Therefore, all else constant, farmers have incentives to sell to nearby buyers in order to avoid transportation cost and obtain a higher price. In a way this protects buyers from competition which may allow them to reduce the price offered to farmers, thereby increasing markdown. The buyer may even go as far as discriminating farmers based on their location, offering a lower plant-gate price to farmers located in close proximity to the plant and a higher plant-gate price to more distant farmers; i.e., buyers may engage in spatial price discrimination (see Graubner et al. 2011; Sesmero 2018).[5] Our goal is to examine empirically whether spatial differentiation introduced by transportation cost allows buyers to engage in corn price markdown and spatial price discrimination.

We develop and estimate a structural model of possibly spatially differentiated buyers in the corn procurement market that closely mimics documented empirical features of this market. The model consists of downstream firms (corn processors, including ethanol firms and wet-milling food processors) buying corn from upstream firms (farmers), while accounting for a competitive fringe comprised of livestock operators, dry-milling food processors, and exporters. Ethanol and wet-milling firms set input prices (also referred to as mill-gate prices) paid to farmers, and farmers pay the transportation cost to ship the corn to buyers. The structural approach allows us to explicitly estimate transportation costs, firm-level production cost parameters, and parameters of the residual corn supply faced by buyers, all of which are necessary for computation of price markdowns in the presence of spatial competition. We also test for spatial price discrimination, examining whether markdowns vary depending on the distance between buyers and sellers. Finally, we use the

[5] Such concerns influenced regulatory interventions including the Robinson-Patman Act (O'Brien and Shaffer, 1994), and the Grain Inspection, Packers, and Stockyards Administration (GIPSA), among others.

structural estimates to conduct counterfactual experiments simulating *mergers* that differ in the distance between merging firms, thereby characterizing further the impact of spatial competition on prices, markdowns, and surplus.

The empirical estimation of parameters necessary to compute markdowns in our structural model is challenging since input prices paid by individual firms are negotiated privately and rarely available to the public. Most input prices and input production data are available only at a more aggregate level. We overcome the aggregation problem by adopting an estimation strategy (similar to Miller and Osborne 2014) that allows us to retrieve firm-specific structural parameter estimates while using aggregate, county-level data. The estimation strategy builds on a firm-level optimization approach that accounts explicitly for spatial differentiation and the distance between buyers and sellers. The optimization approach returns optimal plant-level input prices and shipments. These predictions are then aggregated to the level of data availability such that demand and supply parameters that rationalize the data can be estimated.

In this study, we use county-level information on corn prices and supply in the US state of Indiana from 2004 to 2014. The corn procurement market in Indiana is an ideal setting for several reasons. First, it displays all the features associated with spatial differentiation among buyers, i.e. a few large processors (oligopsonists) purchase corn from a large number of producers who pay transportation costs to deliver products to the buyers. Second, large processors in Indiana are relatively insulated (more so than their counterparts in Illinois, Iowa, or Nebraska) from other large processors in neighboring states, though they are likely to compete among themselves (more so than their counterparts in Minnesota, Ohio, or Wisconsin). Finally, confining the geographical scope of our analysis eases the computational burden of solving our optimization approach, which increases dramatically with the number of counties and plants considered.

Our data show on average that corn is shipped more than 50 miles. The estimation results return a transportation cost of 0.12 cents per bushel per mile (3% of the corn price for average conditions in the sample), which provides evidence of spatial differentiation among buyers. This transportation cost softens competition and allows corn processors to exert buyer power, attaining an average input price markdown of $0.34 per bushel (7% of the corn price) derived from spatial differentiation. Our results also show that, over our study period, firms often set prices under binding capacity constraints, consistent with Bertrand-Edgeworth competition. Once capacity constraints are binding, markdown increases; on average, capacity constraints increase markdown by $0.46 per bushel, more than doubling the effect of spatial differentiation. We also find that the corn prices buyers pay to farmers are independent of distance, which confirms that firms do not engage in spatial price discrimination.

Finally, results from our counterfactual experiments on consolidation among ethanol plants—a prominent trend in the industry in recent years—indicate that a merger between nearby ethanol plants eases competition and increases markdowns attained by merging firms by $0.14 or 20%. We also find that the effect of the merger is not limited to merging plants only; the merger also triggers spillover effects (which increase markdowns) on non-merging firms, but the magnitude of the markdown increases is smaller than those of the merging firms per se. Consequently, we find that mergers reduce farmers' surplus, and it does so beyond a geographically confined area around the merging firms, suggesting strong spatial spillovers. In contrast, a merger between distant ethanol plants has little effect on competition and markdowns. Our results indicate clearly that the market and welfare effects of a merger depend upon the intensity of competition between merging firms, which is determined by their degree of spatial differentiation.

Our study is related to work on spatial differentiation in fast food restaurants (Thomadsen 2005), movie theaters (Davis 2006), coffee shops (McManus 2007), and retail gasoline establishments (Houde 2012). It also relates to Durham and Sexton (1992) in that it estimates residual supplies faced by agricultural processors. However, unlike Durham and Sexton (1992), our study follows an estimation strategy proposed by Miller and Osborne (2014) that will enable us to estimate firm-level structural parameters from market-level outcomes. Other prominent contributions that focus on buying power in the corn procurement market include Saitone, Sexton, and Sexton (2008) and Wang et al. (2019). The main differentiating attribute of our paper relative to these studies is that we do not *impose* buyer power, but *estimate* it. In this sense, our study contributes to a rich empirical literature on buyer power in input markets, as reviewed by Azzam (1996), Sexton (2000), McCorriston (2002), Sexton (2013), Sheldon (2017), and Merel and Sexton (2017), among others. In contrast to these studies, however, our paper explicitly considers the relationship between spatial differentiation and competition. We also estimate the degree of spatial competition and identify it as a source of buying power.

3.2 The Corn Market in Indiana and the Data

In this section, we introduce the main data sources and use information extracted from these sources to document key institutional features of the corn market in Indiana. We identify four market features that lay out the foundation of our empirical structural model.

We use county-level corn prices from Geo Grain. Geo Grain records corn prices at multiple elevator locations across Indiana. These data provide full coverage of Indiana. We use the local corn cash price instead of basis (as is common in other studies of spatial price patterns of corn) because our model identifies parameters based on the difference between observed and predicted county-level prices, differencing out forward prices (that are based on the Chicago Board of Trade). We also use information on location, capacity, and ownership of corn processing plants (which, as will soon be explained, are modeled as oligopsonists), total corn supply in each county in each crop year, and distance between processing plants and county centroids. We also gathered data on supply shifters, including distance between exporting ports and county centroids and corn requirements by the livestock and dry-milling sectors in each county.

We obtained data on corn production, corn storage, and livestock inventory from the National Agricultural Statistics Service of the United States Department of Agriculture (NASS, USDA). Information on corn exports and international prices is taken from the Economic Research Service (ERS) of the USDA and the Federal Reserve Bank of St. Louis (FRED), respectively. The information on ethanol plant location, ownership, capacity, and year built comes from the government of Nebraska, the Renewable Fuel Association (RFA), the US Environmental Information Administration (EIA), and the Biofuel Atlas published by the National Renewable Energy Laboratory (NREL). Information on wet- and dry-milling food processors' capacities and locations is based on Hurt (2012) and the authors' own personal communications. Historical diesel and electricity prices are obtained from the EIA. Distances are calculated using Arc-GIS.

Table 2.1 portrays an aggregate picture of the corn market in Indiana. The top part of table 2.1 shows the presence of five destinations for Indiana corn: ethanol, wet milling, dry milling, livestock, exports, and other. This panel reports the annual shares of Indiana corn sold to each of these sectors during our period of analysis (2004 to 2014). The bottom part of table 2.1 describes the sources of corn supply in Indiana for each year. The numbers show that most of the corn supply in any given year comes from production in that same year. However, supply from storage can amount to more than 10% of the total corn supply.

Our primary concern relates to the possible existence of concentrated procurement markets, which may be conducive to market power. Concentration takes place when a few large producers purchase a substantial fraction of corn supplied within relevant market boundaries, and market boundaries can be confined by transportation costs. Therefore, all else constant, concentration will increase with transportation cost and with the size of a purchasing firm. We now turn our attention to these two aspects.

Corn farmers typically use trucks to ship corn to their buyers (Denicoff et al. 2014; Adam and Marathon 2015) since plants source corn locally and trucking within relatively short distances (i.e., below 500 miles) is less costly than other forms of transportation. According to the Grain Truck and Ocean Rate (GTOR) report from the USDA, the transportation rate of grains in the North Central region[6] in the first quarter of 2016 was 0.23 cents, 0.14 cents, and 0.11 cents per bushel-mile for 25, 100, and 200 miles, respectively.[7] At an average corn price of $3.50 per bushel in 2016, this means that

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[6] The North Central region in the GTOR report includes North Dakota, South Dakota, Nebraska, Kansas, Minnesota, Iowa, Missouri, Wisconsin, Illinois, Michigan, Indiana, Kentucky, Tennessee, and Ohio.
[7] These are converted values from the rate reported in GTOR. GTOR reports the transportation rate per truckload-mile. One truckload is equivalent to 984 bushels of corn.

transportation costs amounted to about 3% to 7% of the price within these distances. This underscores the importance of transportation costs and suggests a possible geographical localization of corn procurement markets; that is, plants tend to source corn locally.

Geographical localization of procurement markets is not by itself sufficient to soften competition. To exert market power, the buyer must be large relative to supply in the procurement market. Information reported in table 3.1 reveals that ethanol plants and wet-milling processors are quite large, while individual livestock operations and dry millers are not. On average, ethanol plants and wet-milling plants are 4,000 times larger than the average individual livestock operator and 6 to 10 times larger than dry millers. Table 2.2 reports the ratio of each large processor's (as identified in table 3.1) annual corn processing capacity to annual corn produced in the county in which the plant operates. In each case, we report the average ratio over the sample period. The ratios reported in table 2.2 show that these processors are large relative to local supply. Most of these plants (88%) have an annual corn processing capacity larger than the corn produced in the county where they are located. In several years, ratios for many of these plants are well above 2.

Table 3.1. Size of Individual Plants by Sector in Indiana in 2014

	Count	Total Capacity	Mean Capacity	Median Capacity	Min Capacity	Max Capacity
Ethanol plants[1]	14	430.74	33.13	91.00	7.41	44.44
Wet-milling plants	5	220.40	44.10	39.40	17.0	75.00
Dry-milling plants	5	28.50	5.7	4.0	4.00	12.10
Livestock operators	19,276[2]	184.19	0.01[3]	N/A	N/A	N/A

Note: Capacity measured in million bushels per year.
[1] Source: Nebraska Department of Environment & Energy (2015), the Biofuels Atlas of NREL, Hurt (2012), NASS, USDA.
[2] 2,823 for hog, 14,106 for cattle, 2,347 for poultry (NASS, USDA).
[3] To estimate this, we divide the total corn demand from livestock operators by the total number of livestock operators in Indiana, due to the lack of data for individual operators. Mean capacity for other sectors is based on the actual data for individual capacities.

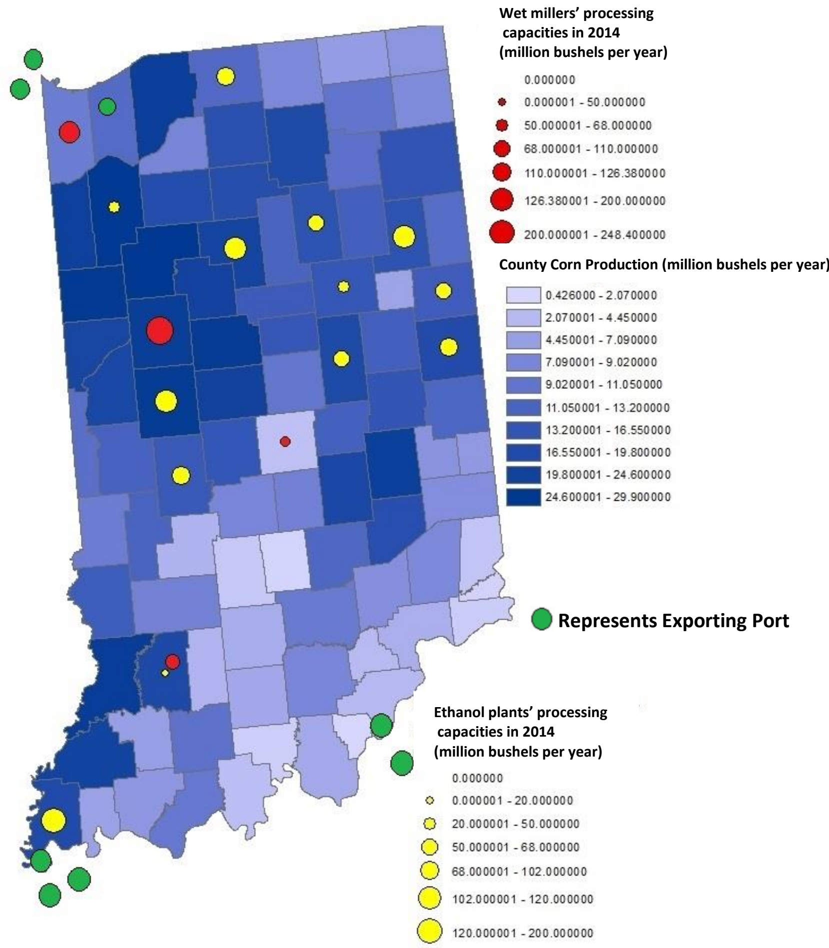
In line with the existence of large firms purchasing a substantial fraction of the corn supplied locally (table 2.2), available reduced-form estimates in the US (McNew and Griffith 2005) and Indiana in particular (Jung et al. 2019) found a positive effect of a plant's sitting on corn prices, but they also indicate that the price effect dissipates with distance. The positive price effect is consistent with large processing plants facing upward-sloping supplies; it means plants must offer higher prices to procure increasing amounts of corn. The dissipation of the price effect with distance is also consistent with procurement markets that are geographically localized due to transportation costs. Finally, many studies note that ethanol plants tend to locate in areas with high corn density (e.g., Li et al. 2018), also consistent with significant transportation costs. In summary:

> **Market Feature 1***: The corn procurement market involves large buyers—ethanol and wet-milling plants—that are spatially differentiated. Corn purchases involve transportation costs, such that firms prefer buying corn from nearby suppliers.*

Notwithstanding the geographically localized nature of procurement, the sheer size of these plants relative to localized supply also suggests that they have to travel considerable distances to procure enough input. This likely results in spatial overlap of these plants' procurement areas, especially when they are spatially clustered. Figure 3.1 shows the locational pattern of ethanol plants (yellow circles) and wet-milling plants (red circles), as well as the spatial pattern of corn production in Indiana in 2014. This figure reveals substantial differences in spatial clustering of ethanol plants. The variations in the local market conditions have an effect on the intensity of competition for corn procurement. But large processors (as indicated by larger circles in figure 3.1) will also compete with the dry-milling sector, the livestock sector, and exports, which are large consumers of corn supplied in Indiana (table 2.1). These facts lead to:

Market Feature 2: *Dry-milling firms, livestock operators, and exporting firms are small buyers acting as a competitive fringe. Large buyers (ethanol and wet-milling firms, as identified in Market Feature 1) compete with the competitive fringe and also among themselves.*

Another important empirical feature of the corn procurement market is the nature of the procurement channels. A portion of the corn produced is sold immediately after harvest, but another portion is stored in elevators and sold throughout the year. Processors buy corn from both farmers and commercial elevators. They purchase corn both in the spot market and through contracts. Contracts are usually signed during the growing season and specify a post-harvest delivery date, a quantity, and a price. The composition of procurement channels matters because our estimation is based on elevator-level cash prices that are then aggregated to the county level. Therefore, measurement error in prices could arise if: (1) a large portion of corn is purchased directly from farmers and those prices differ from elevator prices; or (2) a large portion of corn is purchased through contracts and contract prices differ from cash prices.



Source: Renewable Fuel Association (2017), Geo Grain, and Nebraska Department of Environment & Energy (2017).

Figure 3.1. Oligopsonists' locations and corn production in Indiana counties in 2014

We consider the use of elevator cash prices to be an adequate strategy in our context for two reasons. First, while buyers often bypass elevators and purchase directly from farmers, elevator prices do not deviate substantially and systematically from farm prices. As for the second potential source of measurement error, a substantial fraction of corn procured by the processors is purchased in spot markets. Processors use contracts for hedging and protecting profitability during periods of thin margins, but hedging opportunities are limited by illiquid futures markets on the output side due to limited ethanol and food product storage (see Schill 2016).[8] Moreover, corn futures markets are highly liquid, with efficient price discovery mechanisms, which causes convergence, albeit partial, of forward prices to spot prices.[9]

Another important aspect of pricing is that buyers may offer low mill-gate prices soon after harvest, which nevertheless allows them to procure from local farmers, as they have fewer outside options. As those sources are exhausted, buyers may then increase mill-gate prices to procure from farmers located farther away from the plant. Such a pricing strategy would result in spatial price discrimination; that is, the difference between prices received at the farm gate by suppliers located at varying distances from the buyer will differ from transportation cost (Hardy et al. 2006). This requires a trading model that allows for heterogeneous firm-county price pairs in equilibrium.

We summarize the information on procurement channels and pricing by:

[8] According to Schill (2016) hedging also reduces upside profit potential further limiting the use of contracts.
[9] Ethanol plants considered in our sample are privately owned and, when they contract, they use forward contracts negotiated in the Chicago Board of Trade rather than exclusive contracts with farmers. Therefore, we are not concerned about exclusive vertical relationships as a source of market power.

Market Feature 3: *Large processors procure the majority of their corn in the spot market by posting purchase prices at the mill gate throughout the year, which may result in spatial price discrimination. Transportation costs are covered by the sellers.*

We now turn our attention to market conditions under which oligopsonists sell their processed products. If oligopsonist-owned plants exerted market power downstream, the output price would be a function of quantity processed and supplied, which would itself be a function of corn price. This would add a layer of complexity to our analysis. Beyond a residual input supply, an additional output residual demand function faced by each plant would have to be estimated. However, it is unlikely that individual oligopsonistic plants exert market power downstream for two reasons. There are close substitutes in the market for the main outputs from both ethanol as well as wet-milling firms. The price of ethanol mostly followed the price of gasoline during our study period according to data from the state of Nebraska's website (Nebraska Department of Environment & Energy 2015). Similarly, the price of high fructose corn syrup (one of the main products from wet millers along with starch and ethanol) was influenced strongly by the price of raw sugar (Oral and Bessler 1997). Moreover, capacity utilization of both ethanol (Renewable Fuels Association 2019) and wet-milling plants (Porter and Spence 1982) is typically very high, which limits the role of output price on the procurement decision. These facts determine the following feature:

Market Feature 4: *Corn buyers do not have market power when selling their processed products, and they often, but not always, operate at full capacity.*

In Figure 3.2, we map the spatial structure of processing plants (yellow dots) and county-level corn prices (color brightness) in 2014, the last year in our sample. The map shows a positive correlation between the location and the size of processors (oligopsonists) and corn prices. This pattern appears despite the fact that large processors tend to locate in areas with high corn supply (see Figure 3.1). This suggests that large processors substantially increase local demand for corn, raising local corn prices, which is consistent with *Market Feature 1*. We note that market power exertion would not preclude an increase in local corn price, but it can limit this increase below what it would be in a competitive setting. Other areas without large processors also display relatively high corn prices. Consistent with *Market Feature 2*, these areas are located close to exporting ports (plotted as green dots in Figure 3.2) or livestock production, which causes large shifts in corn demand.

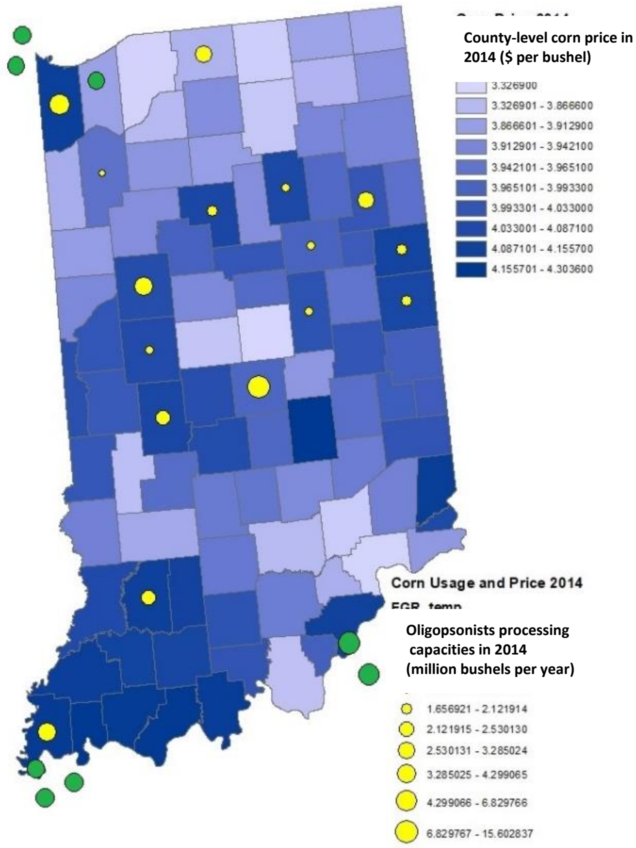


Figure 3.2. Oligopsonists' locations and corn prices in Indiana counties in 2014

3.3 The Empirical Model

We develop and estimate a structural model to evaluate oligopsonists' buyer power while accounting for spatial differentiation. Our structural model consists of a set of equations that describes upstream firms' selling behaviors and downstream firms' buying behaviors. On the demand side, we consider ethanol and wet-milling plants that act as oligopsonists. On the supply side, we consider farmers in counties that sell corn to oligopsonists for plant-specific prices and to the competitive fringe.

The corn buyers' profit optimality conditions characterize optimal corn prices offered by each plant to each farmer in every county. Prices offered by a plant and its competitors in equilibrium will determine the amount of corn purchased by each plant from farmers in each county. The firm-level prices and quantities are then aggregated to the county level. Our estimation algorithm searches over a set of parameters that matches the firm-level predictions (aggregated to the county level) with the observed county-level data. Our estimation algorithm returns optimally predicted corn prices and quantities at the firm level, firm-level procurement and capacity utilization rates, and parameter estimates that characterize marginal processing costs. On the seller side, we estimate parameters that characterize how much each county sells to each buyer. Ultimately, these parameters determine the residual supply of corn faced by each buyer. A key parameter on the seller side is transportation cost, which reflects spatial differentiation and competition intensity among buyers.

3.3.1 Downstream Firms (Ethanol and Wet-Milling Firms)

Our empirical model mirrors closely key features of the trading environment documented in our industry description. Motivated by *Market Feature 1*, the corn procurement market is characterized by an oligopsony, in which large downstream firms (buyers) are spatially differentiated and purchase corn from local small upstream firms (sellers) depending on transportation cost. In our model, oligopsonists compete with each other and with a competitive fringe composed of dry millers, livestock producers, and exports (as documented in *Market Feature 2*). We also model ethanol producers and wet millers as price-setting firms and allow these firms to engage in spatial price discrimination by setting different prices to different sellers such that markdown may vary across sellers, closely mimicking *Market Feature 3*. Finally, and reflecting *Market Feature 4*, we assume ethanol plants and wet millers do not exert market power downstream and operate under capacity constraints that may or may not be binding depending on market conditions.

Turning to our empirical model, we allow oligopsonistic firms *(F)* to own multiple plants (j). The firm determines for every plant *j* the corn price p_{ijt}^{c} (the superscript *c* refers to corn, and the subscript *t* refers to the time period) that is paid to suppliers (farmers) located in county i=1,…,92 in Indiana. Since the structure of the problem is the same in all periods, and for notational simplicity, we drop the time subscript *t*. The firm-specific vector of corn prices $\boldsymbol{p_F^c}$ contains as its elements the county-specific corn prices p_{ij}^{c} that are offered by every plant *j* owned by firm *F* to every county *i*. The quantity of corn shipped from county *i* to plant *j* is denoted by $q_{ij}^{c}(\boldsymbol{p_i^c}; \boldsymbol{x_i}, \boldsymbol{\beta})$,[10] where $\boldsymbol{p_i^c}$ is the vector of corn prices offered by every plant to county i, $\boldsymbol{x}_i$ is a vector of demand shifters that captures procurement by the competitive fringe from county *i*, and $\boldsymbol{\beta}$ is a vector of parameters to be estimated.

Oligopsonists maximize profits every period by determining the optimal corn prices offered by each of their plants to farmers in every county:

$$\max_{p_{ij}^{c}} \pi_F = P^h * \alpha^h * \sum_i \sum_{j \in F} q_{ij}^{c}(\boldsymbol{p}_i^c; \boldsymbol{x}_i, \boldsymbol{\beta}) - \sum_i \sum_{j \in F} p_{ij}^{c} q_{ij}^{c}(\boldsymbol{p}_i^c; \boldsymbol{x}_i, \boldsymbol{\beta}) -$$

$$\sum_{j \in F} FC_j - \sum_{j \in F} \int_0^{Q_j^h} mc(Q; \boldsymbol{w}_j, \boldsymbol{\alpha})\, dQ \qquad (3.1)$$

subject to

$$\alpha^h \sum_{i \in IN^C} q_{ij}^{c}(\boldsymbol{p}_i^c; \boldsymbol{x}_i, \boldsymbol{\beta}) \leq CAP_j \qquad \forall\, j \in F \qquad (3.2)$$

$$\sum_{j \in IN^P} q_{ij}^{c}(\boldsymbol{p}_i^c; \boldsymbol{x}_i, \boldsymbol{\beta}) \leq RSUP_i \qquad \forall\, i \qquad (3.3)$$

---

[10] We assume that corn purchased is equal to corn processed because plants have limited storage relative to production capacity.

The first term in the first line of equation (3.1), $P^h * \alpha^h * \sum_i \sum_{j\in F} q_{ij}^c(\boldsymbol{p}_i^c; \boldsymbol{x}_i, \boldsymbol{\beta})$), is firm F's revenue from selling the processed products denoted by h ($h = eth$ for ethanol, or $h = wm$ for wet-milling products) at the corresponding prices P^h. The scalar α^h is the conversion productivity factor that describes the quantity of output h (ethanol or wet-milling products) obtained per bushel of corn processed. The conversion productivity factors are specific to the outputs but homogeneous across plants. The second through fourth terms in the right-hand side of equation (3.1) represent cost components. The second term, ($\sum_i \sum_{j\in F} p_{ij}^c q_{ij}^c(\boldsymbol{p}_i^c; \boldsymbol{x}_i, \boldsymbol{\beta})$), represents firm F's total costs from buying corn as an input. The third term in equation (3.1), $\sum_{j\in F} FC_j$, is the annualized cost of construction or installation, and it is summed across plants owned by that firm.

The fourth term, ($\sum_j \int_0^{Q_j^h} mc\big(Q; \boldsymbol{w}_j, \boldsymbol{\alpha}\big)\, dQ$) refers to the total processing cost of producing ethanol and wet-milling products, where Q_j^h refers to the corresponding production quantities, *mc* denotes marginal cost, Q is the amount of corn processed, $\boldsymbol{w}_j$ is a vector of cost shifters (natural gas and electricity prices) and a time trend to capture technological and/or efficiency change, and $\boldsymbol{\alpha}$ is a vector of corresponding parameters.

Our model also allows for binding capacity constraints, a distinctive feature of corn processors (*Market Feature 4*). We specify the marginal processing cost function as:

$$mc\big(Q_j^h; \boldsymbol{w}_j, \boldsymbol{\alpha}\big) = \boldsymbol{w}_j' \boldsymbol{\alpha} + \gamma \left\{1 - \frac{\alpha^h \sum_i q_{ij}^c(p_i^c; \boldsymbol{x_i}, \boldsymbol{\beta})}{CAP_j}\right\}. \tag{3.4}$$

Equation (3.4) allows marginal processing cost of plant *j* to depend on capacity utilization $\frac{\alpha^h \sum_i q_{ij}^c(p_i^c; \boldsymbol{x_i}, \boldsymbol{\beta})}{CAP_j}$. If γ is positive (negative) plants display economies (diseconomies) of capacity utilization, and if γ is zero, plants operate under constant marginal processing cost.

Inequality (equation (3.2)) ensures that production by plant j is not higher than what is technologically feasible to produce in any given year (CAP_j denotes capacity of plant j). Finally, inequality (equation (3.3)) ensures that corn purchased by all plants does not surpass the available amount of corn from a county (production plus storage minus demand from livestock and the fringe). $RSUP_i$ refers to the residual corn supply from farmers in each county (the sum of annual corn production and the stock of corn in storage minus demand from the fringe).

The solution to the optimization problem, as shown in equations (3.1)-(3.3), consists of a system of Karush-Kuhn-Tucker conditions fully characterized in Appendix B.

3.3.2 Upstream Firms (Farmers)

We consider corn supplied by farmers in each county to processors and the competitive fringe. Total corn supply in each period is determined by production and inventories[11] carried over from previous years. Inventories are shaped by the previous season's weather, and production is determined by planted acres and growing season weather. Planted acres are driven largely by world market conditions that determine expected corn prices relative to other crops, which we do not model but take as given. While oligopsonists' pricing may have an effect on local planted acres (e.g., Wang et al. 2019), its relation to production (our variable of interest) is much weaker due to the mediating role of growing season weather. In addition, modeling firms' internalization of the effect of pricing on future planted acres

[11] Storage data is available only at the state level (NASS, USDA). We calculate county-level storage by attributing a fraction of state-level storage to each county, which is equal to each county's average share of total production.

and supply would increase greatly the mathematical and computational burden in our analysis. It would require modeling and solving a complex *dynamic* pricing game, possibly rendering a solution intractable. We abstract away from such considerations and focus on a model of shipments and short-run supplies.

Our model predicts corn supplied by each county to each procurement firm. It builds on two premises. First, suppliers can sell corn to one of three sectors: oligopsonists, local competitive fringe (dry millers and livestock producers), and exports competitive fringe. Second, sectors other than oligopsonists do not exert market power. Both of these premises are motivated by *Market Feature 1*. Previous studies have documented that corn demand from the local competitive fringe can be quite inelastic, especially from its larger source, livestock operators (Suh and Moss 2017). Therefore, we simply subtract that from the total supply. In contrast, export prices are determined in the international market and are not influenced by individual exporting firms. A competitive exporting sector implies exporting firms procure excess supply at their marginal value product. This is consistent with the stylized fact that exports are highly (and positively) correlated with production, as revealed by a relatively constant share of exports over time (see table 2.1). We follow Miller and Osborne (2014) and model the export component of the competitive fringe as an additional plant $j = J + 1$ (where J is the number of plants owned by oligopsonists), but a plant that does not engage in markdown and price discrimination.

Suppliers obtain value from selling corn to plant j, where $j = 1, \ldots, J$ if the plant is owned by an oligopsonistic firm and $j = J + 1$ if the plant is an exporting port. Since there are 18 oligopsonistic plants in our sample (14 ethanol plants and four wet-milling plants), $J = 18$. The corn price for exports is determined by the international price. The suppliers have to pay the transportation cost. In terms of exports, the transportation cost is determined by the distance from the county's centroid to the closest exporting port. The value function of supplier n in county i, associated with selling their corn to plant j is given as:

$$v_{ij}^{n} = \beta^{p} p_{ij}^{c} + \beta^{d} d_{ij} + \beta^{e} e_{j} + \varepsilon_{ij}^{n} = \boldsymbol{x}_{\boldsymbol{i}}^{\prime} \boldsymbol{\beta} + \varepsilon_{ij}^{n}, \tag{3.5}$$

where p_{ij}^{c} is the corn price offered by plant j to a farmer in county i, d_{ij} is the distance between the centroid of the supplier's county i and the centroid of the county where plant j is located, $d_{i,J+1}$ denotes the distance between county i and its nearest exporting port (there are three ports located in Clark, Porter, and Posey counties), and e_j is a dummy variable that is set to 1 if plant j is an exporting port ($j = J + 1$).

The negative ratio of the distance coefficient to the price coefficient $(-\beta^{d}/\beta^{p})$ captures corn suppliers' willingness-to-pay for proximity to an oligopsonist. This ratio represents the transportation cost, since corn suppliers save this amount per bushel-mile when located one mile closer to a dominant firm. The error term (ε_{ij}^{n}) captures unobservable match characteristics, such as a supplier n's preference for plant j (due to reputation or relational contract considerations). The error term is extreme value distributed, so we get a closed-form solution for the share of residual corn supplied by each county to each plant:

$$S_{ij}(\boldsymbol{p}_{i}^{c}; \boldsymbol{x}_{i}, \boldsymbol{\beta}) = Prob(Y_{n} = j) = \frac{\exp(\boldsymbol{x}_{i}^{\prime}\boldsymbol{\beta})}{\sum_{j=1}^{J+1} \exp(\boldsymbol{x}_{i}^{\prime}\boldsymbol{\beta})}, \tag{3.6}$$

where $\boldsymbol{x}_{ij}^{\prime} = \left[p_{ij}^{c}, d_{ij}, e_{j}\right]$ and Y_n represents the farmer's choice to sell corn to ethanol and wet-milling plants or to exporters. The quantity sold from county i to plant j can be written as:

$$q_{ij}^{c}(\boldsymbol{p}_i^c; \boldsymbol{x}_i, \boldsymbol{\beta}) = S_{ij}(\boldsymbol{p}_i^c; \boldsymbol{x}_i, \boldsymbol{\beta}) * RSUP_i, \tag{3.7}$$

where residual supply from county i in each period, $RSUP_i$, is determined by the sum of production and inventories, minus demand from livestock and dry-milling firms.

3.4 Estimation Strategy

One empirical challenge in estimating our model is that corn prices are not available at the individual buyer and seller level. The prices and quantities are available only at a more aggregate (county) level. To overcome this challenge, we employ an estimation strategy similar to that developed by Miller and Osborne (2014). We use firms' optimality conditions and iterate over sets of candidate parameters to find a vector of corn prices paid by each plant to farmers in each county and quantities shipped from each county to each plant. We then weigh the plant-specific prices with the plants' share on corn purchases to calculate the *predicted* county-level prices. The *predicted* county-level prices are then compared with the *observed* county-level prices. The process is iteratively repeated until a set of structural parameters is found under which the predicted prices and quantities get sufficiently close to the observed counterparts.

For estimation of the farmers' supply equation (3.6), we employ a multinomial logit system that has been proposed previously in the agricultural economics literature (Hueth and Taylor 2013) and displays several desirable properties. First, it yields an analytical expression for the share and quantity of corn sold by each county to each plant (equations (3.6) and (3.7)), which makes computation less burdensome. Second, the logit structure produces a specification consistent with heterogeneity in suppliers' responses to prices, making the aggregate supply response smooth to changes in corn prices. Otherwise, small price changes would result in corner solutions at the county level and generate discontinuities in supply behavior. Third, it does not artificially constrain farmers to sell corn within a predetermined radius. This is important in our study since plants purchase corn from distant sellers (well beyond 50 miles in some cases).

Next, we use the multinomial logit supply (as shown in equation (3.6)) and the solution to the oligopsonists' profit maximization problem (as shown in equations (3.1)-(3.3)) to generate price predictions based on the set of candidate parameters. Those are matched closely with the observed prices applying a Minimum Distance Estimator while iterating over parameters: [12]

$$\min_{\boldsymbol{\theta}\in\Theta}\frac{1}{T}\sum_{t=1}^{T}[\boldsymbol{p}_t^c-\widetilde{\boldsymbol{p}}_t^c(\boldsymbol{\theta};\boldsymbol{X}_t)]'\boldsymbol{C}_t^{-1}[\boldsymbol{p}_t^c-\widetilde{\boldsymbol{p}}_t^c(\boldsymbol{\theta};\boldsymbol{X}_t)], \tag{3.8}$$

where Θ is a compact parameter space and $\boldsymbol{C}_t^{-1}$ is an identity matrix, which is not only a positive definite matrix, but also uniformly weights equations defined in the vector $\boldsymbol{p}_t^c-\widetilde{\boldsymbol{p}}_t^c(\boldsymbol{\theta};\boldsymbol{X}_t)$. We denote the vector of observed county-level prices in period t by $\boldsymbol{p}_t^c$. We denote the predicted, county-level prices by $\widetilde{\boldsymbol{p}}_t^c(\boldsymbol{\theta};\boldsymbol{X}_t)$, where $\boldsymbol{\theta}=[\,\boldsymbol{\alpha},\boldsymbol{\beta}]'$ is a vector of parameter values and $\boldsymbol{X_t}$ encompasses exogenous variables, including distances (from oligopsonists to county centroids and from exporting ports to county centroids) as well as demand and cost shifters. The estimation process involves an inner loop and an outer loop. The inner loop computes $\widetilde{\boldsymbol{p}}_t^c(\boldsymbol{\theta};\boldsymbol{X}_t)$, and the outer loop minimizes the distance between $\widetilde{\boldsymbol{p}}_t^c(\boldsymbol{\theta};\boldsymbol{X}_t)$ and its empirical analog $\boldsymbol{p}_t^c$.

The inner loop solves for the county-plant pairs of prices ($\widetilde{\boldsymbol{p}}_{ij}^c$) and quantities ($\widetilde{\boldsymbol{q}}_{ij}^c$) for all plants and all counties given the candidate parameters and exogenous variables. It

[12] For expositional clarity, we reintroduce the time subscript.

does so in two steps. First, it generates a vector of *firm-level* Karush-Kuhn-Tucker (KKT) conditions in the Mixed Complementarity Problem structure that solves problem (3.1)-(3.3). Expressions for the KKT conditions are reported in Appendix B. The KKT conditions constitute, in effect, best response functions, as they characterize the price offered by each plant to each county as a function of prices offered by other plants to that county. Therefore, the second step consists of finding the Nash equilibrium of the problem by simultaneously solving the system of KKT conditions. As a result, the inner loop generates $J \times N$ equilibrium predictions of firm-county price pairs in period t, $\widetilde{\boldsymbol{p}}_{ijt}^{c}(\boldsymbol{\theta}; \boldsymbol{X}_t)$, which are functions of candidate parameters and data. Along with these prices, the inner loop also generates $J \times N$ equilibrium predictions of firm-county quantity pairs in period t, $\widetilde{\boldsymbol{q}}_{ijt}^{c}(\boldsymbol{\theta}; \boldsymbol{X}_t)$. The corn prices offered by all plants to each county are weighted using the corresponding procurement shares such that an aggregate, predicted county-level price $\widetilde{\boldsymbol{p}}_{it}^{c}(\boldsymbol{\theta}; \boldsymbol{X}_t)$ is obtained: $\widetilde{\boldsymbol{p}}_{it}^{c}(\boldsymbol{\theta}; \boldsymbol{X}_t) = \sum_j \left(\frac{\widetilde{\boldsymbol{q}}_{ijt}^{c}(\boldsymbol{\theta}; \boldsymbol{X}_t)}{\sum_j \widetilde{\boldsymbol{q}}_{ijt}^{c}(\boldsymbol{\theta}; \boldsymbol{X}_t)}\right) \widetilde{\boldsymbol{p}}_{ijt}^{c}(\boldsymbol{\theta}; \boldsymbol{X}_t)$. These county-level price predictions are then stacked in vector $\widetilde{\boldsymbol{p}}_{t}^{c}(\boldsymbol{\theta}; \boldsymbol{X}_t)$ of equation (3.8).

The outer loop minimizes the distance between the observed and predicted equilibria by iterating over the candidate parameters in $\boldsymbol{\theta}$. The conditions are stacked, and the estimator (see equation (3.8)) compares the aggregated equilibrium predictions $\widetilde{\boldsymbol{p}}_{t}^{c}(\boldsymbol{\theta}; \boldsymbol{X}_t)$ to the empirical analogs in the dataset $\boldsymbol{p}_{t}^{c}$. These comparisons yield total annual deviations between predicted market outcomes and their empirical analogs. The Minimum Distance Estimator minimizes the sum of squared errors.

The iterative estimation algorithm is relegated to Appendix C. We model this problem as a Mathematical Programming with Equilibrium Constraints (**MPEC**) as suggested by Su and Judd (2012)[13] and implement in the General Algebraic Modeling System (GAMS) software.[14] This strategy increases ease of computation, preventing common nonconvergence and infeasibility issues.

3.5 Identification

We consider 92 counties in Indiana over an 11-year time horizon, such that equation (3.8) includes 92x11=1,012 aggregated equilibrium predictions and their empirical analogs. Identification proceeds based on these 1,012 nonlinear conditions stacked in equation (3.8). The vector $\boldsymbol{\theta}$ contains parameters of the farmers' supply equation ($\boldsymbol{\beta}$), along with the parameters characterizing marginal cost of processing corn ($\boldsymbol{\alpha}$).

The vector of parameters $\boldsymbol{\theta}$ that minimizes the sum of squared errors is identified based on variation in $\boldsymbol{X}_t$ and $\boldsymbol{p}_t^c$. The price coefficient β^p is, as revealed by Karush-Kuhn-Tucker conditions in Appendix B, achieved based primarily on the correlation between county-level prices and the joint variation of output price and county-level residual supply. The latter is captured by the interaction term between these variables, which varies across space and over time. The parameter β^d is determined by the relationship between the spatial configuration of large processors' plants relative to the county centroids (distance from all plants to the county centroids) and county-level corn prices. The parameter β^e is identified by the correlation between the distance to the exporting port and corn prices. Distances from county centroids to plants and exporting ports varies only cross-sectionally, so parameters β^d and β^e are identified based on cross-sectional variation.

[13] We summarize the structure of the algorithm implemented in MPEC in Appendix C.
[14] The GAMS programming code is available from the authors upon request.

Marginal cost parameters included in vector $\boldsymbol{\alpha}$ are determined by the correlation between corn price and natural gas price (α^{ng}), corn price and electricity price (α^{elec}), and corn price and a time trend (α^{time}). As noted in our description of the industry (Figure 3.3), prices of natural gas and electricity, as well as the time trend, vary longitudinally but not cross-sectionally. Therefore, identification of cost parameters proceeds based on time series variability. Figure 3.3 presents the evolution of these variables over time. This figure reveals a negative correlation between natural gas price and corn price, no clear correlation between electricity price and corn price, and a positive trend for corn price until 2012, with a reversal afterward.

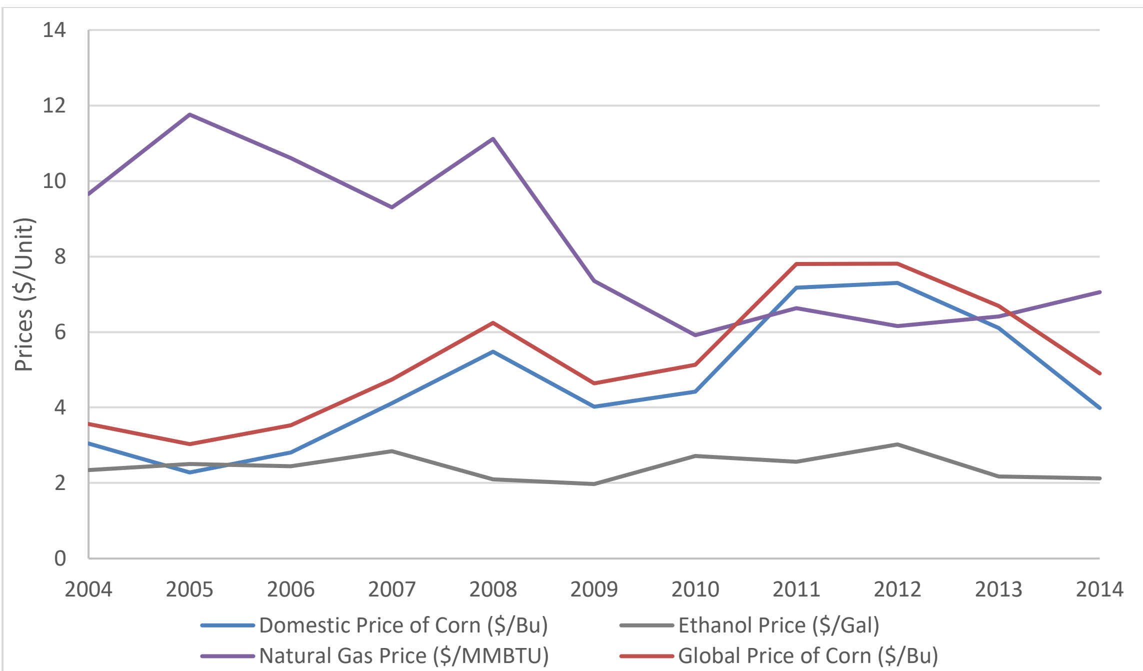


Figure 3.3. Evolution of relevant prices in the corn market

3.6 Estimation Results

In this section, we present the results of the farmers' and the oligopsonists' estimation equations and compute statistics that govern our market and surplus predictions. We pay special attention to estimating markdowns and evaluating the degree of spatial competition in the market. We validate these results based on their ability to generate observed data and against estimates from previous studies.

3.6.1 The Upstream Firms (Farmers)

Parameter estimates of the corn residual supply, as characterized in equation (3.7), are reported in the upper panel of table 3.2.[15] The estimated coefficient for corn price (β^p) is statistically significant and positive. The coefficient shows that the price of corn increases in the amount of corn sold to downstream firms. The positive effect is indicative of a "business-stealing" effect, whereby a downstream firm diverts corn away from its competing firms by offering a higher corn price.

The negative estimate on the coefficient for transportation distance (β^d) shows that farmers supply less corn to oligopsonistic plants that are located farther away. This result is expected since farmers have to pay the transportation cost for corn and a long-distance delivery becomes costly. Selling corn to other more closely located plants becomes an attractive alternative. The transportation cost, as computed by the ratio ($-\beta^d/\beta^p$), amounts to 0.12 cents per bushel per mile. It should be noted that our estimated transportation cost is very close to the 0.16 cents average cost estimate (within 200 miles) as reported by

[15] All standard errors, as shown in Table 3.2, are bootstrapped.

GTOR. The GTOR estimate represents an average for the entire North Central region, which may explain the small deviations from our transportation costs, which are specific to Indiana. The small deviations could be explained by road infrastructure and diesel prices being different between the North Central region states and Indiana.

Evaluating the transportation costs at the average distance of corn delivery and the average corn price paid by oligopsonist-owned plants, our model predicts an average transportation cost of 3% of the corn price. The corn price that farmers receive from plants (after subtracting transportation costs) declines in distance between farmers and plants. Hence, our results show that the presence of transportation costs has an effect on corn price received by the farmers, providing evidence for spatial differentiation being an important aspect to consider.

The transportation costs and the resulting decline in the corn price received by farmers also provide evidence that oligopsonistic firms face upward-sloping residual corn supplies. Our parameter estimates return a firm-level residual indirect average supply elasticity (calculated across plants and time periods) of 0.065.[16] This elasticity suggests that if the average plant in our sample doubles production (increases corn procurement by 29 million bushels), the price of corn would increase by about $0.30 at the plant's gate (it increases from $5 per bushel to about $5.30 per bushel, an equivalent of 6.5%).[17]

Finally, the positive coefficient on the export dummy variable implies that proximity to an exporting port causes an upward shift in the farmers' supply; in other words,

[16] The elasticity is significant at the 1% level.

[17] This is, of course, an oversimplification since such an increase in size would trigger an equilibrium displacement that would tend to make that price increase higher. This value should then be interpreted as a lower bound to the price effect.

exports cause a significant shift in residual supply, consistent with our discussion of figure 3.2.[18]

[18] Recall that other shifters—including demand from livestock and dry millers—have been subtracted from residual supply due to their inelastic nature.

Table 3.2. Parameter Estimates and Derived Statistics

Variables	**Parameters**	**Parameter Estimates**
Residual supply		
Corn price	β^{p}	3.408*** (0.71)
Distance	β^{d}	-0.004*** (1.9e-5)
Export dummy	β^{e}	0.309*** (0.0005)
Marginal costs		
Natural gas price	α^{ng}	0.132*** (0.005)
Electricity price	α^{elec}	0.051*** (0.0015)
Time trend	α^{time}	-0.185*** (0.02)
Extra costs per unit of unutilized capacity	γ	1.58e-4 (2.8e-4)
Derived statistics	*Previous Studies*	*Our Estimates*
Transportation cost ($ per bu-mile)	0.0016[1]	0.0012*** (9.3e-6)
Cap. utilization ratio	0.95[2]	0.98*** (0.007)

Table 3.2. Continued

Marg. processing cost (per gallon)	1.35[3]	1.62***
		(0.16)
Firm elasticity of residual indirect		0.065***
corn supply[4]		(0.016)

Note: Standard errors are computed by bootstrapping and reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels are denoted as *, **, and ***, respectively.
1. GTOR report by Transportation and Marketing Program (TMP) of Agricultural Marketing Service (AMS), USDA
2. Dale and Tyner (2006).
3. Average from Perrin et al. (2009) and Irwin (2018).
4. This is an elasticity of residual corn supply faced by individual plants. We take the average of elasticity across plants over the whole period. This elasticity suggests that if the average plant in our sample doubles production (increases corn procurement by 29 million bushels), the price of corn within the plant's procurement region would increase by $.30 (from $4/bushel to about $4.30/bushel, or 6.5%). This is, of course, an oversimplification since such an increase in size would trigger an equilibrium displacement that would tend to make the price increase higher. This value should then be interpreted as a lower bound to the price effect.

3.6.2 The Downstream Firms (Ethanol and Wet-Milling Firms)

We now focus on the estimation results of the marginal processing costs of the downstream firms (ethanol and wet-milling firms), as characterized in equation (3.4). The middle panel of table 3.2 reports the estimation results.

The positively estimated coefficients for natural gas prices (α^{ng}) and electricity prices (α^{elec}) provide evidence that these operate as cost shifters. An increase in input prices raises marginal processing cost. This effect is especially large for natural gas, which is consistent with the fact that expenditures on natural gas greatly exceed those on electricity. The negatively estimated coefficient for the time trend (α^{time}) shows that plants have become more efficient over time, which is consistent with findings from Hettinga et al. (2009). Our estimated cost parameters predict an average processing cost of

$1.62 per gallon, which is close to the cost estimates (around $1.35 per gallon) reported in Perrin et al. (2009) and Irwin (2018).

The γ parameter measures the change in marginal processing cost per unit of unutilized capacity. The estimate is not statistically significantly different from zero, providing evidence that the marginal processing cost is constant. Constant marginal processing cost is consistent with widely held assumptions made in the literature (see, for example, Gallagher et al. 2005; Perrin et al. 2009), but differs from findings in Sesmero et al. (2016).[19] Our estimated capacity utilization ratio amounts to 0.98, which is close to the ratios reported by Dale and Tyner (2006). In general, our empirical model predictions for revenues and profits of ethanol plants fall within the range published in financial reports (see, for example, Green Plains Renewable Energy 2017) and other independent reports (see also Irwin 2018).

It is important to note that our estimation results generate predictions that closely match anecdotal or statistical evidence, and this lends credence to our parameter estimates. A further important validation exercise relates to our model's ability to generate accurate price predictions, which forms the center of our identification strategy in the empirical model. Figure 3.4 shows the predicted and observed farm-gate prices across counties and over time periods. Each dot represents a combination of an observed price (in a county and a year) and the corresponding predicted price. The dot patterns fragment into clusters because prices differ substantially across years. The correlation between predicted and observed prices is close to 0.99, which supports our model's goodness of fit. The figure

[19] Our coefficient is positive, suggesting economies of capacity utilization as found in Sesmero et al. (2016). However, it is not statistically significant.

illustrates that our structural model does a remarkable job of predicting close to observed prices. It should be noted, however, that our empirical model appears to overpredict prices slightly when observed prices are uncharacteristically low or high. This is less of a concern in our case, however, since we conduct counterfactual experiments around mean conditions, where our model seems to perform best.

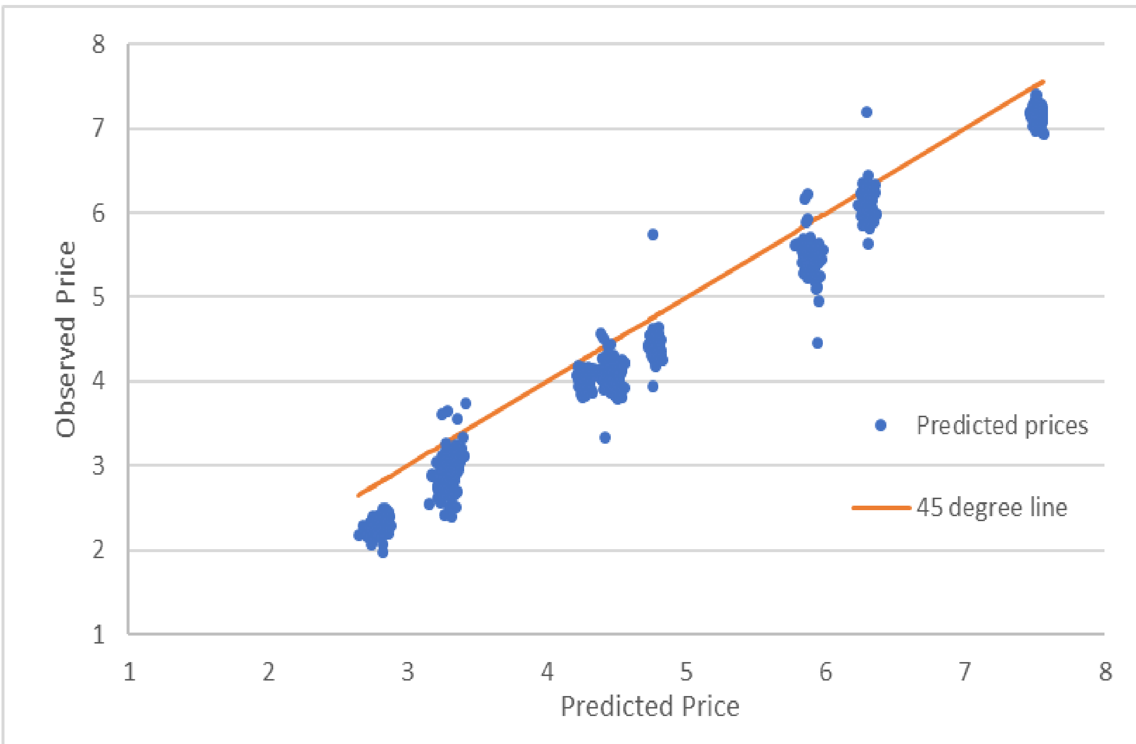


Figure 3.4. Predicted versus observed farm-gate prices

3.7 Corn Prices and Markdowns over Time

In the following, we predict plant-county pair prices paid by ethanol and wet-milling plants and compare these to the value of marginal product of corn (net of marginal processing cost) to calculate markdowns. Figure 3.5 portrays a substantial average price markdown.

The average markdown is around \$0.80 per bushel, or 16% of the average corn price. To put this markdown in context, we note that plants' fixed costs are typically around \$0.60 per bushel (see Irwin 2018). This comparison illustrates the following: While markdowns enabled oligopsonist-owned plants to push the average variable cost below the output price overall, the plants likely experienced economic losses in some periods. This is especially true in 2012, when a historical drought pushed the residual corn supplies from farmers ($RSUP_i$s) down (i.e., pushed the inverse residual supplies upward) such that corn prices increased for all ethanol firms.

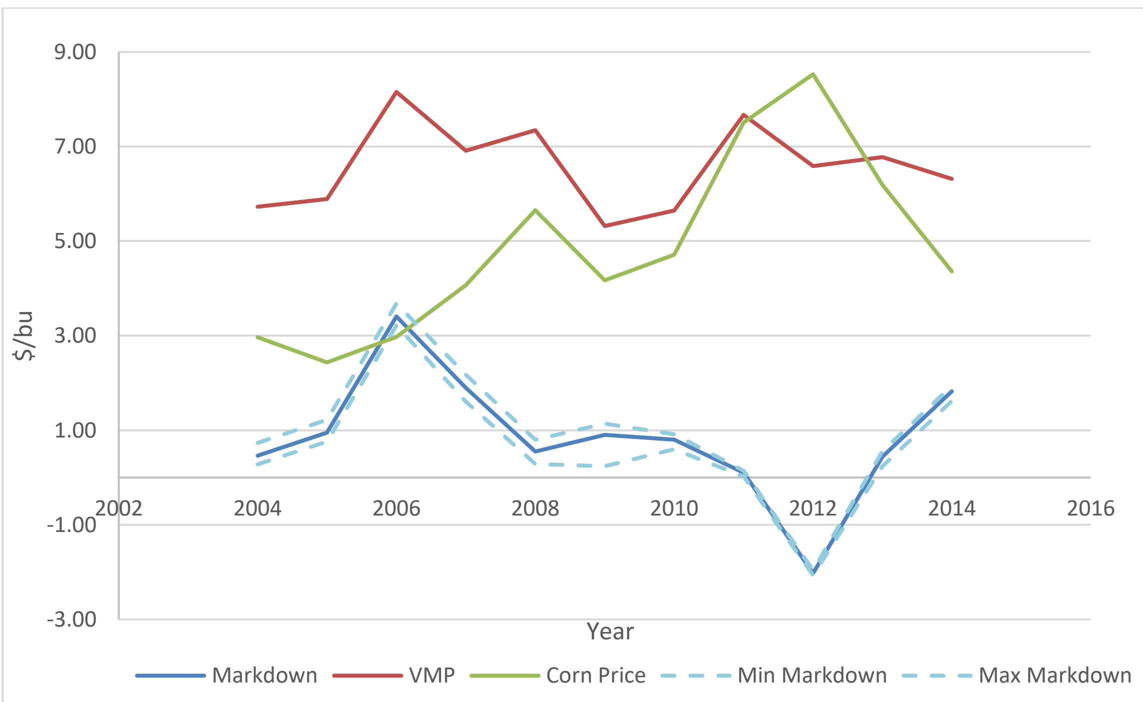


Figure 3.5. VMP, Predicted corn prices, and markdown

Figure 3.5 shows that the markdowns vary widely over time (they drop significantly from 2006 to 2012 and then recover). Fluctuations over time are explained mostly by macroeconomic factors affecting the price of corn, and they are largely absorbed by $RSUP_i$s in our model. Nevertheless, conditional on residual supply, our model also finds substantial markdown variation across plants within a year, as suggested by the minimum and the maximum markdown curves in figure 3.5. The difference between the largest and smallest markdowns in a year averages \$.50 per bushel over the study period but varies in magnitude from almost no variation in 2012 to \$1 in 2009.

To explain the variation of markdowns across firms, we refer to the derived statistics reported in Table 3.2. The statistics emphasize two potential explanatory factors. The first factor relates to the spatial differentiation aspect and the fact that oligopsonistic firms face an upward-sloping residual input supply, which creates a wedge between marginal factor cost and input supply. The second factor relates to our finding that most firms operate at full capacity, with an average capacity utilization rate of 0.98. This creates a wedge between the value of marginal product and input supply. Therefore, our estimation results reveal a salient feature of the corn market—namely that spatially differentiated oligopsonistic firms often operate in Bertrand-Edgeworth competition.

In figure 3.6, we provide a graphical representation of markdown for an individual firm in this context. A profit-maximizing oligopsonist will operate at the level of production for which the value of marginal product is equal to the marginal factor cost. Markdown is equal to the distance between the value of marginal product and residual supply. However, if capacity is smaller than the profit-maximizing production quantity, then the plant will operate at capacity, and markdown is determined by the distance between the value of marginal product and residual supply at capacity. By construction, this distance is larger than the wedge between marginal factor cost and residual supply.

Given the two potential factors underlying markdown in our context, it follows that if the value of marginal product of corn is sufficiently low relative to residual supply (for example, due to a reduction in output price or a bad corn crop), then firms operate below their maximum capacity limit and markdown is determined exclusively by spatial differentiation. But, if marginal product of corn is sufficiently high relative to residual supply (firms operate at capacity), markdown would also be determined by capacity constraints (above and beyond the spatial differentiation factor).

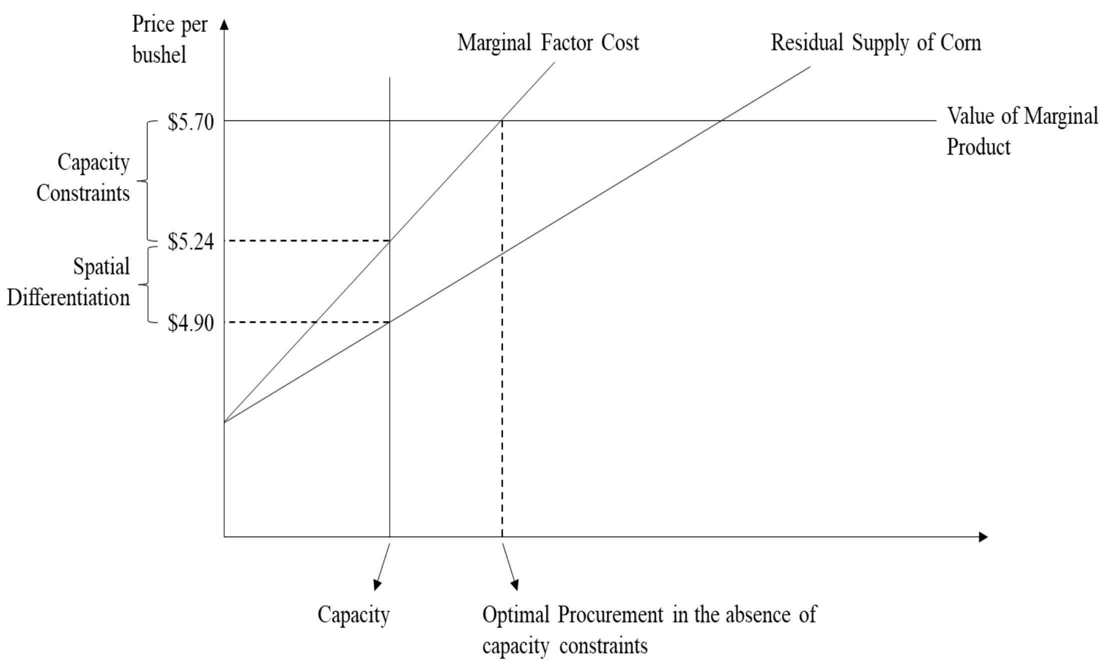


Figure 3.6. Sources of markdown for average plant in our sample

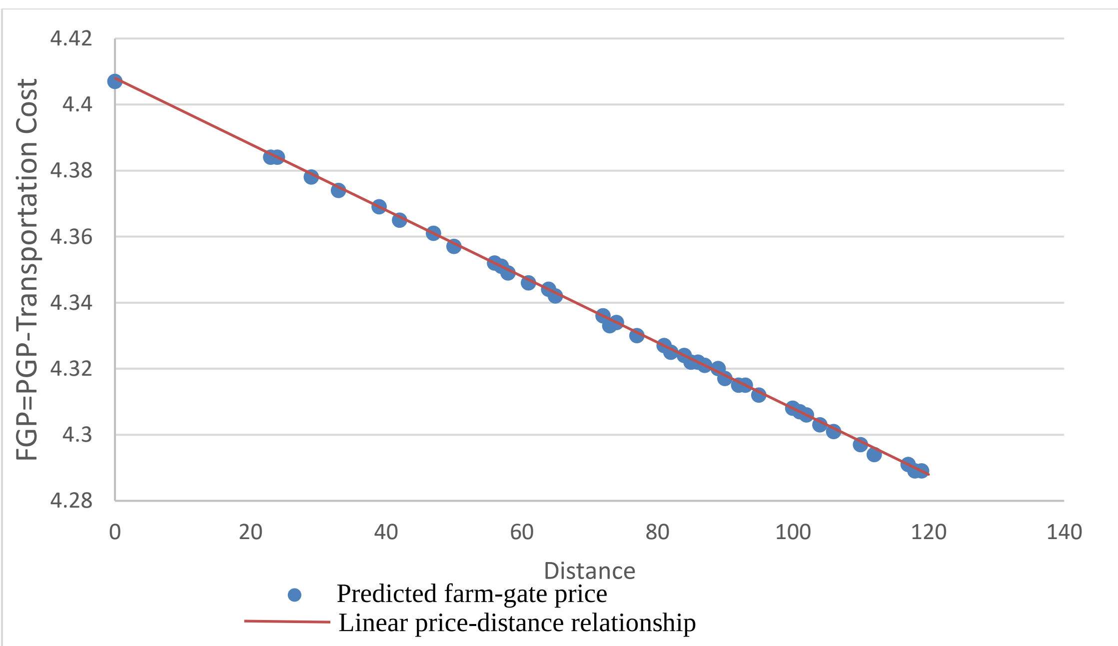
Our results indicate that, on average, capacity constraints prevail, and markdowns are determined by the distance between the value of marginal product and residual supply at capacity. Therefore, as depicted in figure 3.6, markdowns are larger than they would be in the absence of those constraints. Specifically, for the average observation in our sample (average across firms and over time), the wedge between the value of marginal product and residual supply at capacity is \$0.80, while the wedge between supply and marginal factor cost at capacity is \$0.34. These findings are consistent with Bertrand-Edgeworth competition (a setting in which binding capacity constraints deliver a certain degree of localized market power to otherwise Bertrand-pricing buyers of spatially differentiated inputs).

We should note that oligopsonists cannot pay a price to farmers that is below their reservation price; i.e., the price they can get from the competitive fringe. Our model accommodates this by: 1) subtracting corn demand from the local competitive fringe (livestock) from local supply (due to its inelastic nature), and 2) including demand from exports (the non-local competitive fringe) as a shifter in shares (due to its elastic nature). Therefore, our model guarantees that even if oligopsonists pay a price below the competitive benchmark, the price they pay is above the farmers' reservation price.

3.8 Spatial Price Discrimination

An additional focus in our study is whether oligopsonists engage in spatial price discrimination and vary markdown by distance. This is an important question, as spatial price discrimination is another source of deviation from the competitive benchmark and represents a further argument that determines the degree of spatial competition.

In the absence of spatial price discrimination, the corn buyer pays the same mill price (before transportation costs) to all sellers, regardless of their locations. Consequently, the farm-gate prices lie on the linear price-distance gradient, as shown in figure 3.7. In the presence of spatial discrimination, however, corn buyers pay mill prices such that markdowns are higher for corn supplies from nearby farmers. In this case, the farm-gate prices received by farmers located close to the corn buyers would lie below the linear price-distance gradient depicted in figure 3.7. The rationale is as follows: The corn buyer accounts for the sellers' alternative selling options. The corn sellers that are close to the purchasing plant are presumably far from other plants, which makes it more costly to transport corn to them. The additional transportation cost is considered as a reference point and subtracted from the purchasing price, so corn sellers located in close proximity to the buyer are paid a lower mill price. This enables the ethanol plant to set higher markdowns to closely located farmers.



[a] Ratio of plant capacity to county corn supply is 2 for all three plants/counties. This makes plants comparable and allows us to tease out the effect of competition on the spatial pattern of corn purchases.

Figure 3.7. Spatial price discrimination for a selected plant in our sample [a]

Figure 3.7 displays the predicted price-distance gradient (farm-gate prices received by suppliers located at varying distances from these plants), as well as the linear price-distance gradient for a selected plant. The plant we selected operates under rather average conditions in all important dimensions: ratio of capacity to local supply and distance to the nearest exporting port and competitors. Our analysis shows that the firm does not engage in spatial price discrimination, as demonstrated by the absence of deviations of predicted farm-gate prices from the linear price-distance gradient. We have computed these gradients for all the firms in our sample, and our finding on the absence of price discrimination holds for all of them. This indicates that firms do not price discriminate, regardless of their size, distance to competitors and exporting ports, or conditions under which they operate (livestock and local supply).

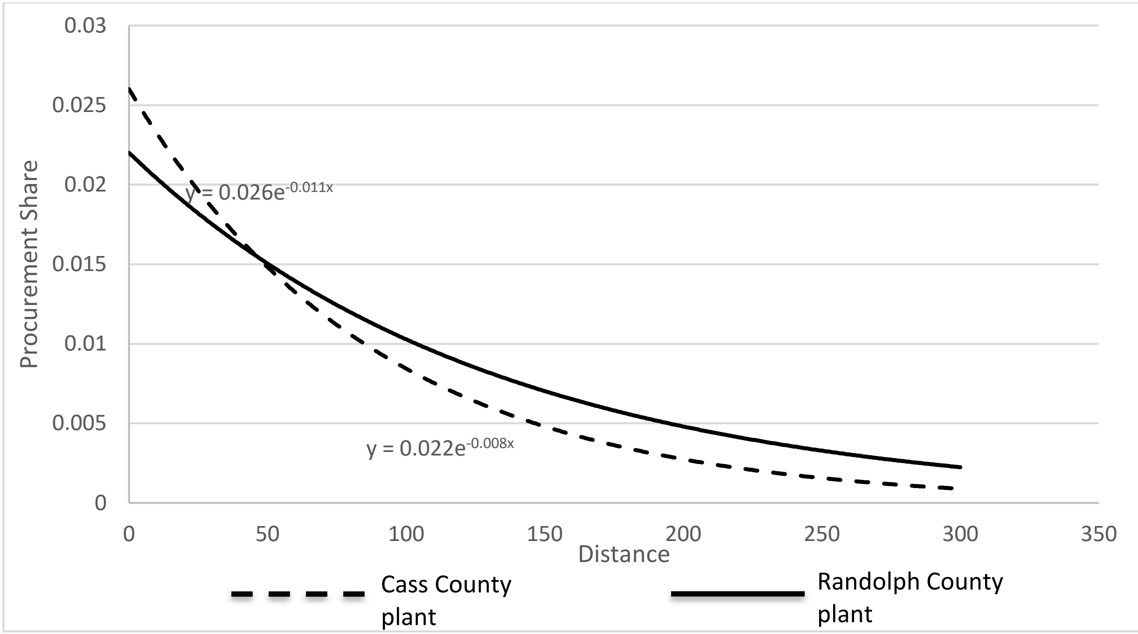
The absence of spatial price discrimination suggests that cash or mill-gate prices posted by firms at the plant gate throughout the year (documented in *Market Feature 3*) are, in fact, honored and that private transactions regarding which party pays for transportation costs are mostly absent; suppliers pay for transportation costs and receive the posted price at the plant gate, regardless of their location relative to the plant. This is consistent with previous descriptions of corn marketing to large processors (see Edwards 2017). Our model cannot elucidate why firms do not price discriminate spatially. Possible reasons could be related to antitrust concerns or the presence of transaction costs since spatial price discrimination would require the plant to decide whether it would absorb a fraction of transportation costs depending on the location of each supplier.

3.9 Spatial Purchase Patterns by Downstream Firms

We further explore the relationship between spatial differentiation and competition. We examine how the quantity of corn purchased by oligopsonistic plants depends on the distance between their plants and farmers. We also consider how competition affects such spatial procurement patterns.

The spatial pattern of corn purchases is determined by many factors, including capacity, geographical distribution of corn production, and local competition. Since we are especially interested in evaluating the spatial competition effect on the plants' spatial pattern of procurement, we report the purchase-distance relationship for two plants that differ in the degree of spatial competition they face, but are similar otherwise (i.e., the plants display a ratio of capacity to local corn residual supply close to 2, and they are located far away from exporting ports). Figure 3.8 compares the spatial procurement patterns for two plants. The first plant faces no nearby competitors and is located in Cass County. The second plant faces a close competitor plant, and it is operating in Randolph County. The figure shows that these plants procure most of their corn within a distance of 50 miles (as revealed by calculating the area below procurement curves), but also likely purchase corn at greater distances. The predicted procurement patterns coincide with previous descriptions of procurement regions under similar corn supply conditions (e.g., Kang et al. 2010). This finding further validates our estimates and lends credence to our analysis.[20]

[20] These procurement patterns also support our choice of the logit supply specification. The logit specification allows for overlapping regions, but by imposing that competition is global (all plants purchase a positive amount from all counties), it may lead to an overprediction of local competition. However, our estimated model predicts that very little corn is procured from distances farther than 100 miles, suggesting the risk of overprediction of spatial competition is limited.



[a] Ratio of plant capacity to county corn supply is 2 for both plants considered. This makes plants comparable and allows us to tease out the effect of competition on spatial pattern of corn purchases.
[b] In the equations, y represents procurement share and x represents distance from plant to farm.

Figure 3.8. Predicted corn purchases by distance for selected plants in our sample [a,b]

Next, we turn to the relationship between spatial competition and corn procurement. Figure 8 shows that the plant facing more spatial competition (there is a competitor in close proximity) is forced to travel greater distances (in the direction of their uncontested markets) to procure corn. It should be recognized that, given a certain level of spatial competition, plant size relative to local corn supply (which could be explained by plant expansion, a bad crop, or growth in corn demand shifters like livestock) would shift the functions in figure 3.8 upward and exert a similar effect as local competition.

3.10 Counterfactual Experiments: Mergers, Markdowns, and Farm Surplus

We have shown that spatial differentiation between oligopsonist-owned plants determines competition and the prices and quantities of corn purchased from farmers at various distances. To deepen our understanding of the effect of spatial differentiation on prices and surpluses, we evaluate the effect of different types of mergers between ethanol plants. These mergers are characterized by varying distances between merging partners.

Mergers in the downstream market between ethanol plants are especially interesting in our context for two reasons. First, a merger enables firms to internalize competitive externalities having an effect on corn demand, prices, and production. As shown earlier, ethanol plants operate within geographically localized procurement areas, which implies they compete with plants located nearby, but not with distant ones. Hence, spatial differentiation between ethanol plants will presumably play a critical role in evaluating merger effects.

Second, large corn processors do not have opportunities to relocate plants (because of prohibitively high costs) and seldom expand capacity; therefore, changing the ownership structure is a popular expansion strategy. In fact, a wave of consolidations virtually doubled the sales-based Herfindahl-Hirschman Index from 260 to 500 in the period 2013 to 2018, as indicated in the Federal Trade Commission's 2018 *Report on Ethanol Market Concentration*. But while mergers have been a pervasive feature of the ethanol industry in recent years, they have not taken place among plants in Indiana. Consequently, Indiana offers an unconfounded marketplace for merger simulations, which seems particularly timely given recent trends in other states.

A merger between plants j and k allows the merging firm to internalize competitive externalities that would not have been otherwise internalized. Suppose plants j and k are owned by different firms, then the firms set their prices noncooperatively and do not account for any cross-price effects $\frac{\partial q_{ij}^{c}(\boldsymbol{p}_i^{c};\boldsymbol{x}_i,\boldsymbol{\beta})}{\partial p_{ik}}$ in the ownership matrix $\boldsymbol{\Omega}(\boldsymbol{p}^{c})$, which is a critical element of firms' first-order conditions (as shown in equation (B3), Appendix B).[21] Hence, the corresponding element in the ownership matrix is zero. The firm that owns plant j does not account for the effect that a price change by plant j has on the supply of corn to plant k.

If plants j and k are owned by the same firm via merger, then plant j considers the fact that an increase in its corn price to county i causes a shift in the residual supply of corn from that county to plant k, represented by the cross-price effect in the ownership matrix. As indicated in the Karush-Kuhn-Tucker conditions in Appendix B, this change in ownership structure will result in a different Nash equilibrium of the pricing game.

The cross-price effect governing the impact of mergers depends upon the spatial differentiation between plants k and j which, in our context, is determined by the distance between these plants, the estimated transportation cost, and the spatial pattern of corn supply. Since merger effects are likely dependent on the degree of spatial differentiation, we consider two mergers that differ in their geographical proximity between the merging ethanol plants.

In the first merger, Poet purchases the plant in Randolph County, which is located close to two of its other plants in Jay County and Shelby County. Figure 3.9a shows the

[21] See Appendix B for a detailed description of this matrix and its elements.

plants owned by Poet before the merger as yellow dots surrounded by black circles; and the plant purchased by Poet through the merger is highlighted by a black dot. In the second merger, Poet purchases a more isolated plant (the average distance between this plant and those owned by Poet before the merger is larger than the average distance between the plant in Randolph County and Poet-owned plants) in Cass County, also denoted as a black dot, but in figure 3.9b.

Figure 3.10 reports post-merger changes in markdowns for both merger cases. Focusing on the first merger case, in which Poet-owned plants merge with a nearby competing plant, we find substantial increases in markdowns. Based on our structural parameter estimates, we predict that plants owned by merging firms will increase markdown further, on average by $0.14 (which corresponds to a 20% increase in markdown for the average plant in our sample). Our analysis shows that under 2014 market conditions, consolidated plants operate at capacity before and after the merger. Therefore, the increase in markdown is not explained by reduced procurement, but by a downward shift in corn residual supply faced by each firm due to internalization of the competitive externalities.

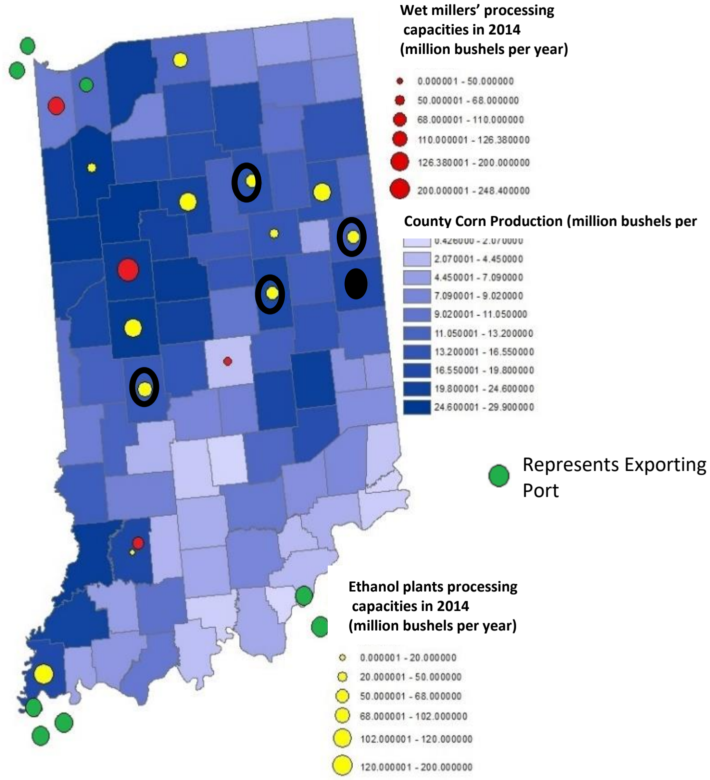


Figure 3.9. Merging and non-merging plants in counterfactual simulations
Figure 3.9a. Merger with a nearby competitor

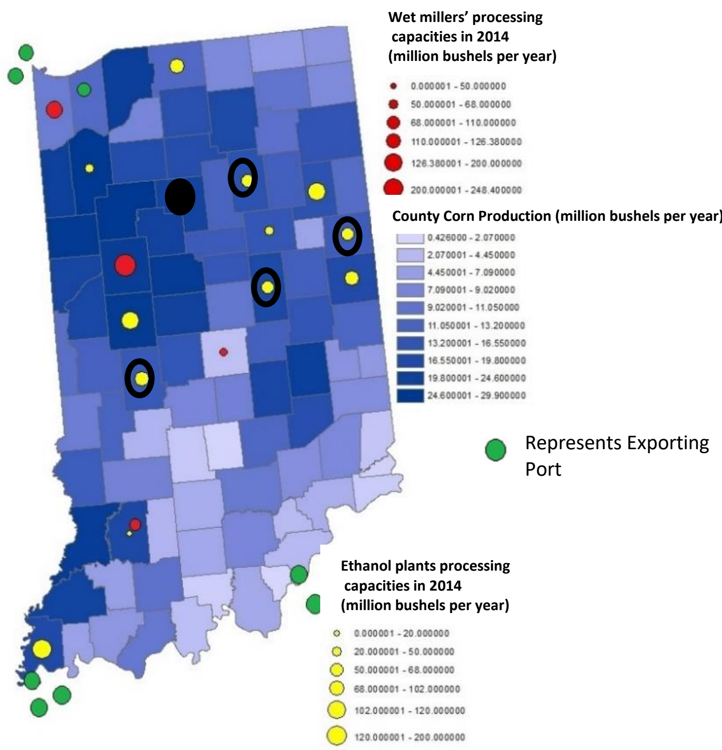


Figure 3.9b. Merger with a distant competitor

Turning to the second merger case in which Poet merges with a distant competitor, this merger has a much smaller effect on markdown by merging firms, as reported in figure 3.10a. A comparison between this and the effect of a merger with a nearby competitor clearly indicates that the magnitude of the downward shift in corn residual supplies as a result of a merger depends upon the degree of spatial differentiation between consolidating firms. In other words, a merger is likely to increase markdown, but only if it takes place between firms that are not strongly spatially differentiated.

While consolidation between nearby ethanol plants increases markdown by the consolidated firms, it may also trigger competitive spillover effects to other, non-consolidating firms. As consolidating firms reduce corn prices due to internalization of competition externalities, close competitors may benefit from weakened competition and reduce corn prices themselves. Our counterfactual simulation uncovers evidence of spillover effects; that is, non-consolidating firms also attain higher markdown due to the fact that mergers soften competition. In fact, as reported in figure 3.10b, a non-consolidating firm located 49 miles away from Poet's plants increases markdown by $0.12, and a non-consolidating firm located 103 miles away from Poet's plants increases markdown by $0.07.

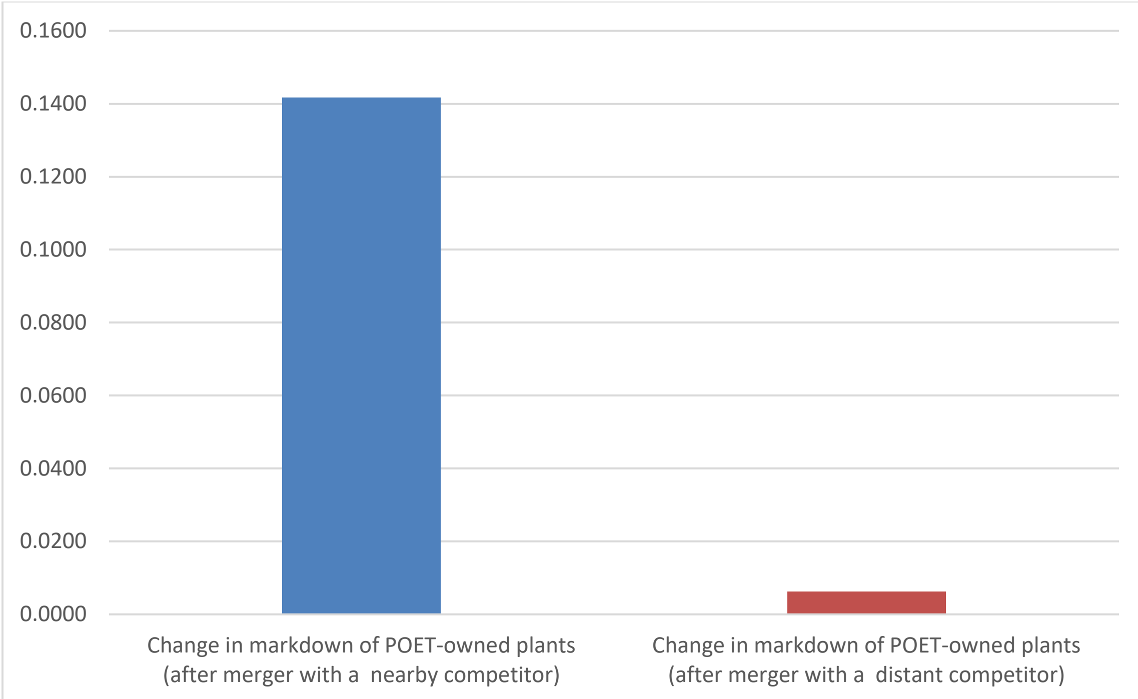


Figure 3.10. Spatial pattern of consolidation and change in markdown
Figure 3.10a. Comparison between the merger with a nearby and a distant competitor

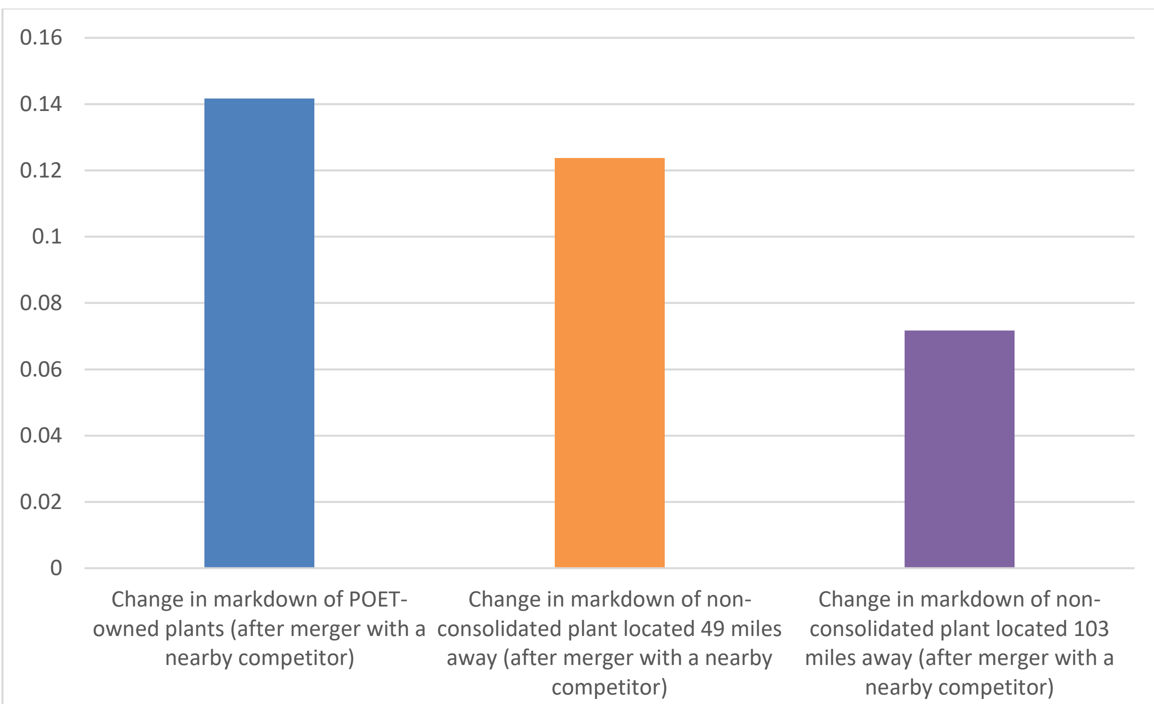


Figure 3.10b. Spillover effect of the merger with a nearby competitor

Price effects of mergers have a direct corollary on farm surplus. For the scenario where merging plants are located nearby, the spatial pattern of merger-induced changes in farm surplus is plotted in figure 3.11. Darker colors denote larger reductions in farm surplus due to weaker competition. Some of the largest reductions take place in close proximity to merging firms. But adverse effects on farm surplus extend well beyond the geographical confines of merging plants, revealing strong competitive spillover effects of mergers. Reductions in farm surplus across Indiana vary from \$0 to \$8 million per county, amounting to roughly a total of \$300 million at the state level.

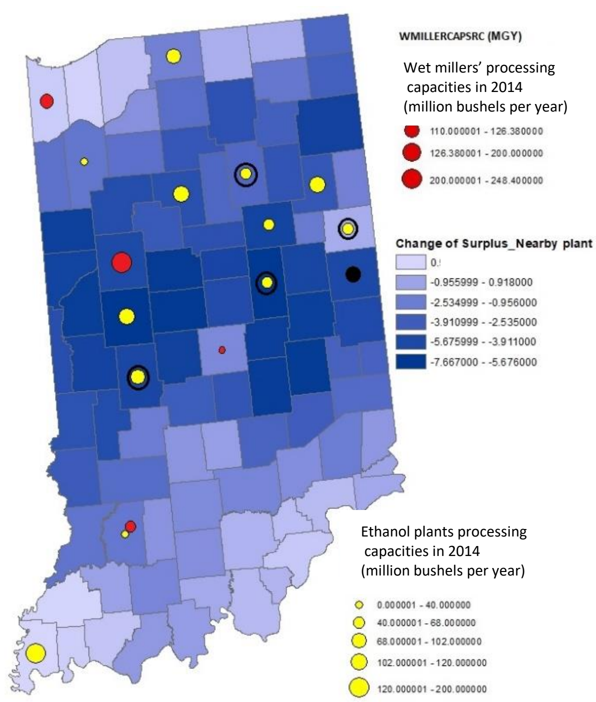


Figure 3.11. Change in producer surplus (million dollars) due to merger with nearby plant

3.11 Conclusion

This study conducts an empirical investigation of the existence of spatial oligopsonistic market power and spatial price discrimination in the corn procurement market. While the literature has devoted some attention to models of spatial differentiation in output markets, there is a remarkable lack of empirical evidence on spatial differentiation in input markets. This is particularly relevant for agriculture, since market power exertion by processors buying from farmers—in combination with the high cost to transport products from farms to plants—has long concerned researchers and policy makers.

We adopt an estimation strategy recently proposed by Miller and Osborne (2014) to estimate firm-level structural parameters in a model of spatial competition based on market-level data. Our model extends this framework to include binding capacity constraints (which are common in our setting). Therefore, our extended framework can accommodate a model of Bertrand competition with differentiated inputs or a model of Bertrand-Edgeworth competition with binding capacities.

Our estimation results return significant transportation costs and markdowns in the corn market, which characterize the relationship between spatial differentiation and competition. Our counterfactual simulations indicate that the effect of mergers among corn procurement oligopsonists (particularly in the corn ethanol industry, where mergers seem increasingly common) depends upon the spatial pattern of such mergers. A merger between plants in close proximity not only increases their markdown, but also triggers competitive spillover effects that allow nearby non-consolidating plants to increase markdown as well. Competitive spillovers amplify the negative impact of mergers on farm surplus and result in substantial losses for the farm sector. However, a merger between plants located far apart is much less consequential for markdown and farm surplus. This suggests that assessments of mergers between corn-purchasing firms should explicitly consider the location of merging firms' plants. While our primary focus is consolidation counterfactuals, our structural model can be used also to simulate counterfactual scenarios on expansion, entry, and policies. However, this goes beyond the scope of this paper, and we plan to address this in future studies.

More generally, our analysis indicates that assessment of mergers between spatial competitors in agricultural procurement markets should perhaps consider distance more explicitly. Previous studies have characterized efficiency gains associated with mergers that would restore premerger equilibrium prices and quantities (i.e., that would offset increased market power effect) after the merger takes place (e.g., Werden-Froeb Index) and, thus, should not raise anticompetitive concerns. Our analysis suggests the need to develop such an index in agricultural procurement markets, which display two distinct features: (1) spatial differentiation; and possibly (2) binding capacity constraints. The development of a regulatory index of this nature seems relevant for both scientists and policy makers.

4. THE DYNAMIC RESPONSE OF LOCAL CORN PRICES TO ETHANOL PLANT ENTRY: IMPLICATIONS FOR SHORT- AND LONG-RUN CORN SUPPLY ELASTICITIES

4.1 Introduction

The expansion of the corn ethanol industry is perhaps one of the most consequential events in agriculture over the last few years. It was, to a great extent, a result of aggressive public policies and constituted an unprecedented demand shock for corn farmers. In light of the fact that ethanol plants are very large and geographically scattered, in addition to the geographically localized nature of corn procurement due to transportation cost (see Essays 1 and 2 of this dissertation), plant entry is expected to have an impact on corn prices and production (due to farmers converting land to corn in response to price signals). The literature quantifying the local impacts of ethanol plant entry can be classified in two strands. One strand looks at the effect of entry on local land use and mostly finds that plant entry increases conversion of land to corn in the area surrounding the new plant. The other strand looks at the effect of entry on local corn price and delivers ambiguous findings; some studies find a positive price effect while others do not.

A superficial look at these strands of literature suggest an inconsistency; the land use literature does find ethanol expansion affects farmers' behavior while the corn price literature finds that ethanol expansion may or may not affect prices. But further reflection suggests that the supply response found by the land use literature (farmers convert more land to corn) may totally offset the demand shock embedded in ethanol expansion, thereby preventing a change in corn price as found by some papers in the corn price literature. On the other hand, supply response may only partially offset the demand shock so that ethanol expansion induces an increase in corn price as found by other papers in the corn price literature. Clearly, therefore, the debate seems to be one of supply elasticity; i.e., is supply sufficiently elastic to absorb the demand shock and keep the price effect low? But supply elasticity, especially in agriculture is an inherently temporal notion. How much can supply adjust in the short-run? What about the long-run? And, as a result, what is the temporal pattern of price effects associated with plant entry? These are the empirical questions that this study addresses.

We use temporally and spatially explicit data on plant entry and elevator-level corn prices to examine the temporal pattern of price effects triggered by entry of ethanol plants. We use an Autoregressive Distributed Lag (ARDL) model that allows us to distinguish the contemporary (year of entry), one-year lag, and two-year lag effect of plant entry on price. Econometric identification is challenging due to the dynamic nature of corn prices (serial correlation) and the endogeneity of plants' locations which causes selection bias. We implement multiple estimation strategies to remove biases from serial correlation and endogeneity. Our results indicate that entry of ethanol plants does not significantly affect corn prices in the vicinity of the plant the year of entry. However, we do find rather strong effects afterwards; one or two years after entry, depending on the specification.

Our results imply that supply elasticity is larger in the short-run than it is in the long-run. This result is in line with previous studies in the agricultural economics literature (e.g. Hendricks, Smith, and Sumner 2014). This seemingly strange result is likely due to agronomic factors that distinguish agricultural supply from supply of other products. Agricultural production is characterized by strong rotational benefits. In the Corn Belt, fields where corn is planted in successive years tend to display lower yields and also higher prevalence of weeds and pests that require higher chemical input usage (Hennessy 2006). The combination of these forces makes successive planting of corn less profitable and strengthens incentives for farmers to rotate and revert back to soybeans. Similar effects result from plating soybeans successively over time.

With these considerations in mind, entry of an ethanol plant (or even anticipation of entry) sends a clear and strong price signal to farmers, especially those located in close proximity to the entrant (entry and location of entry are typically announced publicly several years before the plant starts operation). As a result, farmers plant corn. This supply response offsets the positive demand shock that is entry of a new ethanol plant. However, after one or two years, rotational benefits partly offset price signals, and farmers around the plant start to revert back to soybeans, reducing corn supply. Yet, entry of a plant is a permanent demand shock, especially considering the cost structure of these plants, which makes them operate close to capacity whenever possible. This results in an increase in local corn prices a year or two after entry when demand remains the same, but supply reverts back closer (but not fully) to its pre-entry level.

Most importantly, our results indicate that the apparent inconsistency between studies that look at the effect of plant entry on corn prices may be due to the lag between plant entry and the period of time considered by these studies. In fact, looking at the literature, studies that did find an effect of plant entry on prices tend to examine price observations that take place well-after entry. Similarly, studies that did not find a strong price effect tend to examine price observations that take place not long after plant entry.

4.2 Literature Review

The ethanol boom in the US over the 2005 and 2011 period might have led to changes in land use and crop prices, particularly for corn which is the main feedstock for ethanol production. Most of the previous studies estimating corn acreage/supply responses to ethanol production have drawn a common conclusion; entry of ethanol plants prompts farmers, particularly farmers in close proximity to the plant, to convert land to corn (Miao, 2013; Brown et al., 2014; Fatal and Thurman, 2014; Motamed, McPhail, and Williams, 2016; Li, Miao, and Khanna, 2018; Wang et al. 2020).

Another strand of literature focuses on the effect of ethanol expansion (particularly plant entry) on corn price. Unless corn supply is perfectly elastic, a positive demand shock that diverts a substantial portion of corn produced, around 40%, to the ethanol sector will raise the price of corn. Yet, several studies found no effect of ethanol expansion on prices (FAPRI, 2005; Gallagher et al., 2005; O'Brien, 2009; Katchova, 2009; Lewis, 2010; Behnke and Fortenbery, 2011). On the other hand, other studies did find a positive impact of plant entry on corn price, albeit rather large variations in magnitude (Urbanchuk and Kapell, 2002; Ferris and Joshi, 2004; McNew and Griffith, 2005; Parcel and Fort, 2006;

Taylor et al., 2006; Fortenbery and Park, 2008; Roberts and Schlenker, 2013; Zilberman et al., 2013; Grashuis, 2019; Katchova and Sant'Anna, 2019; Jung, Sesmero, and Siebert, 2019). These studies also found that, when plant entry does raise price, it does so for farmers located in close proximity to the plant (Gallagher, Wisner, and Brubacker, 2005; McNew and Griffith, 2005; O'Brien, 2009; Katchova, 2009; Lewis, 2010; Jung, Sesmero, and Siebert, 2019). For example, McNew and Griffith (2005) found that on average across the plants corn price increases by 12.5 cents at the plant site which decays with distance up to 68 miles (0.18 cents per mile). In addition, Jung, Sesmero, and Siebert (2019) estimated that the increase in price declines by 0.2 cents per bushel-mile from the plant site.

Some of these studies looked at prices right before entry/expansion (McNew and Griffith, 2005; Parcel and Fort, 2006; Taylor et al., 2006; Fortenbery and Park, 2008; Motamed, McPhail, and Williams, 2016; Katchova and Sant'Anna, 2019) and some looked at prices after a considerable time had elapsed since the entry/expansion took place (Roberts and Schlenker, 2013; Zilberman et al., 2013; Li, Miao, and Khanna, 2018; Grashuis, 2019; Jung, Sesmero, and Siebert, 2019). The former set of studies are, in fact, estimating short-run price effects while the latter set of studies are estimating long-run effects. These may be substantially different considering that short- and long-run supply responses may differ widely. Whatever the case, though, neither set of studies can recover the dynamic evolution of prices.

Examining the temporal pattern of price effects may provide additional insights both on the apparent inconsistency of findings in the empirical literature, and on our understanding of pricing and procurement strategies by large corn processors such as ethanol plants. It also provides information to anticipate the effects of future entry of large corn processors.

Ethanol expansion may motivate farmers to switch to corn as they expect a higher price in the next year due to increased demand from plant entry. However, corn farmers in the US Corn Belt tend to rotate corn and soybeans year by year to capture the benefits of crop rotation, including increased yields and lower usage of chemical inputs to control for weeds and pests (Hennessy 2006). Therefore, the effect of entry on farmers' production decisions and ultimately price is an inherently dynamic process. In this study, we set to better understand this dynamic process.

We study the dynamics of the average treatment effect of ethanol plant entries on local corn prices – the short- and long- run responses - by exploiting Autoregressive Distributed Lag Model approach based on panel data. This is based on our assumption that farmers responses to price shock vary over time. Menezes and Piketty (2012) estimate a regression model containing a lagged dependent variable, Autoregressive Process of Order One (AR(1)), to address partial adjustment. They conclude that farmers in Brazil gradually respond to price shocks over time (Menezes and Piketty, 2012); i.e., the short-run response is smaller than the long-run response. This is consistent with findings by Nerlove (1958) and Askari and Cummings (1977). On the other hand, Hendricks, Smith, and Sumner (2014) apply first-order Markov transition probabilities with field-level data, and estimate that short-run corn supply elasticities in Iowa, Illinois, and Indiana are 37% higher than its long run counterparts. They also estimate the same model with county-level data and draw an opposite finding, the short-run response to price shock is 20% smaller than the long-run responses. Hendricks, Smith, and Sumner (2014) points out that using field-level data may alleviate biases from aggregating micro-level units into county-level when there exists coefficient heterogeneity across fields in the same county (Robertson and Symons, 1992; Pesaran and Smith, 1995).

Our estimation is closer to that of Menezes and Piketty (2012) in the sense that the main estimation strategy of this study stems from a distributed lag model intended to capture short-run and long-run impact due to permanent changes in corn demand by ethanol plant entries. This study contributes to the literature looking at the impact of ethanol plant entry on local corn prices by deepening our understanding of the *dynamic* response of prices to plant entry. This is important for at least three reasons. First, it sheds light on the apparent inconsistency of empirical findings in the literature that looks at the effect of plant entry on corn prices. Second, understanding the dynamic response of price to entry reveals important information regarding the short- and long-run corn supply elasticity. Third, understanding the temporal dimension of supply elasticity is informative of how these plants may decide their pricing and procurement strategies. In turn, this has direct implications in terms of how the surplus from the ethanol industry is distributed along the vertical supply chain.

4.3 The Corn Procurement Market in Indiana

Corn has multiple uses and destinations. Corn is consumed by the ethanol industry, the food industry, the livestock sector, and it is also exported. Corn ethanol is a prominent industry in Indiana. A total of l,431 million bushels of corn (37% of total corn produced) were processed to produce ethanol in 2014 (NASS, USDA). Likewise, food processors constitute a substantial source of demand for Indiana corn. We classify food processors into two categories: wet- and dry-milling plants. Wet-milling plants produce starch products, gluten feed, gluten meal, and corn oil and dry-milling plants produce cereals, corn meal, or corn flour. Food processors consumed 21% (259 million bushels) of corn supplied in 2014 (18% for wet-mills and 3% for dry-mills). Exports and livestock operators each consumed about 16% of total corn supply in 2014. But this snapshot of corn usage in 2014 conceals some drastic changes over the previous 10 years.

Table 2.1 in this dissertation reports the share of total corn supplied annually in Indiana that is consumed by each sector during our period of analysis (2004-2013). On average, about 20% of corn is consumed by the wet milling sector of the food processing industry. This share has remained relatively constant, except for 2012 which was a drought year. Two other important corn users are animal feeding operations and exports. The share of total corn consumed by the animal sector is also historically stable around 18%. Exports fluctuate between a minimum of 15% and a maximum of 20%. Storage, while important, is also widely volatile. It varies from being the destination of 38% of corn produced in 2004 to the source of 2% of corn used in 2011 (44% of the corn used in the drought year 2012). The dry milling sector (another sub-sector of the food processing industry) consumes somewhere between 2.5 and 3% of corn supplied each year (again, for years other than 2012). The corn ethanol industry clearly stands out, among corn consumers. It starts by consuming only 3.85% of corn supplied and grows spectacularly due to entry of new ethanol plants and reaches almost 40% of total corn supplied by 2011 (it consumed 65% in drought year 2012).

As partly documented in essay 1 of this dissertation, corn procurement is geographically localized. This is an important feature, because we will examine the temporal pattern of price effects associated with entry of a new ethanol plant, in the vicinity of the plant; i.e. we consider the evolution over time of prices paid by elevators located in the county where the plant locates and neighboring counties. Geographical localization stems from the fact that transporting corn is costly. Domestic hauling of corn is primarily handled by trucks, followed by rail and barge. Adam and Marathon (2015) estimates that the share of corn transported by truck gradually increased over time from 67 percent in 1998 to 82 percent in 2013. This is mostly due to ethanol production which increased by 294 percent from 1995 to 2013. Since plants are located in local corn producing regions and trucking is less costly than other forms of transportation within relatively short distances (i.e. below 500 miles), corn farmers typically ship corn in trucks to ethanol plants (Denicoff et al., 2014).

The Transportation and Marketing Programs (TMP) of the Agricultural Marketing Service (AMS) at USDA issues quarterly information on transportation costs through its Grain Truck and Ocean Rate (GTOR) report. According to GTOR, the transportation rate of grains in the North Central region[22] inclusive of Indiana on the 1st quarter of 2016 was 0.33 cents, 0.21 cents, and 0.20 cents per bushel-mile for 25, 100, and 200 miles, respectively.[23] This means that transportation cost can amount to about 5 to 10% of procurement cost within these distances. This underscores the importance of transportation costs and suggests a possible geographical localization of corn procurement markets.

[22] The North Central region in the GTOR report includes North and South Dakota, Nebraska, Kansas, Minnesota, Iowa, Missouri, Wisconsin, Illinois, Michigan, Indiana, Kentucky, Tennessee, and Ohio.
[23] These is the converted value from the rate reported in GTOR. GTOR reports the transportation rate per truckload-mile. One truckload is equivalent to 984 bushels of corn.

Transportation cost limits the supply available to ethanol plants. But ethanol plants are likely to have an effect on price if their capacity is large, relative to localized supply. Table 2.2 reports the ratio of each ethanol plant's annual corn processing capacity to annual corn produced in the county in which the plant operates. In each case ratios are reported for the years the plant is in operation within our study period. Values reported in table 2.2 clearly document a high level of concentration in local corn procurement markets by ethanol plants. The ratios reported in table 2.2 indicate that most plants (85%) have an annual corn processing capacity larger than all the corn produced in the county where they are located. About half of these plants have an annual processing capacity more than twice as large as the county annual production; and 3 out of 13 plants require more than three times more corn than produced in their county.

These key features of the corn ethanol industry in Indiana suggest that plants are large enough relative to a geographically delimited supply to perhaps have an impact on land use and corn price. But these impacts are not independent. The effect of plant entry on local prices will depend on the change in land use (conversion of land to corn) induced by entry. In other words, the overall price impact will depend on the elasticity of local corn supply with respect to price. However, supply elasticity is an inherently temporal parameter. As producers have more time to adjust, they will make different decisions rendering a fundamental difference between short- and long-run elasticity. This will, in turn, result in a dynamic response of corn price to entry.

In the next section, we develop an empirical model that allows us to more precisely examine the dynamic response of local corn prices to plant entry. While we do not explicitly estimate a corn supply elasticity, we know the size of the demand shock (size of ethanol plants) associated with entry, and our empirical analysis tells us the magnitude of the price change over time. This information can be leveraged to back out the implicit short- and long-run supply elasticities.

4.4 Econometric Model

This study exploits a perfectly balanced panel data with 268 elevators in 92 Indiana counties over 11 years from 2004 to 2014. Considering that it stays at the initial location and capacity remains almost unchanged once an ethanol plant enters the Indiana market (Official Nebraska Government, 2019), we first propose Autoregressive Distributed Lag (ARDL) model over 2 years (Equation 4.1).[24] Since the last ethanol plant enter the market in 2012 while we have the data until 2014, we assume that there will be no further changes in impact after two years so that we would not lose any entry impact in recent years.[25] The proposed ARDL equation is:

$$Price_{eit} = \beta_0 + \beta_1 Price_{eit-1} + \beta_2(Preexist_{it} \cdot Ratio_{it}) + \sum_{k=0}^{2} \beta_{3+k} Entry_{it-k} + \sum_{k=0}^{2} \beta_{6+k} Entry_{it-k}(Ratio_{it-k} - \overline{Ratio_i}) + \sum_{k=0}^{2} \beta_{9+k} Entry_{it-k} Distance_{eit-k} + \beta_{12} IMR_{it} + \beta_{13} LivestockDem_{it} + \sum_{t=1}^{8} \beta_{13+t} Time_t + \varepsilon_{eit} \quad (4.1)$$

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[24] We start from Finite Distributed Lag (FDL) model without lagged below. Then, we test serial correlation for panel data following Wooldridge (2002, p.282-283) and Drukker (2003). The test provides F-value of 5996.81 which is statistically significant at 0.01 level, suggesting the ARDL model as Equation 1.

$$Price_{eit} = \beta_0 + \beta_2\left(Preexist_{it+j} \cdot Ratio_{ct}\right) + \sum_{k=0}^{2} \beta_{3+k} Entry_{it-k} + \sum_{k=0}^{2} \beta_{6+k} Entry_{it-k}\left(Ratio_{it-k} - mean(Ratio_i)\right) + \sum_{k=0}^{2} \beta_{9+k} Entry_{it-k} Distance_{eit-k} + \beta_{12} IMR_{it} + \beta_{13} LivestockDem_{it} + \sum_{t=1}^{8} \beta_{13+t} Time_t + \varepsilon_{eit}$$

[25] For the ethanol plant entry in 2012, it has 2 year-lag impact on local corn price in 2014.

where the outcome variable $Price_{eit}$ is farm gate corn price (FGP) offered to an elevator e ($e \in \{1, \cdots, 268\}$) in a county i ($i \in \{1, \cdots, 92\}$) and year t ($t \in \{2004, \cdots, 2014\}$). $Ratio_{it}$ represents a ratio of ethanol plant capacity over corn supply in a county i where the plant is located and year t. Since the price is affected by the relative relationship between supply and demand, using the ratio is more likely to account for the impact on price than using plant capacity. $Entry_{it-k}$ is a variable indicating a plant entry in a county i and year $t-k$. k captures lagged years from contemporaneous ($k=0$) to 2 year-lag ($k=2$). Following Wooldridge (2002) and Banerjee and Siebert (2017), we control for unobserved county-specific heterogeneity by including additional time-invariant county-specific regressor, which is a time average of the ratio in county i ($\overline{Ratio_i}$). An interaction between $Entry_{it-k}$ and ($Ratio_{it-k} - \overline{Ratio_i}$) captures heterogeneous effect of entry by the ratio. In order to examine impact of proximity on corn price, we measure distance between elevator e in a county i and year t and its closest ethanol plant, $Distance_{eit-k}$. Potential selection bias is addressed by using Inverse Mills Ratio, IMR_{it}, for a county i and year t.[26] $LivestockDem_{it}$ is a time-varying county-specific shifter of corn demand from livestock operators in county i and its neighboring counties in year t. Finally, we control for time-specific fixed effects using time dummies, $Time_t$.

The initial step of adopting ARDL model is to test whether the data series, the dependent variable in particular, is integrated of order one I(1) or *unit root*. We employed the Levin-Lin-Chu (LLC) unit test based on Augmented Dickey-Fuller (ADF) for panel

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[26] We estimate IMR by running probit regression of plant entry on corn supply in a county, railroad density in a county, distance to the nearest exporting port, county population, and corn demand from livestock operators. After estimating fitted value for the plant entry, we calculate IMR which is the ratio between the probability density function and cumulative density function of standard normal distribution.

data suggested by Baltagi (2001). It is tested under the null hypothesis of a unit root. All the data series reject the null hypothesis at 1% significance level suggesting that all variables are stationary and there is no concern for cointegration between dependent and independent variables (Table 4.1). Therefore, we estimate the suggested ARDL model per se (Equation 4.1).

Table 4.1. Results for the LLC Unit root test

Variables	T-statistic	P-value
$Price_{ict}$	-32.6984	0.0000
$Preexist_{ct+j} \cdot Ratio_{ct}$	-5.5932	0.0000
$Entry_{ct-k}$	-13.7491	0.0000
$Entry_{ct-k}(Ratio_{ct-k} - \overline{Ratio_c})$	-14.6489	0.0000
$Entry_{ct-k}Distance_{ict-k}$	-13.6122	0.0000
$LivestockDem_{ct}$	-3.3581	0.0004

Even so, there may be an endogeneity issue in the model for such variables as $Price_{eit-1}$, $Entry_{it-k}$, $Entry_{it-k}(Ratio_{it-k} - \overline{Ratio_i})$, and $Entry_{it-k}Distance_{eit-k}$. First, $Price_{eit-1}$ suffers from endogeneity due to its serial correlation and if supply responses to the demand shock caused by plant entry in a year persist over time, correlation between lagged prices and unobservable factors may affect current prices. $Entry_{it-k}$ is more likely to suffer from omitted variables, which is unobservable in the error term. Interaction terms are still endogenous if $Entry_{it-k}$ is endogenous. We check endogeneity by conducting Hausman test for multiple endogenous variables, $Price_{eit-1}$, $Entry_{it-k}$, $Entry_{it-k}(Ratio_{it-k} - \overline{Ratio_i})$, $Entry_{it-k}Distance_{eit-k}$ over $k = 0,1,2$. Instrumental Variables (IV) for each endogenous variable are summarized in Table 4.2. The entry of an ethanol plant is determined by factors such as corn supply nearby, access to exporting port, railroad density to transport produced ethanol, and whether it is rural area. Therefore, we choose corn supply, railroad density, population in a county where elevators are located and distance to the nearest exporting port as instrumental variables (IVs).

Table 4.2. Instrumental Variables

Variables	Instrumental Variables
$Price_{eit-1}$	$Corn\ Supply_{it-1}$
$Entry_{it-k}$	$Corn\ Supply_{it-k}$, $Railroad\ Density_{it-k}$, $Distanct\ to\ the\ nearest\ exporting\ port_{it-k}$
$Entry_{it-k}(Ratio_{it-k} - \overline{Ratio_i})$	$Corn\ Supply_{it-k}(Ratio_{it-k} - \overline{Ratio_i})$, $Railroad\ Density_{it-k}(Ratio_{it-k} - \overline{Ratio_i})$, $Distance\ to\ exporting\ port_{it-k}(Ratio_{it-k} - \overline{Ratio_i})$
$Entry_{it-k}Distance_{eit-k}$	$Corn\ Supply_{it-k}Distance_{eit-k}$, $Railroad\ Density_{it-k}Distance_{eit-k}$, $Distanct\ to\ the\ nearest\ exporting\ port_{it-k}Distance_{eit-k}$

Two important features in this model are 1) there are multiple endogenous explanatory variables and 2) some of them are interaction terms. To address the multiple endogenous variables, we aggregate all of the IVs for different endogenous variables plus other exogenous variables from the 2 stage model (equation 4.1) such as $Pre - exist_{ct+j} \cdot Ratio_{ct}$, $LivestockDem_{ct}$, and time dummies ($Time_{ict}$) when we run the 1st stage regression for each endogenous variable as Wooldridge (2002) suggests. As for the endogenous interaction terms, Wooldridge (202) suggests that we should generate extra IVs for the interaction terms by interacting IVs with a variable that is interacted with the corresponding endogenous explanatory variable. Therefore, we interact IVs for $Entry_{ct-k}$ with $(Ratio_{ct-k} - \overline{Ratio_c})$ and $Distance_{ict-k}$, respectively, to generate stronger IVs for interaction terms (Table 4.2).

Considering all the above, we run 2 Stage Least Squares (2 SLS) on panel data after conducting Hausman endogeneity test beforehand.[27] A set of the chosen IVs are endogenous based on the joint hypothesis test at 1% significance level with F-statistic at 6.30.[28] IVs are all strong for all endogenous variables but $Entry_{ct-1}Distance_{ict-1}$ and $Entry_{ct-2}Distance_{ict-2}$. In addition, Therefore, using 2 SLS model is validated.

4.5 Data

For a general description of the data, see Essay 1 of this dissertation. In this essay, I am primarily concerned with the temporal evolution of prices after entry, which is partly governed by the supply response triggered by entry. Therefore, we start by comparing the temporal evolution of prices in counties that host a plant before and after entry against the temporal evolution of prices in the average country that did not host an ethanol plant. Figure 4.1 plots time series of corn prices, corn production, and plant entry in Indiana. This figure shows a positive trend on all three of them. But also shows that as temporal increases in production and price are negatively correlated.

[27] Inverse Mill's Ratio (IMR) is removed in the 2 SLS estimation because endogeneity in $Entry_{ct-k}$ is addressed by IVs.

[28] Null and alternative hypotheses for the Hausman test is:

$$H_0: \beta_1 = \beta_3 = \beta_4 = \cdots = \beta_{11} = 0$$

$$H_a: H_0 \; is\; not\; true\; for\; at\; least\; one\; \beta_i$$

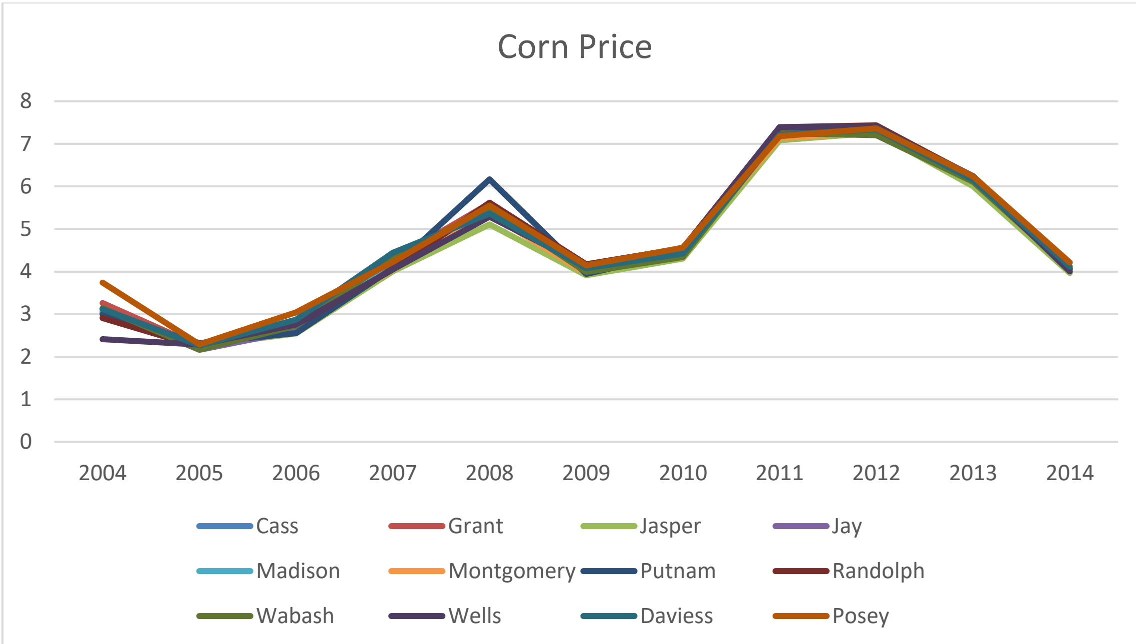

Figure 4.1. Time Series of Corn Price, Production, and the Number of Ethanol Plants

Figure 4.1.1. Time Series of Corn Price

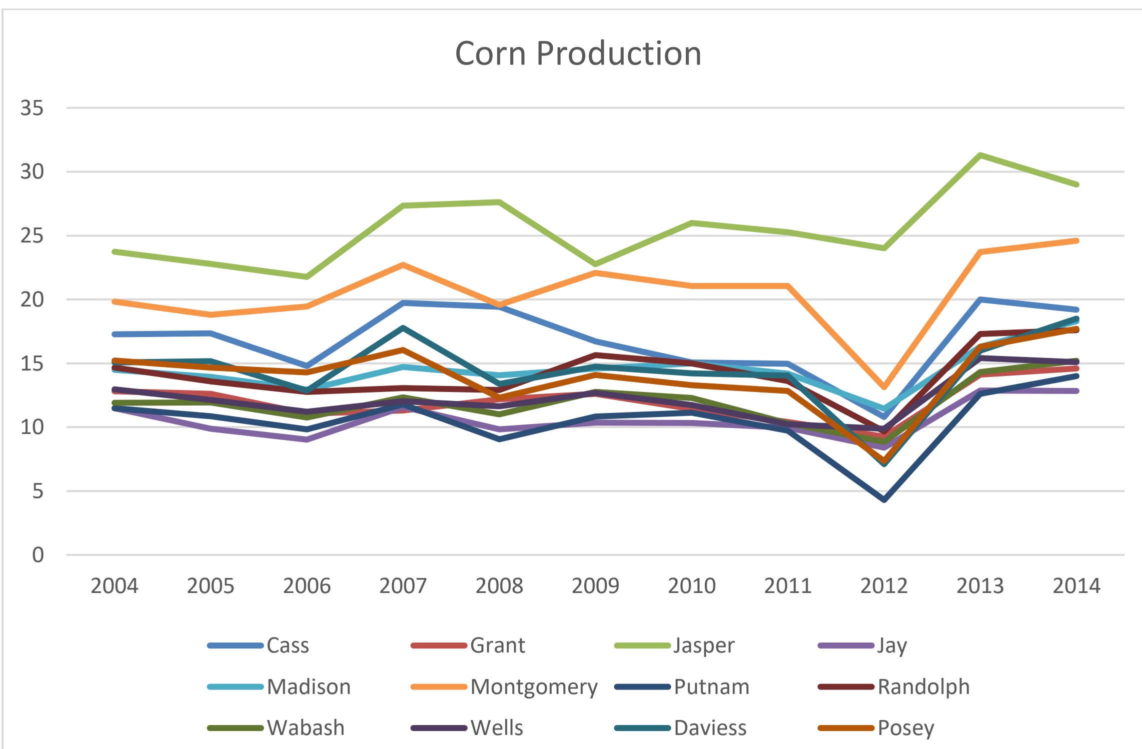

Figure 4.1.2. Time Series of Corn Production

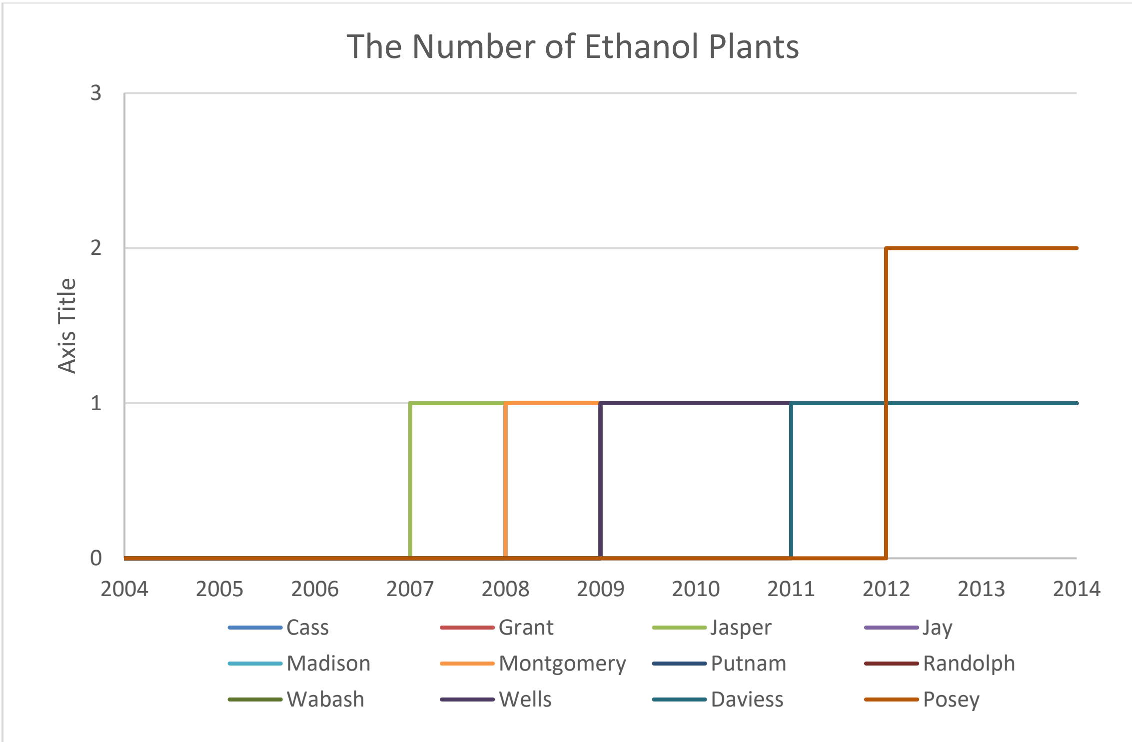

Figure 4.1.3. Time Series of the Number of Ethanol Plants

4.6 Results

Table 4.3 describes results for parameter estimates for the ARDL model. The first column shows the parameter estimates without IVs incorporated. The second column describes the parameter estimates when IVs are applied only to the lagged dependent variables, $Price_{ict-1}$. The third column is the results after IVs for all endogenous variables are applied.

First of all, parameter estimates less than one for the lag price confirms weak dependence of AR(1) indicating stationary of the dependent variable, which again confirms the validity of taking the ARDL approach. The ARDL model presents substantial heterogeneity in price impact dynamics. The model without IVs estimates that impact propensity (contemporaneous impact) of a plant entry is \$0.0024 (0.24 cents) at its average ratio across the plant of 2.44 at the plant gate. One year later, the entries reduce corn prices by \$0.0138 (1 cents). Then, corn prices increase \$0.0923 (9 cents) again in the second year of the entries. On the other hand, a 2 SLS model with IVs for both the lagged corn price and entry variables suggests the opposite; price decreases contemporaneously by \$0.0094 (1 cents) and bounces up by 11 cents a year later. Oscillation between positive and negative effects suggest heterogeneity in farmers responses to the demand shock in terms of crop rotation (soybean-corn or corn-corn) after ethanol plants enter to adjust themselves between benefits of rotation and higher expected price from ethanol expansion.

Smaller increases (0.24 cents) or even decreases in prices (-0.94 cents) in the current year indicate that farmers expect immediate price increases and plant as a large amount of corn so as to overwhelm price increases led by the demand shock from ethanol expansion. This is more consistent with findings that short-run price elasticity of corn supply is larger than is long-run counterparts (Hendricks, Smith, and Sumner, 2014) even though our estimation strategy is more likely to be the one that Menezes and Piketty (2012) use. The result of more elastic short-run and less elastic long-run supply is also supported by findings by Chavas and Holt (1996) that soybean's cross-price elasticity (with respect to corn price) is larger than its own-price elasticity. Corn and soybean acreage may be more responsive to expected corn prices because corn is more profitable in most regions (Rask, 1998; Hendricks, Smith, and Sumner, 2014). Therefore, expecting higher profits from increased corn prices, farmers change their crops from soybean to corn imminently and increase corn supply as much as limiting the positive impact of ethanol expansion on corn prices.

Table 4.3. Results of the ARDL models

$Price_{ict}$	An ARDL model with $Price_{ict-1}$	ARDL model with instrumented $Price_{ict-1}$	ARDL with instrumented $Price_{ict-1}$ and Entry[1]
Intercept (β_0)	3.8003*** (0.4102)	1.9426*** (0.5236)	1.1762*** (0.2669)
$Price_{ict-1}$ (β_1)	-0.0889*** (0.0220)	0.5134*** (0.1075)	0.6901*** (0.1203)
$Pre-exist_{ct+j} \cdot Ratio_{ct}$ (β_2)	0.0096*** (0.0023)	0.0090*** (0.0023)	0.0087*** (0.0023)
$Entry_{ct}$ (β_3)	0.0024 (0.0307)	0.0177 (0.0307)	-0.0094 (0.0604)
$Entry_{ct-1}$ (β_4)	-0.0138 (0.0303)	-0.0012 (0.0304)	0.1151** (0.0623)
$Entry_{ct-2}$ (β_5)	0.0923*** (0.0300)	0.0977*** (0.0300)	0.1492 (0.1146)
$Entry_{ct}(Ratio_{ct} - \overline{Ratio_c})$ (β_6)	-0.0107 (0.0114)	-0.0129 (0.0113)	-0.0029 (0.0180)
$Entry_{ct-1}(Ratio_{ct-1} - \overline{Ratio_c})$ (β_7)	-0.0351*** (0.0115)	-0.0381** (0.0114)	-0.0976*** (0.0183)
$Entry_{ct-2}(Ratio_{ct-2} - \overline{Ratio_c})$ (β_8)	-0.0065 (0.0116)	-0.0085 (0.0119)	-0.0535** (0.0272)
$Entry_{ct}Distance_{ict}$ (β_9)	-0.0007 (0.0010)	-0.0009 (0.0010)	-0.0000 (0.0019)
$Entry_{ct-1}Distance_{ict-1}$ (β_{10})	-0.0017* (0.0010)	-0.0019* (0.0011)	-0.0064*** (0.0019)
$Entry_{ct-2}Distance_{ict-2}$ (β_{11})	-0.0013 (0.0010)	-0.0009 (0.0010)	-0.0013 (0.0036)
IMR_{ct} (β_{12})	-0.4856** (0.2171)	-0.2039 (0.2224)	-
$LivestockDem_{ct}$ (β_{13})	0.0025 (0.0068)	-0.0037 (0.0069)	-0.0062 (0.0069)
Instrumented	No	$Price_{ict-1}$	All endogenous variables
Elevator Fixed Effect	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes

Inverse Mill's Ratio is dropped to avoid repetition with the instrumented entry variable.

Signs of the parameter estimates switched from positive to negative for the contemporaneous impact and from negative to positive in the consecutive year when we apply IVs. First stage of 2 SLS model indicates that plant entry and corn supply have a statistically significant positive correlation (Table 4.4). Entry of an ethanol plant may occur in regions where there is excess corn supply so that increased demand by the ethanol expansion has a limited impact on local corn prices (Katchova and Sant'Anna, 2019). Without IVs, entry impact is overestimated because corn supply has not been instrumented. Instrumenting the entry variable by corn supply and other IVs mitigates the overestimation. Increases in corn production in response to higher corn price expected by ethanol plant entry are substantial enough to even lower the corn price in the first year. Then in the next year, farmers may switch to soybean to enjoy the rotation benefits and as a result a corn price increases.

Table 4.4. Parameter estimates for the first stage model

$Entry_{ct}$	Parameter Estimates	
$Corn\ Supply_{ct}$	0.0044***	(0.0009)
$RailroadDensity_{ct}$	0.0015**	(0.0008)
$DistanceExport_{ct}$	0.0063***	(0.0011)
$CountyPopulation_{ct}$	-1.47e-06***	(4.52e-07)

The increases in corn price decay with distance and with a bigger ratio of capacity over corn supply for all years (Figure 4.2). When it comes to distance, it is estimated that price impact decreases by 0.17 to 0.64 cents per mile from the plant gate depending on estimation strategies, which means that transportation cost is not negligible. The estimation is consistent with previous studies (McNew and Griffith, 2005; Transportation and Marking Programs (TMP) of the Agricultural Marketing Service (AMS), 2016; Jung, Sesmero, and Siebert 2019). The finding that price increases in the vicinity of the new plant and declines with distance underscore the importance of transportation cost and may render the markets geographically localized.

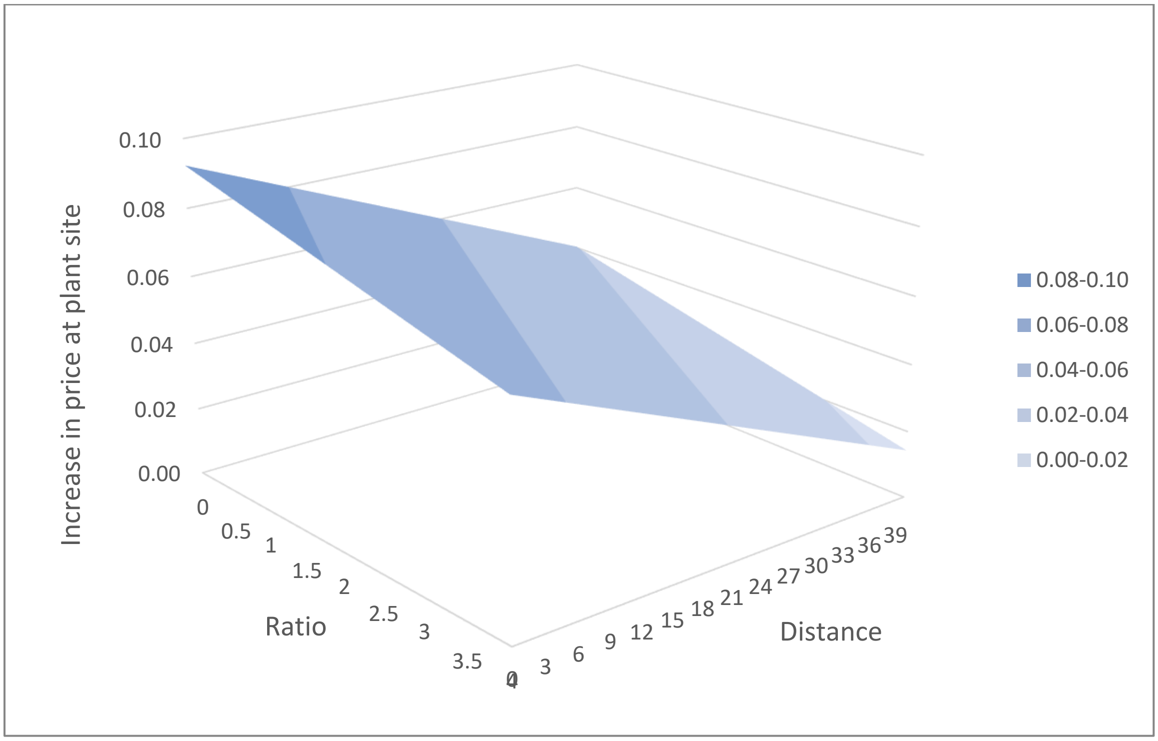

Figure 4.2. Price increase and its movement with the ratio and distance from a plant

In addition, if the ratio increases by 1 from its average value at 2.44, or equivalently when capacity becomes bigger than corn supply by the amount of supply, price impact decreases by 4 to 10 cents. This seems to be contradictory to the usual demand and supply relationship. With the importance of transportation cost and localized market boundary in mind, however, this introduces a potential existence of oligopsonies in local markets. In local markets based on high transportation cost such as one single county, there are a few, mostly a single giant corn buyer (ethanol plant) and they may be able to exercise oligopsonistic market power because farmers around the plants have limited bargaining power ending up being a price taker. This can be more so if farmers have limited or no access to spot markets (Katchova, 2010).

4.7 Interpretation and Implication of Results

Our results imply that short-term supply elasticity is very large. In fact they indicate that supply, in the short run, is close to perfectly elastic (horizontal indirect supply curve). On the other hand, results indicate that the one- or two-year supply curve is upward sloping. Using our parameter estimates, we find that an increase in demand (from entry of an average-sized plant) of 20 million bushels induces no increase in local price the year of entry and an increase in local price of about 10 cents after two years. A 20 million-bushel plant entry amounts to a 100% increase in quantity. A 10 cent-increase in price amounts to a 4% change. Therefore, the implied supply elasticity at the *individual plant level* is about 24; a supply typically consistent with monopsonistic competition (Roberts and Schlenker 2013), and very consistent with the structural estimate of essay 2.

The dynamic supply response just described may have important implications for ethanol plants' pricing strategy. In essay 2 of this dissertation, we estimated a structural model that characterizes plants' pricing strategies. But that model is static; meaning that we do not consider whether plants, in addition to competing during the growing season for available corn, also look at intertemporal externalities from prices. When plants suppress prices, they obtain a benefit in the short run. But if price suppression induces farmers to switch away from corn and towards other crops, they will face higher input costs in the future. This is likely to take place if long-run supply is more elastic than short-run supply.

Our results indicate this is not the case, lending credence to our static optimization model in essay 2.

4.8 Conclusions

This study estimates dynamics of price impact of ethanol expansions in Indiana. Although previous studies examined the link between corn price and ethanol plant expansion, they are based on limited period of time, too short to show enough information or too long to expose dynamics of the price impact. With the pattern of ethanol plant entries and farmers' crop rotation decisions considered, understanding dynamics of plant entry effect on local corn price is crucial. Therefore, this article revisited the apparent relationship by applying ARDL model with more disaggregate level of data at individual elevators.

We use panel-data for corn price at each elevator in Indiana market for the period from 2004 to 2014 which encompasses the whole ethanol boom era (2005 to 2011). The ARDL model carefully addresses the impact of permanent increase in corn demand from plant entry in local corn markets, providing impact propensity (contemporaneous effect) and lagged effect of ethanol plant entry on local corn prices. In addition to the dynamics, this model also captures roles that distance to the nearest plant and plant capacity relative to corn supply play in varying degrees of price impact.

The results suggest price impacts differ year by year, suggesting that farmers may adjust their crop rotation decisions for demand shocks. Consistent with previous studies (Chavas and Holt, 1996; Hendricks, Smith, and Sumner, 2014), farmers supply decision may respond to the demand shock more elastically so that there is negative relationship between plant entry and local corn prices. However, farmers switch back to soybean after one year and corn price increases enough to compensate the reduction in the first year. This price impact at the plant site declines with distance by 0.17 to 0.63 cents per mile. This underscores the importance of transportation cost in corn markets, which suggests a potential existence of oligopsonies in corn procurement markets. This feature of oligopsonies can be highlighted by the estimates for the ratio variables. If the capacity is bigger than the amount of corn supply in its local market, the positive price impact is weakened.

Our findings are consistent with previous studies and provide extended information about price impact dynamics. However, there are also important topics for future research. Our estimation strategies are limited in terms of methodological approach. For example, there are many other options for testing unit root and/or for eliminating endogeneity in ARDL model. Individual approach may result in different estimates. Another topic for future research is to incorporate forward-looking price expectations into the model because new entry of a plant is announced one or two years in advance and farmers may adjust their planting decision beforehand.

Finally, our findings point to a very important direction for future research. There is an emerging consensus among agricultural economists that potential oligopsony power by large processors of certain farm products is limited by the dynamic supply response of farm supply. Oligopsonists realize that if they suppress prices, their competitors may do so as well, compromising future supply as low prices deter farmers from planting the crop procured by oligopsonists. In fact, certain studies suggest that more concentrated markets may result in higher inputs prices because fewer producers can better internalize these dynamic supply externalities (Merel and Sexton 2017). This may be true for crops that do not display strong rotational benefits or have no choice but to sell to oligopsonists. Our results indicate that this does not seem to be the case with corn. The direct corollary of this finding is that the role of supply dynamics as a mechanism of market discipline is, ultimately, an empirical and crop-specific question. But even if dynamic supply externalities are strong, the extent to which oligopsonists internalize them is unclear. This question seems ripe to be researched.

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APPENDICES

APPENDIX A. RESULTS OF THE ROBUSTNESS CHECKS

Table A1. Descriptive Statistics for Main Characteristics of Counties (without Posey county)

	Treatment Group		Matched Group		Control Group
# of observation	n=420	Normalized Difference	n=1680	Normalized Difference	n=116
Corn Price (Post-Treatment)	5.047 (0.131)	-0.02	-	-	5.035 (0.102)
Corn Price (Pre-Treatment)	2.680 (0.088)	0.04	2.711 (0.067)	0.02	2.748 (0.097)
Corn Production (Post-Treatment)	14.729 (6.011)	-0.14	-	-	7.253 (5.433)
Corn Production (Pre-Treatment)	12.391 (4.944)	-0.07	10.284 (4.411)	-0.05	6.019 (4.764)
Livestock Demand (Post-Treatment)	2.704 (3.380)	-0.05	-	-	1.278 (2.048)
Livestock Demand (Pre-Treatment)	2.640 (2.923)	-0.04	1.710 (1.709)	-0.02	1.226 (1.568)
Distance to Port (Post-Treatment)	81.057 (36.464)	-0.06	-	-	57.736 (29.026)
Distance to Port (Pre-Treatment)	81.057 (36.464)	-0.05	73.947 (21.972)	-0.03	57.736 (29.026)
Railroad Density (Post-Treatment)	82.981 (70.021)	-0.04	-	-	65.877 (57.246)
Railroad Density (Pre-Treatment)	82.981 (70.021)	-0.02	68.378 (46.548)	-0.00	65.877 (57.246)
Population (Post-Treatment)	71,316 (93,232)	-0.00	-	-	71,662 (148,775)
Population (Pre-Treatment)	68,825 (88,762)	-0.00	48,619 (75,342)	0.01	69,906 (140,899)

* Note: Treatment Group refers to counties which has either of direct- or indirect- plant entries. Both Entries means that entries happen both in its own county and any neighboring county. Direct Entries accounts for counties that have entries only in itself while Indirect Entries includes counties with entries only in any neighboring county. Control Group refers to counties that has no entry at all neither in itself and neighboring counties. Matched Group presents the same information on Treatment Group, but the information is based on counites in comparison group that are selected in the matching process of using 4 Nearest Neighbors Matching (NNM (4)). ND abbreviates Normalized Difference in means between the treated and control groups. ND in one of the Treatment Group columns is the one before the matching procedure. ND in one of the Matched Group is the one after the matching procedure.

Table A2. Results from the OLS (*Robustness Test*)

$Corn\ Price_{it}$	Coef.	Std. Err.	Coef.	Std. Err.
$DIST_{et}$	-0.0084***	0.0004	-0.0090***	0.0004
$Ratio_{ect}$	0.1888***	0.0179	0.1817***	0.0180
$LSTOCK_{ct}$	-0.0176**	0.0095	-0.0142	0.0095
Intercept	5.0589***	0.0570	5.1145***	0.0576
R-Square	0.2791		0.2848	
Posey County	Included		Excluded	

Table A3. Results from the Regular DID (*Robustness Test*)

$Corn\ \ Price_{it}$	Coef.	Std. Err.	Coef.	Std. Err.
$Post_t$	2.4212***	0.0344	2.4208***	0.0339
$Treat_e$	-0.0446	0.0277	-0.0527*	0.0274
$Post_t * Treat_e$	0.0793**	0.0389	0.0822**	0.0384
$TOTLSTOCKDEMAND_{it}$	-0.0051*	0.0030	-0.0040	0.0030
Intercept	2.7260***	0.0247	2.7245***	0.0243
R-Square	0.9784		0.9791	
Posey county	No		Yes	

Table A4. Results from the Fixed Effect Model based on Panel Data (*Robustness Test*)

$Corn\ Price_{it}$	Coef.	Std. Err.	Coef.	Std. Err.
$Ratio_{ect} * Treat_{et}$	0.0334***	0.0075	0.0393***	0.0080
$Ratio_{ect} * DIST_{et} * Treat_{et}$	-0.0023***	0.0007	-0.0028***	0.0007
$Ratio_{ect} * DIST_{it}^2 * Treat_{et}$	3.49E-05**	1.37E-05	4.29E-05***	1.41E-05
$LSTOCK_{ct}$	0.0072	0.0054	0.0064	0.0054
Intercept	3.0225***	0.0176	3.0136***	0.0177
R-Square	0.9820		0.9822	
Posey county	No		Yes	

Table A5. Impact of Entries of Dominant (Ethanol) Plants on Local Corn Prices (Linear and Quadratic Distance) (without Posey county)

	$Corn\ \ Price_{ect}$	Main model	Eliminating county-fixed effect	Eliminating year-fixed effect	Eliminating both fixed-effect
DID	$Ratio_{ect} * Treat_{et}$	0.1021*** (0.0345)	0.0883*** (0.0244)	1.5177*** (0.1927)	1.1184*** (0.1200)
	$Ratio_{ect} * DIST_{et} * Treat_{et}$	-0.0059*** (0.0021)	-0.0060*** (0.0016)	-0.0174 (0.0140)	-0.0135 (0.0085)
	$Ratio_{ect} * DIST_{it}^2 * Treat_{et}$	0.0001** (0.00003)	0.0001*** (0.00002)	0.0002 (0.0002)	0.0001 (0.0001)
	$LSTOCK_{ct}$	0.0014 (0.0086)	-0.0056* (0.0029)	-0.1027* (0.0579)	-0.0446*** (0.0155)
	$Intercept$	2.6705*** (0.0229)	2.6871*** (0.0132)	3.3947*** (0.1477)	3.4711*** (0.0598)
	R-Square	0.9793	0.9797	0..4300	0.4344
NNM (1)	$Ratio_{ect} * Treat_{et}$	0.0960*** (0.0314)	0.0887*** (0.0245)	1.4139*** (0.1965)	1.0980*** (0.1216)
	$Ratio_{ect} * DIST_{et} * Treat_{et}$	-0.0056*** (0.0021)	-0.0060*** (0.0016)	-0.0131 (0.0141)	-0.0129 (0.0085)
	$Ratio_{ect} * DIST_{it}^2 * Treat_{et}$	0.0001** (0.00004)	0.0001*** (0.000003)	0.0001 (0.0002)	0.0001 (0.0001)
	$LSTOCK_{ct}$	0.0082 (0.0073)	-0.0058* (0.0032)	0.0503 (0.0494)	-0.0226 (0.0171)
	$Intercept$	2.6582*** (0.0170)	2.6847*** (0.0126)	3.0596*** (0.1126)	3.4154*** (0.0585)
	R-Square	0.9787	0.9796	0.4148	0.4274
	Year-fixed effect	Yes	Yes	No	No
	County-fixed effect	Yes	No	Yes	No

Table A5 continued

	$Corn\ \ Price_{ect}$	Main model	Eliminating county-fixed effect	Eliminating year-fixed effect	Eliminating both fixed-effect
NNM (2)	$Ratio_{ect} * Treat_{et}$	0.1012*** (0.0180)	0.0905*** (0.0172)	1.4825*** (0.1118)	1.1128*** (0.0854)
	$Ratio_{ect} * DIST_{et} * Treat_{et}$	-0.0058*** (0.0012)	-0.0060*** (0.0011)	-0.0153* (0.0081)	-0.0133** (0.0060)
	$Ratio_{ect} * DIST_{it}^2 * Treat_{et}$	0.0001*** (0.00002)	0.0001*** (0.00002)	0.0001 (0.0001)	0.0001 (0.0001)
	$LSTOCK_{ct}$	0.0020 (0.0036)	-0.0071*** (0.0023)	-0.0247 (0.0247)	-0.0357*** (0.0121)
	$Intercept$	2.6695*** (0.0095)	2.6884*** (0.0091)	3.2062*** (0.0616)	3.444*** (0.0422)
	R-Square	0.9792	0.9797	0.4289	0.4302
NNM (4)	$Ratio_{ect} * Treat_{et}$	0.1015*** (0.0118)	0.0896*** (0.0122)	1.4856*** (0.0729)	1.1050*** (0.0605)
	$Ratio_{ect} * DIST_{et} * Treat_{et}$	-0.0058*** (0.0008)	-0.0060*** (0.0008)	-0.0153*** (0.0053)	-0.0131*** (0.0605)
	$Ratio_{ect} * DIST_{it}^2 * Treat_{et}$	0.0001*** (0.00001)	0.0001*** (0.00001)	0.0001 (0.0001)	-0.0131*** (0.0043)
	$LSTOCK_{ct}$	0.0014 (0.0019)	-0.0065*** (0.0016)	-0.0242* (0.0132)	0.0001 (0.0001)
	$Intercept$	2.6170*** (0.0054)	2.6864*** (0.0064)	3.2022*** (0.0341)	-0.0286*** (0.0086)
	R-Square	0.9793	0.9797	0.4279	3.4277*** (0.0295)
	Year-fixed effect	Yes	Yes	No	No
	County-fixed effect	Yes	No	Yes	No

Table A5 continued

	$Corn\ \ Price_{ect}$	Main model	Eliminating county-fixed effect	Eliminating year-fixed effect	Eliminating both fixed-effect
PSM (1)	$Ratio_{ect} * Treat_{et}$	0.1064***	0.08955***	1.5903***	1.1134***
		(0.0323)	(0.0245)	(0.1955)	(0.1213)
	$Ratio_{ect} * DIST_{et} * Treat_{et}$	-0.0059***	*0.0060***	-0.0189	-0.0133
		(0.0021)	(0.0010)	(0.0139)	(0.0085)
	$Ratio_{ect} * DIST_{it}^2 * Treat_{et}$	0.0001**	0.0001***	0.0002	0.0001
		(0.00004)	(0.00003)	(0.0002)	(0.0001)
	$LSTOCK_{ct}$	-0.0016	-0.0064*	-0.0799***	-0.0361**
		(0.0047)	(0.0034)	(0.0313)	(0.0177)
	$Intercept$	2.6771***	2.6869***	3.3087***	3.1112***
		(0.0140)	(0.0131)	(0.0851)	(0.0603)
	R-Square	0.9794	0.9797	0.4285	0.4300
PSM (2)	$Ratio_{ect} * Treat_{et}$	0.1073***	0.0898***	1.4789***	1.1028***
		(0.0179)	(0.0173)	(0.1118)	(0.0858)
	$Ratio_{ect} * DIST_{et} * Treat_{et}$	-0.0059***	-0.0060***	-0.0152*	-0.0130***
		(0.0012)	(0.0011)	(0.0081)	(0.0060)
	$Ratio_{ect} * DIST_{it}^2 * Treat_{et}$	0.0001***	0.0001***	0.0001	0.0001
		(0.00002)	(0.00002)	(0.0001)	(0.0001)
	$LSTOCK_{ct}$	-0.0032	-0.0067***	-0.0139	-0.0264**
		(0.0025)	(0.0024)	(0.0168)	(0.0125)
	$Intercept$	2.6798***	2.6864***	3.1821***	3.4227***
		(0.0075)	(0.0090)	(0.0473)	(0.0418)
	R-Square	0.9795	0.9797	0.4269	0.4279
	Year-fixed effect	Yes	Yes	No	No
	County-fixed effect	Yes	No	Yes	No

Table A5 continued

	$Corn\ Price_{ect}$	Main model	Eliminating county-fixed effect	Eliminating year-fixed effect	Eliminating both fixed-effect
PSM (4)	$Ratio_{ect} * Treat_{et}$	0.1050***	0.0885***	1.4858***	1.1062***
		(0.0117)	(0.0122)	(0.0728)	(0.0605)
	$Ratio_{ect} * DIST_{et} * Treat_{et}$	-0.0059***	-0.0060***	-0.0154***	-0.0132***
		(0.0008)	(0.0008)	(0.0053)	(0.0043)
	$Ratio_{ect} * DIST_{it}^2 * Treat_{et}$	0.0001***	0.0001***	0.0001	0.0001
		(0.00001)	(0.00001)	(0.0001)	(0.0001)
	$LSTOCK_{ct}$	-0.0014	-0.0059***	-0.0192*	-0.0298***
		(0.0015)	(0.0016)	(0.0100)	(0.0086)
	$Intercept$	2.6765***	2.6852***	3.1933***	3.4308***
		(0.0048)	(0.0064)	(0.0302)	(0.0296)
	R-Square	0.9794	0.9796	0.4277	0.4288
	Year-fixed effect	Yes	Yes	No	No
	County-fixed effect	Yes	No	Yes	No

Table A6. Impact of Entries of Dominant (Ethanol) Plants on Local Corn Prices (Linear Distance only) (wo Posey County)

	$Corn\ Price_{ect}$	Main model	Eliminating county-fixed effect	Eliminating year-fixed effect	Eliminating both fixed-effect
DID	$Ratio_{ect} * Treat_{et}$	0.0592**	0.0449**	1.4255***	1.0553***
		(0.0236)	(0.0186)	(0.1331)	(0.0862)
	$Ratio_{ect} * DIST_{et} * Treat_{et}$	-0.0017***	-0.0018***	-0.0086*	-0.0075***
		(0.0006)	(0.0005)	(0.0045)	(0.0027)
	$LSTOCK_{ct}$	0.0032	-0.0054*	-0.0987*	-0.0444***
		(0.0086)	(0.0029)	(0.0575)	(0.0155)
	Intercept	2.6659***	2.6868***	3.3856***	3.4709***
		(0.0229)	(0.0132)	(0.1469)	(0.0598)
	R-Square	0.9789	0.9794	0.4301	0.4338
NNM (1)	$Ratio_{ect} * Treat_{et}$	0.0547**	0.0452***	1.3584***	1.0364***
		(0.0237)	(0.0186)	(0.1372)	(0.0878)
	$Ratio_{ect} * DIST_{et} * Treat_{et}$	-0.0017***	-0.0018***	-0.0078*	-0.0070***
		(0.0006)	(0.0005)	(0.0045)	(0.0027)
	$LSTOCK_{ct}$	0.0094	-0.0057*	0.0518	-0.0225
		(0.0073)	(0.0033)	(0.0492)	(0.0171)
	Intercept	2.6561***	2.6844***	3.0568***	3.4153***
		(0.0171)	(0.0127)	(0.1122)	(0.0585)
	R-Square	0.9783	0.9794	0.4139	0.4268
NNM (2)	$Ratio_{ect} * Treat_{et}$	0.0586***	0.0469***	1.4124***	1.5051***
		(0.0137)	(0.0131)	(0.0782)	(0.6165)
	$Ratio_{ect} * DIST_{et} * Treat_{et}$	-0.0017***	-0.0018***	-0.0085***	-0.0073***
		(0.0004)	(0.0037)	(0.0025)	(0.0019)
	$LSTOCK_{ct}$	0.0027	-0.0069***	-0.0236	-0.0355***
		(0.0037)	(0.0023)	(0.0247)	(0.0121)
	Intercept	2.6681***	2.6881***	3.2042***	3.4437***
		(0.0096)	(0.0092)	(0.0616)	(0.0422)
	R-Square	0.9789	0.9794	0.4282	0.4296
	Year-fixed effect	Yes	Yes	No	No
	County-fixed effect	Yes	No	Yes	No

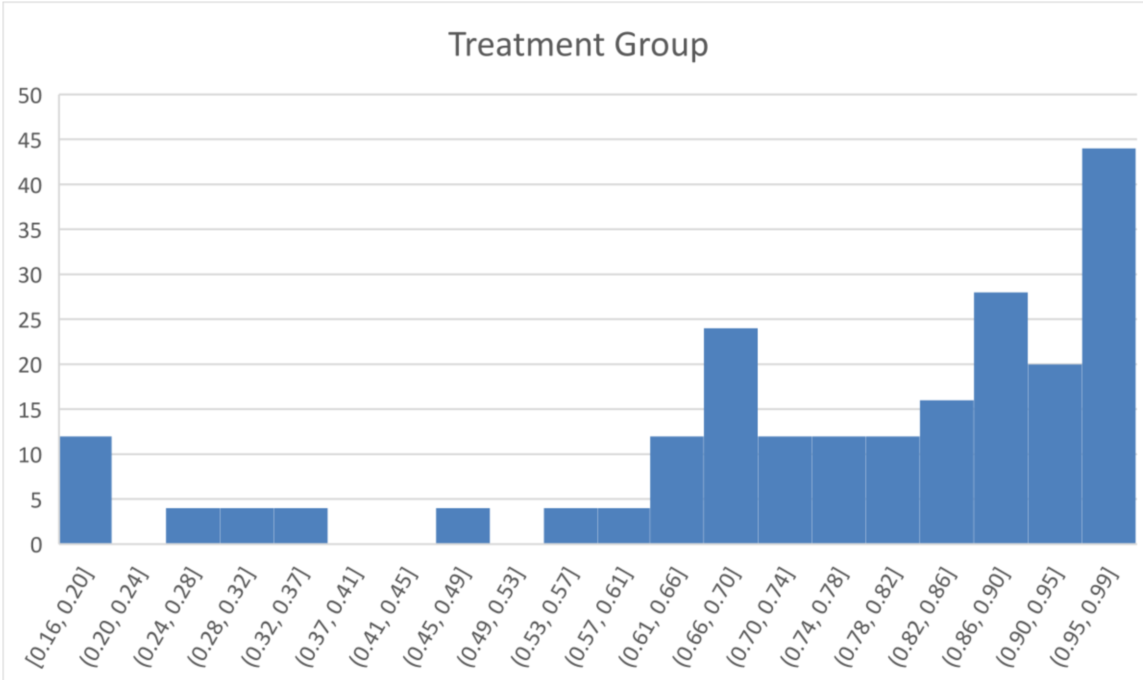
Table A6 Continued

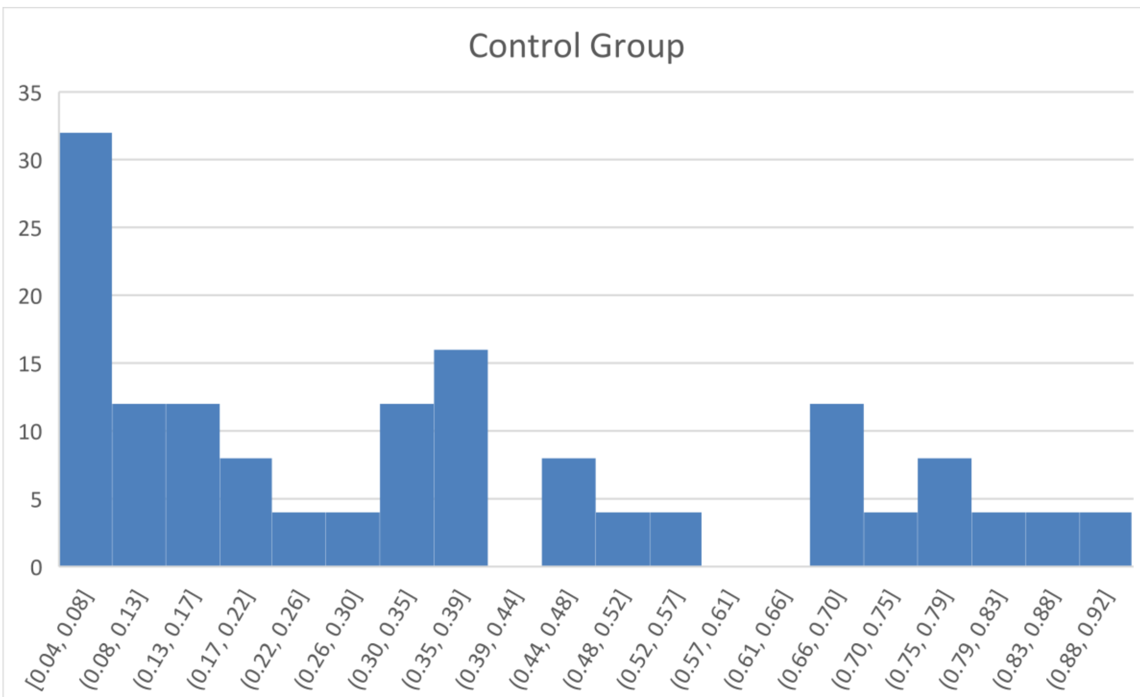
	$Corn\ \ Price_{ect}$	Main model	Eliminating county-fixed effect	Eliminating year-fixed effect	Eliminating both fixed-effect
NNM (4)	$Ratio_{ect} * Treat_{et}$	0.0589***	0.0461***	1.4156***	1.0429***
		(0.0089)	(0.0093)	(0.0511)	(0.0437)
	$Ratio_{ect} * DIST_{et} * Treat_{et}$	-0.0017***	-0.0018***	-0.0086***	-0.0071***
		(0.0002)	(0.0002)	(0.0017)	(0.0014)
	$LSTOCK_{ct}$	0.0018	-0.0063***	-0.0234*	-0.0284***
		(0.0019)	(0.0016)	(0.0.132)	(0.0086)
	$Intercept$	2.6701***	2.6862***	3.2010***	3.4275***
		(0.0054)	(0.0064)	(0.0342)	(0.0295)
	R-Square	0.9790	0.9794	0.4273	0.4279
	Year-fixed effect	Yes	Yes	No	No
	County-fixed effect	Yes	No	Yes	No

Table A6 Continued

	$Corn\ \ Price_{ect}$	Main model	Eliminating county-fixed effect	Eliminating year-fixed effect	Eliminating both fixed-effect
PSM (1)	$Ratio_{ect} * Treat_{et}$	0.0624***	0.0459**	1.5019***	1.0507***
		(0.0247)	(0.0187)	(0.1377)	(0.0875)
	$Ratio_{ect} * DIST_{et} * Treat_{et}$	-0.0018***	-0.0018***	-0.0105**	-0.0073***
		(0.0007)	(0.0005)	(0.0045)	(0.0027)
	$LSTOCK_{ct}$	-0.0010	-0.0062*	-0.0787**	-0.0358**
		(0.0047)	(0.0034)	(0.0312)	(0.0177)
	$Intercept$	2.6758***	2.6866***	3.3065***	3.4439***
		(0.0141)	(0.0131)	(0.0849)	(0.0603)
	R-Square	0.9791	0.9794	0.4280	0.4294
PSM (2)	$Ratio_{ect} * Treat_{et}$	0.0639***	0.0463***	1.4105***	1.0408***
		(0.0136)	(0.0131)	(0.0784)	(0.0620)
	$Ratio_{ect} * DIST_{et} * Treat_{et}$	-0.0018***	*0.0019***	-0.0086***	-0.0071***
		(0.0004)	(0.0003)	(0.0026)	(0.00.19)
	$LSTOCK_{ct}$	-0.0028	-0.0065***	-0.0134	-0.0262**
		(0.0025)	(0.0024)	(0.0168)	(0.0125)
	$Intercept$	2.6792***	2..6861***	3.1813***	3.4225***
		(0.0075)	(0.0091)	(0.0473)	(0.0418)
	R-Square	0.9792	0.9794	0.4263	0.4273
PSM (4)	$Ratio_{ect} * Treat_{et}$	0.0621***	0.0451***	1.4171***	1.0440***
		(0.0089)	(0.0093)	(0.0511)	(0.0463)
	$Ratio_{ect} * DIST_{et} * Treat_{et}$	-0.0018***	-0.0018***	-0.0087***	0.0071***
		(0.0002)	(0.0002)	(0.0017)	(0.0013)
	$LSTOCK_{ct}$	-0.0011	-0.0056***	-0.0188*	-0.0296***
		(0.0015)	(0.0016)	(0.0100)	(0.0.086)
	$Intercept$	2.6760***	2.6849***	3.1927***	3.4306***
		(0.0048)	(0.0064)	(0.0302)	(0.0296)
	R-Square	0.9791	0.9794	0.4272	0.4282
	Year-fixed effect	Yes	Yes	No	No
	County-fixed effect	Yes	No	Yes	No

Figure A1. Distribution of Propensity Scores in the treatment and controlled groups





APPENDIX B. ESTIMATION STRATEGY

B.1 Solution of the game and market equilibrium prediction. In this Appendix, we provide detailed information on how prices offered by each oligopsonist plant to each county are computed. Optimal prices are characterized by a system of Karush-Kuhn-Tucker (KKT) conditions:

(B1) $$\frac{\partial \mathcal{L}_F(\cdot)}{\partial \boldsymbol{p}_F^c} = -\boldsymbol{q}^c(\boldsymbol{p}^c;\boldsymbol{\beta}) + \boldsymbol{\Omega}(\boldsymbol{p}^c)\{\boldsymbol{\Gamma} - \boldsymbol{p}_F^c - \mathbf{M} - \boldsymbol{\Lambda}\} \geq \mathbf{0},\ \boldsymbol{p}_F^c \geq \mathbf{0},\ \boldsymbol{p}_F^c\left\{\frac{\partial \mathcal{L}_F(\cdot)}{\partial \boldsymbol{p}_F^c}\right\} = 0$$

$\forall\ i$ and $j \in F$

(B2) $$\frac{\partial \mathcal{L}_F(\cdot)}{\partial \lambda_j} = -\alpha_j^h \sum_{i \in IN^c} q_{ij}^c(\boldsymbol{p}_i^c;\boldsymbol{x}_i,\boldsymbol{\beta}) + CAP_j \geq 0,\ \lambda_j \geq 0,\ \lambda_j\left\{\frac{\partial \mathcal{L}_F(\cdot)}{\partial \lambda_j^c}\right\} = 0\ \ \forall\ j \in F,$$

where $\boldsymbol{\Omega}(\boldsymbol{p}^c)$ is a block diagonal matrix that combines $i = 1,\cdots,92$ submatrices accounting for all the counties in Indiana, each of dimension $J \times J$ where J is the total number of oligopsonist plants in Indiana:

(B3) $$\Omega_{jk}^i(\boldsymbol{p}_i^c;\boldsymbol{\beta}) = \begin{cases} \dfrac{\partial q_{ij}^c(\boldsymbol{p}_i^c;\boldsymbol{x}_i,\boldsymbol{\beta})}{\partial p_{ik}} & if\ plants\ j\ and\ k\ have\ the\ same\ owner \\ 0 & otherwise \end{cases}.$$

The reason that $\boldsymbol{\Omega}(\boldsymbol{p}^c)$ is a block diagonal structure is that $q_{ij}^c(\boldsymbol{p}_i^c;\boldsymbol{x}_i,\boldsymbol{\beta})$ is a function of prices offered to that county by all plants $\boldsymbol{p}_i^c$, but independent of prices offered by those plants to other counties $\boldsymbol{p}_{-i}^c$. Therefore, $\boldsymbol{\Omega}(\boldsymbol{p}^c)$ is constructed based on two premises: (1) farmers in one area choose among all J oligopsonist plants in Indiana; and

(2) corn supply in one county i is unaffected by prices received by farmers in other counties, $-i$.

Moreover, the elements of each submatrix reflect the extent to which a plant internalizes competition externalities imposed on another plant in the sample. Each plant j sources corn from multiple counties. If firm F owns multiple plants, then it will internalize pricing externalities across its plants. In other words, if plant 1 increases its corn bid to county i (an increase in p_{i1}), it will reduce the residual supply of corn from that county faced by plant 2 (all else constant, it will reduce q_{i2}^c)—which is the business stealing effect. If the same firm owns both plants, it will fully internalize this negative externality, $\frac{\partial q_{i2}^c(\boldsymbol{p}_i^c;\boldsymbol{x}_i,\boldsymbol{\beta})}{\partial p_{i1}}$. Otherwise, the plant would not internalize the externality, and $\frac{\partial q_{i2}^c(\boldsymbol{p}_i^c;\boldsymbol{x}_i,\boldsymbol{\beta})}{\partial p_{i1}}$ would take a value of zero.

Matrix $\boldsymbol{\Omega}(\boldsymbol{p}^c)$ is multiplied by $\boldsymbol{\Gamma}$, which is a vector of marginal value products $P^h * \alpha_j^h$. $\mathbf{M}$ is a vector of $\alpha_j^h * mc\left(Q_j^h;\boldsymbol{w}_j,\boldsymbol{\xi}\right)$, which represents the change in marginal processing cost associated with producing below capacity, and $\boldsymbol{\Lambda}$ is a vector of Lagrangian multipliers $\lambda_j^{\boldsymbol{c}}$.

There is no analytical solution to the system (B1)-(B2), so we solve it numerically using a nonlinear equation solver. The solution consists of 1,656 (18*92) Nash equilibrium prices—one offered by each plant to each county—along with shadow prices for capacity constraints. The prices offered by all plants to a county are aggregated to a single county-level price *prediction*. The aggregation procedure consists of weighting plant-specific prices by the plant's share on total corn purchases:

(B4) $$\widetilde{\boldsymbol{p}}_{\boldsymbol{i}}^{\boldsymbol{c}}(\boldsymbol{\theta}, \boldsymbol{X}_{\boldsymbol{t}}) = \sum_{\boldsymbol{j} \in F} \left[\left\{ \frac{q_{ij}^{c,*}(\boldsymbol{p}_i^{c,*}; \boldsymbol{x}_i, \boldsymbol{\beta})}{\sum_{\boldsymbol{j}} q_{ij}^{c,*}(\boldsymbol{p}_i^{c,*}; \boldsymbol{x}_i, \boldsymbol{\beta})} \right\} p_{\boldsymbol{ij}}^{\boldsymbol{c},*} \right].$$

These predicted prices are compared to observed prices, as described in the following section.

B.2 Summary of the economic modeling in MPEC structure. We now turn our attention to the estimation of structural parameters. Our estimation strategy consists of choosing a set of parameters that minimize the sum of squared errors in predictions subject to equilibrium constraints:

(B5) $$\min_{\boldsymbol{\theta} \in \Theta} \frac{1}{T} \sum_{t=1}^{T} [\boldsymbol{p}_t^c - \widetilde{\boldsymbol{p}}_t^c(\boldsymbol{\theta}; \boldsymbol{X}_t)]' \boldsymbol{C}_t^{-1} [\boldsymbol{p}_t^c - \widetilde{\boldsymbol{p}}_t^c(\boldsymbol{\theta}; \boldsymbol{X}_t)]$$

subject to

(B1)

(B2)

(B6) $$RSUP_i - \sum_j q_{ij}^c(\boldsymbol{p}_i^c; \boldsymbol{x}_i, \boldsymbol{\beta}) \geq 0 \qquad \forall\, i.$$

Constraints (B1) and (B2) guarantee that predicted prices are computed based on Nash equilibrium plant-county prices calculated as a Mixed Complementary Program (MCP). Therefore, the problem above has a Mathematical Programming with Equilibrium Constraints (**MPEC**) structure. Equation (B6) adds to the equilibrium constraints and guarantees that the total amount of corn purchased by all plants from a county is not larger than the residual supply of corn from that county. The MPEC structure is solved in the General Algebraic Modeling System (GAMS) software[29] by using the algorithm solver developed by Dirkse and Ferris (1998). These problems are stated as a single problem - albeit one that requires a hierarchical perspective wherein the constraint set is an equilibrium system stated as an MCP. This is a very special sort of problem that has a highly non-convex feasible region. However, Dirkse and Ferris (1998) who have developed solvers for this class of problems exploit the specific sort of non-convexity in order to develop algorithms that are effective for these problems. We apply a bootstrap method to compute standard errors of each parameter.

[29] The GAMS code is available from the authors upon request.

APPENDIX C. ALGORITHM OF THE ITERATIVE PARAMETER ESTIMATION