A Structural Estimation of Spatial Differentiation and Market Power in Input Procurement

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We estimate the degree of spatial differentiation–primarily driven by transportation costs–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 U.S. 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 0.5 cents per bushel per mile (10% of the corn price under average conditions), which provides evidence of spatial differentiation among buyers. The estimated average markdown is \$0.67 per bushel (13% of the average corn price in the sample), of which \$0.49 is explained by spatial differentiation and the rest by the fact that firms operated under binding capacity constraints. 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 18%, and triggers a sizable reduction in farm surplus. In contrast, a merger between distant buyers has negligible effects on competition and markdowns.

Key words: buyer power, corn procurement, merger, spatial differentiation, transportation costs.

JEL codes: D43, L11, L13, L43, Q11, Q13.

Economists and regulators are paying increasing attention to spatial competition in agricultural procurement markets, defined as markets in which downstream firms purchase products from upstream farmers to use as inputs in their production processes (Durham, Sexton, and Song 1996; Alvarez et al. 2000; Zhang and Sexton, 2000; Fousekis 2011b; Graubner, Balmann, and Sexton 2011; Hamilton and Sunding, 2020; Wang et al. 2020). 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 engage in input price markdown, defined as firms' ability to price inputs below their marginal value product net of processing costs. In this paper, we examine the extent to which transportation cost and the resulting spatial differentiation among buyers of farm products affects prices, markdowns, and surpluses.

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 the transportation cost that is paid by the

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farmer. 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. Our goal is to examine empirically whether spatial differentiation introduced by transportation cost allows buyers to engage in corn price markdown and how spatial differentiation affects mergers among firms that vary in geographic distances to each other.

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 comprising livestock operators, dry-milling food processors, and exporters. Ethanol and wet-milling firms set input prices paid to farmers at the plant gate, 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. Finally, we use the structural estimates to conduct counterfactual experiments simulating *mergers* that differ in the distance between merging firms, thereby characterizing the efficiency and distributional effects of industry consolidation.

The empirical estimation of parameters necessary to compute markdowns in our structural model is challenging because 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 U.S. 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: 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). Third, we did not observe any consolidation between firms in Indiana that may complicate estimation that allows to, instead, evaluate merger effects in our counterfactual analysis. 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 that corn is shipped around fifty miles on average. The estimation results return a transportation cost of 0.5 cents per bushel per mile (10% 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 (difference between marginal value product net of processing cost and price of corn) of \$0.49 per bushel (9% 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 \$0.18 per bushel, 37% more in the effect of spatial differentiation.

Finally, consolidation among firms has been a prominent trend in the corn ethanol industry over the last few years (Federal Trade Commission 2018). Understanding the efficiency and distributional implications of mergers among large corn buyers is of key importance for antitrust authorities and agencies in charge of agricultural policies. Yet, relatively little is known about merger effects in oligopsonistic markets characterized by spatial competition. The framework we develop here can fill this gap because our estimated structural parameters allow us to evaluate the market and welfare effects of ownership changes between nearby and distant firms.

The results from our counterfactual experiments on consolidation among ethanol plants indicate that a merger between nearby ethanol plants eases competition and increases markdowns attained by merging firms by $0.20 or 18%. We also find that the merger also triggers spillover effects on non-merging firms that allows them to increase their markdowns as well, though to a lesser extent than merging firms. 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 shows no effect on competition and markdowns. Our results indicate clearly that the market and welfare effects of a merger between firms depend upon their degree of spatial differentiation, which determines the intensity of competition via transportation costs and distance.

Our study is related to work on spatial differentiation in fast food restaurants (Thomadsen 2005), movie theaters (Davis 2006), and retail gasoline establishments (Houde, 2009). 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. (2020). 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.

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 locations of processing plants and county centroids. We also gathered data on supply shifters, including distance between locations of 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 U.S. Environmental Information Administration (EIA 2020), the Biofuel Atlas published by the National Renewable Energy Laboratory (NREL 2020), and the Homeland Infrastructure Foundation-Level Data (HIFLD 2018). 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. Information on the specific locations of U.S. Exporting Port Facilities is available at HIFLD (2020). Distances are calculated using Arc-GIS.

Table 1 portrays an aggregate picture of the corn market in Indiana. The top part of table 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 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 processors purchase a large 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.

Corn farmers typically use trucks to ship corn to their buyers (Denicoff et al. 2014; Adam and Marathon 2015) because plants source corn locally, and trucking within relatively short distances (i.e. less than 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[1] 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 (AMS of USDA 2016; Edwards 2017).[2] At an average corn price of $3.50 per bushel in 2016, this means that 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 2 reveals that ethanol plants and wet-milling processors are quite large, whereas 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 six to ten times larger than dry millers. Table 3 reports the ratio of each large processor's (as identified in table 2) 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 3 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.

In line with the existence of large firms purchasing a substantial fraction of the corn supplied locally (table 3), available reduced-form estimates in the U.S. (McNew and Griffith 2005) and Indiana in particular (Jung et al. 2019) found a positive effect of a plant's siting 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 sales involve transportation costs such that, all else constant, sellers prefer selling corn to nearby plants.*

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

[1]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.

[2]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.

Table 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	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	18.97
Livestock	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	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 Ind.)	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	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Annual production	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	5.88	6.32	11.70	8.74	7.22	9.14	7.52	8.00	8.85	6.18	3.38

Note: Data sources are as follows: (1) Hurt (2012) for the period from 2007 to 2012 and (2) authors' estimation (NASS Quick Stats, USDA; ERS, USDA) for the period from 2013 to 2014. Estimated share used by ethanol plants is based on the information of ethanol plants capacities. Estimated share of corn used for feeding livestock is 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 (four 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). Corn export data is sourced from state export data (ERS, USDA) and survey data for global price of corn (FRED, Federal Reserve Bank of St. Louis 2020). 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 (Survey data (2015); Quick Stats. NASS, USDA; Hurt (2012); and authors' estimation). Annual production of corn in 2012 is extremely low due to drought. Corn stock is from the previous *crop year of corn*.

distances to procure enough input. This likely results in spatial overlap of these plants' procurement areas, especially when they are spatially clustered. Figure 1 shows the locational pattern of ethanol plants (yellow circles), wet-milling plants (red circles), exporting ports (green 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 1) will also compete with the dry-milling sector, the livestock sector, and exports, which are large consumers of corn supplied in Indiana (table 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 procurement channels. A portion of the corn produced is sold shortly after harvest, but another portion is stored in elevators and sold throughout the year. Processors buy corn from farmers and commercial elevators. They purchase corn in the spot market and through contracts, and sellers typically pay for transportation cost. Contracts are usually signed during the growing season and specify a post-harvest delivery date, a quantity, and a price. The nature 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: (*a*) a large portion of corn is purchased directly from farmers and those prices differ from elevator prices, or (*b*) a large portion of corn is purchased through contracts and contract prices differ from cash prices.

We consider the use of elevator cash prices to be an adequate strategy in our context for two reasons. First, although 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 large fraction of corn procured by the processors is purchased in spot markets.

Table 2. Size of Individual Plants by Sector in Indiana in 2014

	Count	Total capacity	Mean capacity	Median capacity	Min capacity	Max capacity
Ethanol plants	14	430.74	33.13	34.07	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	184.19	0.01	N/A	N/A	N/A

Note: Capacity is measured in million bushels per year. Data sources for the ethanol plants are as follows (1) Nebraska Department of Environment & Energy (2015), (2) the Biofuels Atlas of NREL, (3) Hurt (2012), and (4) NASS, USDA. The total count of livestock operators is composed of (1) 2,823 for hog, (2) 14,106 for cattle, and (3) 2,347 for poultry (NASS, USDA). To estimate the mean capacity of livestock operators, 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.

Table 3. Ratio of Ethanol and Wet-Milling Plants' Corn Processing Capacity to Corn Production in the County where the Plant Is Located

Sector	Firm	County	Ratio	Ownership
Ethanol plants	The Andersons Clymers Ethanol, LLC	Cass	2.49	Corporate
	Grain Processing Corp.	Daviess	0.61	Corporate
	Central Indiana Ethanol, LLC	Grant	1.42	Corporate
	Iroquois Bio–Energy Company, LLC	Jasper	0.56	Corporate
	POET Bio-Refining	Jay	2.41	Corporate
	POET Bio-Refining	Madison	1.73	Corporate
	Valero Renewable Fuels Company, LLC	Montgomery	2.08	Corporate
	Abengoa Bioenergy Corp.	Posey	3.59	Corporate
	POET Bio-Refining	Putnam	3.79	Corporate
	Cardinal Ethanol	Randolph	2.61	Cooperative/ Corporate
	Noble Americas South Bend Ethanol LLC	St. Joseph	3.38	Corporate
	POET Bio-Refining	Wabash	2.12	Corporate
	Green Plains Renewable Energy	Wells	3.58	Corporate
Wet millers	Tate & Lyle	Tippecanoe	5.43	Corporate
	Cargill	Lake	6.93	Corporate
	Grain Processing Corp.	Daviess	2.89	Corporate
	Ingredion	Marion	24.31	Corporate
	Below 1[1]		2	
	Above 1[2]		15	

Note: Data are from (1) Renewable Fuel Association (2016) and (2) the Biofuels Atlas, NREL. All counties have one ethanol plant, except for Posey County, which has two ethanol plants. Status over the previous periods, 2004 through 2013, is available from authors. "Below 1" indicates the number of counties that ethanol plants demand less corn than produced among counties where at least one ethanol plant is located. "Above 1" means the number of counties in which ethanol plants demand more corn than produced among counties where at least one ethanol plant is located. Grain Processing Corp. (GPC) operates an ethanol plant and a wet-milling plant in Daviess County.

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).[3] Moreover, corn futures markets are highly liquid, with efficient price discovery mechanisms, which causes convergence, albeit partial, of forward prices to spot prices.[4]

[3]According to Schill (2016) hedging also reduces upside profit potential further limiting the use of contracts.

[4]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.

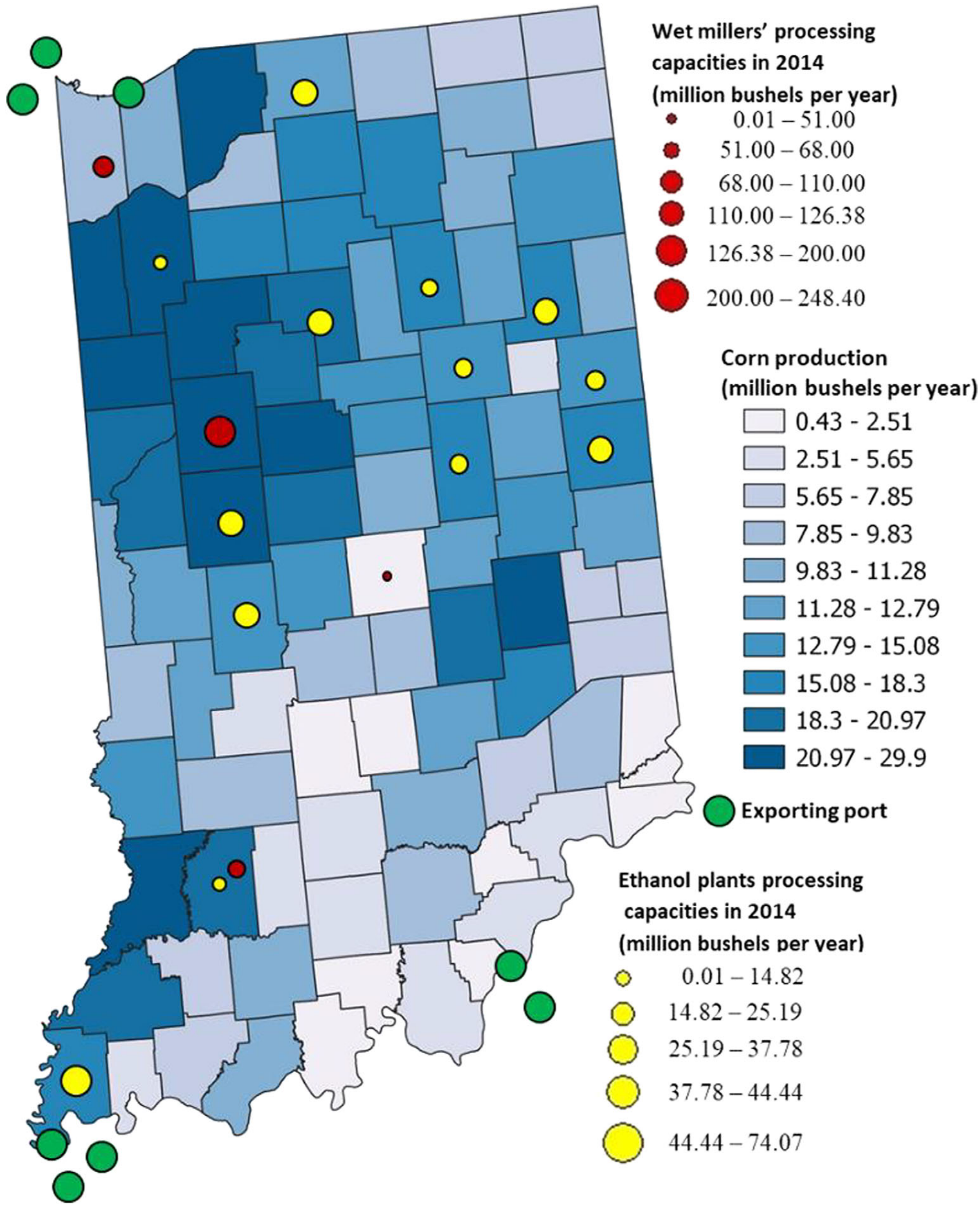

Figure 1. Oligopsonists' locations and corn production in Indiana counties in 2014

Notes: This is based on sources as follows: (1) Renewable Fuel Association (2017), (2) Geo Grain, and (3) Nebraska Department of Environment & Energy (2015).

We summarize the information on procurement channels and pricing by:

> **Market Feature 3:** *Large processors procure the majority of their corn in the spot market by posting purchase prices at the plant gate throughout the year. 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 the data stored on the state of Nebraska's website (http://www.neo.ne.gov/programs/stats/inf/66.html). 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 2016) and wet-milling plants (Porter and Spence 1982) is typically 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 2, we map the spatial structure of oligopsonistic processing plants and county-level corn prices 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 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 or livestock production, which causes large shifts in corn demand.

The Empirical Model

We develop and estimate a structural model to evaluate oligopsonists' buyer power while accounting for spatial differentiation. Our structural model builds on a short-term equilibrium model and consists of a set of equations that describes upstream firms' (farmers) selling behaviors and downstream firms' (oligopsonists) 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.

Downstream Firms (Ethanol and Wet-Milling Firms)

Our empirical model mirrors 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*). As mentioned in *Market Feature 3*, we model processors that procure their corn in the spot market. They post corn prices at the plant gate and transportation costs are covered by the farmers. Finally, and reflecting *Market Feature 4*, we

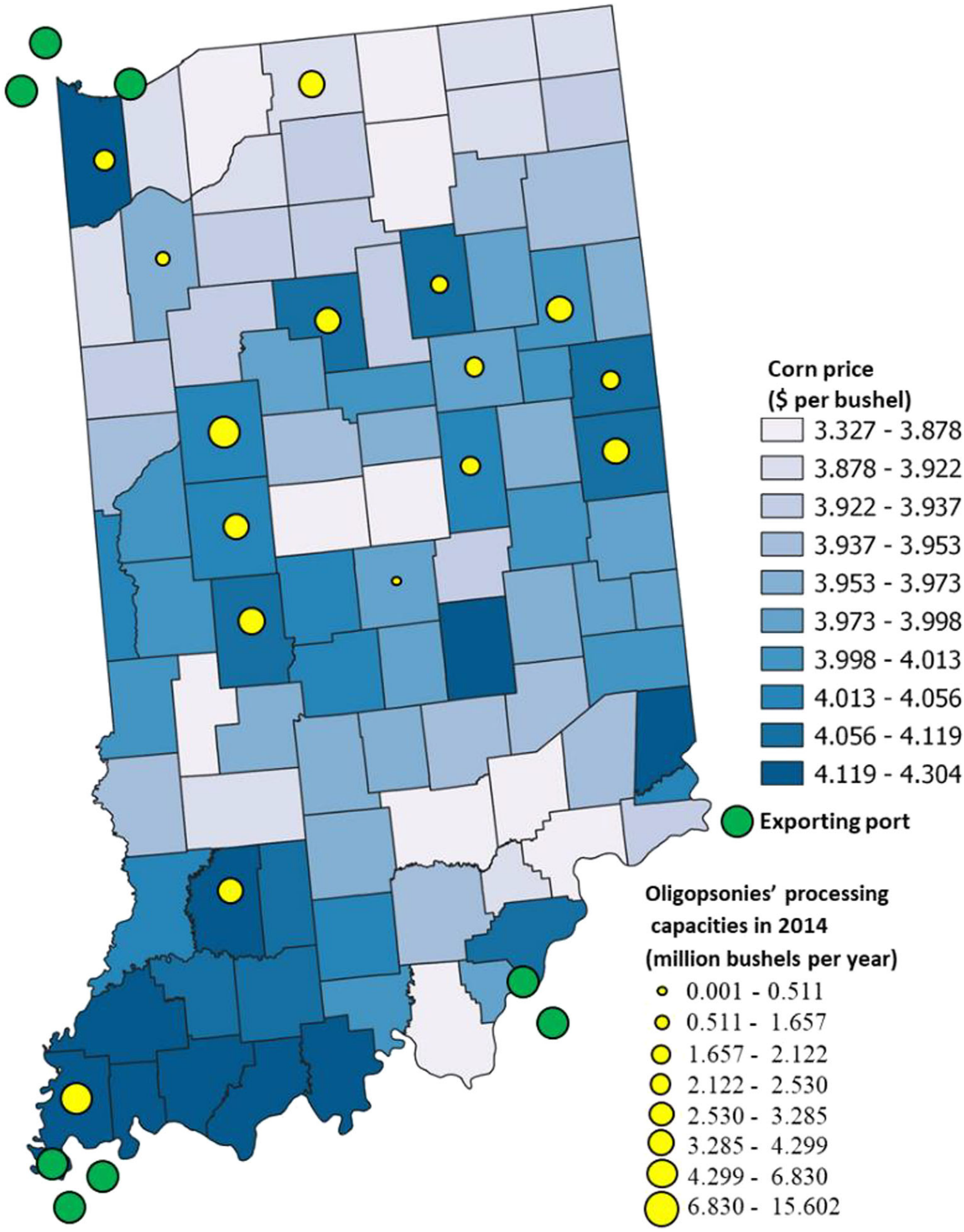

Figure 2. Oligopsonists' locations and corn prices in Indiana counties in 2014

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.

We allow oligopsonistic firms *(F)* to own multiple plants (j). The firm determines for every plant j the corn price p^c_{ijt} (the superscript c refers to corn, and the subscript t refers to the time period) that is paid to sellers (farmers) located in county $i = 1,\ldots,92$ in Indiana. We take ownership and location of plants as given. We allow firms to internalize negative competitive externalities imposed on other plants that are jointly owned by the firm. Because 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 $\boldsymbol{p^c_F}$ contains as its elements the county-specific corn prices p^c_{ij} 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 $q_{ij}^{c}(\boldsymbol{p}_i^c;\boldsymbol{x}_i,\boldsymbol{\beta})$,[5] 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.

An important aspect to consider in our model is vertical integration. An oligopsonist that is vertically integrated with corn sellers would price corn differently from its non-integrated competitors because it would maximize joint (sellers' and buyer's) profits (Urbanchuk ; Bain 2011; Miller et al. 2012; Boone and Özcan 2013; Grashuis 2019). All firms, but one, in our sample are investor owned; that is, they are not vertically integrated with corn sellers. The only firm that is owned by a farmers' cooperative in Indiana is Cardinal Ethanol (table 3). However, a careful look at SEC filings from Cardinal Ethanol reveals two facts. First, the cooperative is largely owned by farmers that are not local and, thus, do not sell to the plant. Second, a significant share of the cooperative is owned by investors that are not farmers. Both of these facts suggest limited, if any, vertical integration between the firm and corn sellers. Hence, we assume oligopsonists in our model are not vertically integrated.

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

$$
\begin{aligned}
\max_{p_{ij}^c} \pi_F = {} & P^h * \alpha^h * \sum_i \sum_{j \in F} q_{ij}^c(\boldsymbol{p}_i^c;\boldsymbol{x}_i,\boldsymbol{\beta}) \\
& - \sum_i \sum_{j \in F} p_{ij}^c q_{ij}^c(\boldsymbol{p}_i^c;\boldsymbol{x}_i,\boldsymbol{\beta}) - \sum_{j \in F} FC_j \\
& - \sum_{j \in F} \int_0^{Q_j^h} mc(Q;\boldsymbol{w}_j,\boldsymbol{\alpha},\gamma)\,dQ
\end{aligned} \tag{1}
$$

subject to

$$\alpha^h \sum_{i \in IN^C} q_{ij}^c(\boldsymbol{p}_i^c;\boldsymbol{x}_i,\boldsymbol{\beta}) \le CAP_j \quad \forall j \in F \tag{2}$$

$$\sum_{j \in IN^P} q_{ij}^c(\boldsymbol{p}_i^c;\boldsymbol{x}_i,\boldsymbol{\beta}) \le RSUP_i \quad \forall i. \tag{3}$$

subject to.

[5]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 (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 price of ethanol P^{eth} (which varies over time) comes from the state of Nebraska's website and the scalar α^{eth} (constant over time and equal to 2.7 gallons per bushel) from USDA's U.S. Bioenergy Statistic tables (https://www.ers.usda.gov/data-products/us-bioenergy-statistics/documentation/). Computing the conversion factor and output price for wet millers is more challenging because these plants produce multiple outputs that sell at different prices. Therefore, we compute VMP directly by dividing value of output/corn used (Galitsky et al. 2003). We note that the VMP for wet millers is virtually the same as that of ethanol plants. This is partly because during our period of analysis there was a rather strong correlation between the price of sugar (which drives prices of outputs from wet-milling firms) and the price of ethanol.

The second through fourth terms in the right-hand side of equation (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 (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, $\sum_j \int_0^{Q_j^h} mc(Q;\boldsymbol{w}_j,\boldsymbol{\alpha},\gamma)\,dQ$, refers to the total processing cost of producing ethanol and wet-milling products, where Q is the amount of corn processed, Q_j^h refers to the corresponding production quantities, and mc denotes marginal processing cost. We specify the marginal processing cost function as:

$$
\begin{aligned}
mc\left(Q_j^h;\boldsymbol{w}_j,\boldsymbol{\alpha},\gamma\right) = {} & \boldsymbol{w}_j'\boldsymbol{\alpha} \\
& + \gamma\left\{1 - \frac{\alpha^h \sum_i q_{ij}^c(\boldsymbol{p}_i^c;\boldsymbol{x}_i,\boldsymbol{\beta})}{CAP_j}\right\},
\end{aligned} \tag{4}
$$

where $\boldsymbol{w}_j$ 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. Equation (4) allows marginal processing cost of plant j to depend on capacity utilization $\frac{\alpha^h \sum_i q^c_{ij}\left(\boldsymbol{p}^c_i;\boldsymbol{x}_i,\boldsymbol{\beta}\right)}{CAP_j}$. If γ is positive (negative) plants display economies (diseconomies) of capacity utilization, and if γ is zero, plants operate under constant marginal processing cost.

Our model also allows for binding capacity constraints, a distinctive feature of corn processors (*Market Feature 4*). Condition (2) ensures that production by plant is not higher than what is technologically feasible to produce in any given year (denotes capacity of plant *j*). Finally, condition (3) ensures that corn purchased by all plants does not surpass the available amount of corn from a county denoted by "RSUP_i", which refers to the residual corn supply from county i (annual corn production plus storage minus demand from livestock and dry millers).

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The solution to the optimization problem (1)–(4) is a system of Karush-Kuhn-Tucker conditions fully characterized in Appendix A. Simultaneous solution of these conditions for all firms results in a set of equilibrium prices. If capacity constraints are not binding, then the solution is a Bertrand-Nash equilibrium in prices with spatially differentiated products.[6] If, on the other hand, capacity constraints are binding, then the solution is a Bertrand-Edgeworth equilibrium in prices with spatially differentiated products (Benassy 1989; Canoy 1996; Somogyi 2020).

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 carried over from previous years.[7] Inventories are shaped by the previous season's weather, and production is determined by acres planted to corn and growing season weather. Acres planted to corn are driven largely by world market conditions that determine expected corn prices relative to other crops, which are exogenous in our model. This is in contrast to farmers' decisions on who to sell corn already produced, which are likely shaped by local prices set by oligopsonists. But even if oligopsonists' pricing had an effect on local corn acreage (e.g. Wang et al. 2020), its relation to production (our variable of interest) is much weaker due to the mediating role of growing season weather. Hence, we assume total corn supply (not destination of that supply) is independent of oligopsonists' pricing and focus on a model of shipments and short-run supplies.[8]

Our model of shipments predicts the share of total corn supply sold by each county to each procurement firm. It builds on two premises. First, sellers 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

[6]Our paper follows the tradition in empirical models of discrete choice and differentiated products and assumes a Bertrand-Nash equilibrium (Berry 1994). In a Bertrand-Nash equilibrium, firms set prices ignoring potential strategic reactions by other firms. This is equivalent to Hotelling-Smithies conjectures in the standard Hotelling (1929) set up of spatially differentiated products.

[7]Storage data are 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.

[8]According to the modern agricultural markets paradigm, buyers of agricultural products are limited in their ability to suppress prices for farm products when they trade through stable contractual relationships. This is because suppressing prices too much could result in substantial reductions in future input supply (Crespi, Saitone, and Sexton 2012; Sexton 2013). In our setting, reductions in supply would take place through a decrease in corn acreage in the future. This paradigm does not fit the corn procurement market well primarily for three reasons. First, a substantial portion of purchases by corn ethanol plants and wet millers are conducted in the spot market rather than through stable contractual relationships (Market Feature 3). Second, the main price signal farmers respond to when making planting decisions is the world market price, which determines farmers' reservation price when trading with local oligopsonists rather than local prices set by oligopsonists. Third, the longer term response of corn acreage to past oligopsonists' pricing (or price signals in general) is limited by strong benefits of rotating corn and soybeans (Hendricks et al. 2014).

competitive fringe can be quite inelastic in the short run, 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 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.

Sellers 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. Because there are eighteen oligopsonistic plants in our sample (fourteen ethanol plants and four wet-milling plants), then $J = 18$. The sellers have to pay the transportation cost. The value function of seller n in county i, associated with selling their corn to plant j is given as:

$$(5) \quad v_{ij}^{n} = \beta^{p} p_{ij}^{c} + \beta^{d} d_{ij} + \beta^{e} e_{j} + \varepsilon_{ij}^{n} = \boldsymbol{x}_{\boldsymbol{i}}'\boldsymbol{\beta} + \varepsilon_{ij}^{n},$$

where p_{ij}^{c} is the corn price offered by plant j to a farmer in county i (the corn price for exporting ports, p_{iJ+1}^{c}, is exogenous and determined by the international price), d_{ij} is the distance between the centroid of county i and the specific location of plant j, $d_{i,J+1}$ denotes the distance between the centroid of county i and the specific location of 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 ($j = J + 1$). For distance we proxy driving distance by computing the straight-line distance between plants (or exporting ports) and country centroids, and then multiplying this distance by a circuity factor of 1.2, which has been used in the literature to capture road infrastructure in Indiana (Tyner and Rismiller 2012).

The negative of the ratio of the distance coefficient to the price coefficient ($-\beta^{d}/\beta^{p}$) captures corn sellers' willingness to pay for proximity to an oligopsonist. We interpret this ratio as transportation cost, because corn sellers save this amount per bushel-mile when located one mile closer to a dominant firm. Both interpretations (willingness to pay for proximity and transportation cost) are not necessarily equivalent. They may differ if distance affects sellers' value for other reasons generally associated with relational contracts or switching costs (e.g., reduced reliability, increased transaction costs, etc.). Having said this, we believe transportation cost is likely the overwhelming force governing the link between distance to a plant and the value for the farmer of selling to that plant. This is because plants purchase the majority of their corn in the spot market from a very large number of relatively small farms. Hence, with the appropriate caveats, we interpret $-\beta^{d}/\beta^{p}$ as transportation cost.[9]

The error term (ε_{ij}^{n}) captures unobservable match characteristics, such as reputation or relational contract considerations that are not captured by distance, that affect county i suppliers' preference for trading with plant j. 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:

$$(6) \quad S_{ij}\left(\boldsymbol{p}_{i}^{c};\boldsymbol{x}_{i},\boldsymbol{\beta}\right) = Prob(Y_{n} = j) = \frac{\exp\left(\boldsymbol{x}_{\boldsymbol{i}}'\boldsymbol{\beta}\right)}{\sum_{j=1}^{J+1}\exp\left(\boldsymbol{x}_{\boldsymbol{i}}'\boldsymbol{\beta}\right)},$$

where $\boldsymbol{x}_{ij}' = \left[p_{ij}^{c}, d_{ij}, e_{j}\right]$ 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:

$$(7) \quad q_{ij}^{c}\left(\boldsymbol{p}_{i}^{c};\boldsymbol{x}_{i},\boldsymbol{\beta}\right) = S_{ij}\left(\boldsymbol{p}_{i}^{c};\boldsymbol{x}_{i},\boldsymbol{\beta}\right) * RSUP_{i},$$

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.

[9]The error term would also include an error in variable, stemming from the fact that the distance between the individual seller in some county i and plant j is imperfectly captured by d_{ij}. This is because sellers are geographically dispersed within counties, whereas the regressor measures distance from the plant to the county centroid. However, notice that the seller-specific error in distance is, by construction, orthogonal to the distance between plant and county centroid (Miller and Osborne 2014).

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 county-level prices and quantities get sufficiently close to their observed counterparts.

For estimation of the farmers' supply equation (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 (6) and (7)), which makes computation less burdensome. Second, the logit structure produces a specification consistent with heterogeneity in sellers' 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 because plants' actual procurement area is ex ante unknown.

Next, we use the multinomial logit supply (as shown in equation (6)) and the solution to the oligopsonists' profit maximization problem (as shown in equations (1)–(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: [10]

$$(8) \quad \min_{\boldsymbol{\theta}\in\Theta}\frac{1}{T}\sum_{t=1}^{T}\left[\boldsymbol{p}_t^c-\tilde{\boldsymbol{p}}_t^c(\boldsymbol{\theta};\boldsymbol{X}_t)\right]'\boldsymbol{C}_t^{-1}\left[\boldsymbol{p}_t^c-\tilde{\boldsymbol{p}}_t^c(\boldsymbol{\theta};\boldsymbol{X}_t)\right]$$

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 $\boldsymbol{p}_t^c-\tilde{\boldsymbol{p}}_t^c(\boldsymbol{\theta};\boldsymbol{X}_t)$. 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 $\tilde{\boldsymbol{p}}_t^c(\boldsymbol{\theta};\boldsymbol{X}_t)$, where $\boldsymbol{\theta}=[\boldsymbol{\alpha},\boldsymbol{\beta},\gamma]'$ 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 $\tilde{\boldsymbol{p}}_t^c(\boldsymbol{\theta};\boldsymbol{X}_t)$, and the outer loop minimizes the distance between $\tilde{\boldsymbol{p}}_t^c(\boldsymbol{\theta};\boldsymbol{X}_t)$ and its empirical analog $\boldsymbol{p}_t^c$.

A technical description of the iterative estimation algorithm is relegated to Appendix B. We model this problem as a Mathematical Programming with Equilibrium Constraints (***MPEC***) as suggested by Su and Judd (2012)[11] and implement the double-loop structure in the General Algebraic Modeling System (GAMS) software.[12] This strategy increases ease of computation, preventing common nonconvergence and infeasibility issues.

Identification

We consider ninety-two counties in Indiana over an eleven-year time horizon such that equation (8) includes $92 \times 11=1{,}012$ aggregated equilibrium predictions and their empirical analogs. Identification proceeds based on these 1,012 nonlinear conditions stacked in equation (8). The vector $\boldsymbol{\theta}$ contains parameters of the farmers' supply equation ($\boldsymbol{\beta}$), along with the parameters characterizing marginal cost of processing corn ($\boldsymbol{\alpha},\gamma$).

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

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

[11]We summarize the structure of the algorithm implemented in MPEC in Appendix B.

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

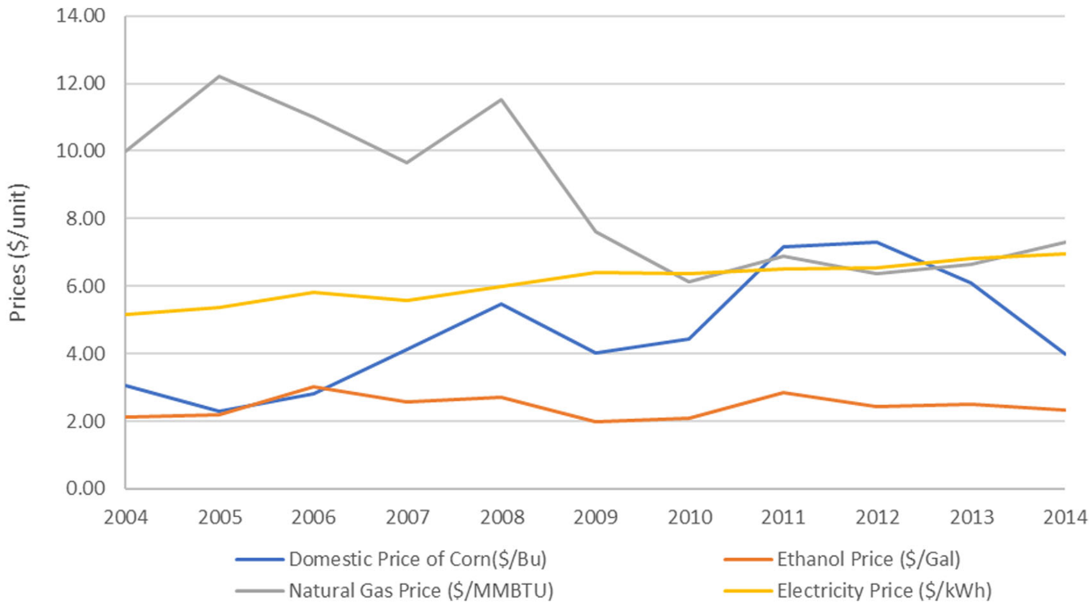


Figure 3. Evolution of relevant prices in the corn market

conditions in Appendix A, achieved based primarily on the correlation between county-level corn prices and the joint variation of output price (which, as shown in Figure 3, is positively correlated with corn 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. Distance from county centroids to exporting ports varies only cross sectionally, so the parameter β^e are identified based on cross-sectional variation.

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), 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 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.

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 focus on 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.

The Upstream Firms (Farmers)

Parameter estimates of the corn residual supply, as characterized in equation (7), are reported in the upper panel of table 4.[13] The estimated coefficient for corn price (β^p) is statistically significant and positive. The coefficient shows that the amount of corn sold to a downstream firm increases with the price offered by

[13] All standard errors, as shown in table 4, are bootstrapped.

Table 4. Parameter Estimates and Derived Statistics

Variables	Parameters	Parameter estimates
Residual supply		
Corn price	β^p	9.573*** (1.053)
Distance	β^d	−0.050*** (0.007)
Export dummy	β^e	0.1e−4 (0.008)
Marginal costs		
Natural gas price	α^{ng}	0.098** (0.062)
Electricity price	α^{elec}	0.1e−3 (0. 4e−3)
Time trend	α^{time}	−0.155*** (0.03)
Extra costs per unit of unutilized capacity	γ	0. 1e−3 (1.5e−3)
Derived statistics	Previous studies	
Transportation cost ($ per bu-mile)	0.002	0.005*** (0.001)
Cap. utilization ratio	0.95	0.970*** (0.078)
Marg. processing cost (per gallon)	1.35	1.680*** (0.403)
Firm elasticity of residual inverse corn supply		0.097*** (0.002)

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. Transportation cost from previous study is based on GTOR report by Transportation and Marketing Program (TMP) of Agricultural Marketing Service (AMS), USDA. Dale and Tyner (2006) report capacity utilization ratio at 0.95. Marginal processing cost of 1.35 is based on average from Perrin et al. (2009) and Irwin (2018). Firm elasticity of residual inverse corn supply 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 $.39 (from $4/bushel to about $4.39/bushel, or 9.7%). This is, of course, an oversimplification because 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.

that firm. The positive effect is indicative of a "business-stealing" effect, whereby a downstream firm diverts corn away from its competitors 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 because 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 0.5 cents per bushel per mile. It should be noted that our estimated transportation cost is higher than the 0.16 cents average cost estimate (within 200 miles) as reported by GTOR. The GTOR estimate represents an average for the entire North Central region, which may explain the deviations from our transportation costs, which are specific to Indiana. The 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 11% 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 inverse supply elasticity (average across plants and time periods) of 0.097.[14] 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 $0.49 at the plant's gate (it increases from $5 per bushel to about $5.49 per bushel, an equivalent of 9.7%).[15]

The Downstream Firms (Ethanol and Wet-Milling Firms)

We now focus on the estimation results of the marginal processing costs of the downstream

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

[15]This is, of course, an oversimplification because 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.

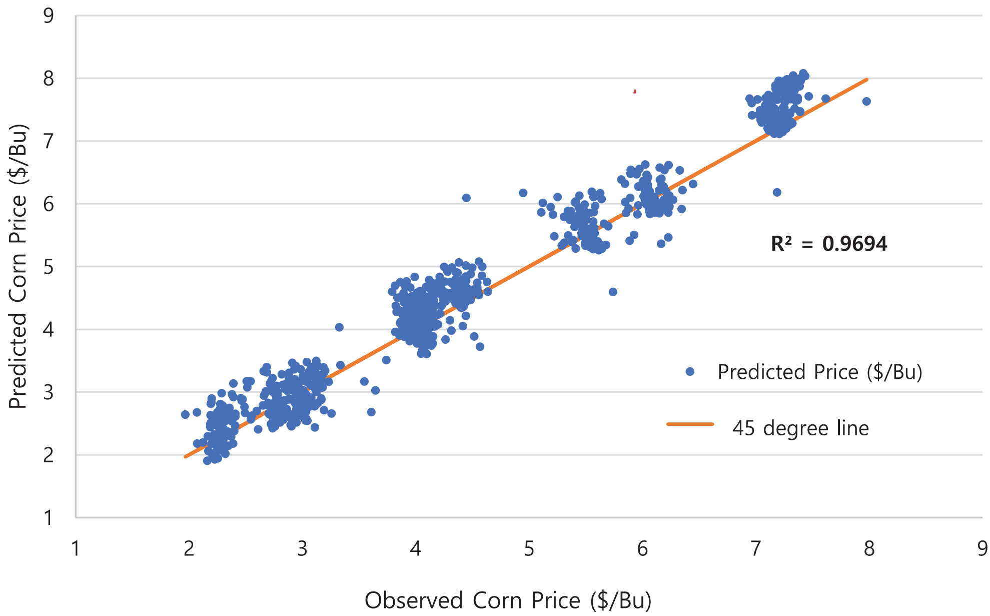


Figure 4. Predicted versus observed farm-gate prices

firms (ethanol and wet-milling firms), as characterized in equation (4). The middle panel of table 4 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 $1.68 per gallon, which is close to the cost estimates reported in Perrin et al. (2009) and Irwin (2018). Parameter γ is not statistically significantly different from zero, providing evidence that the marginal processing cost is constant, which 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).[16] Our estimated capacity utilization ratio amounts to 0.97, 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 previous reports (Green Plains Renewable Energy 2017; 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 is at the center of our identification strategy. Figure 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 figure shows no systematic under- or overprediction of prices within sample. The correlation between predicted and observed prices is close to 0.97. The figure and correlation indicate that our structural model does a remarkable job of predicting observed prices.

Corn Prices and Markdowns over Time

In the following, we predict plant–county pair prices paid by ethanol and wet-milling plants

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

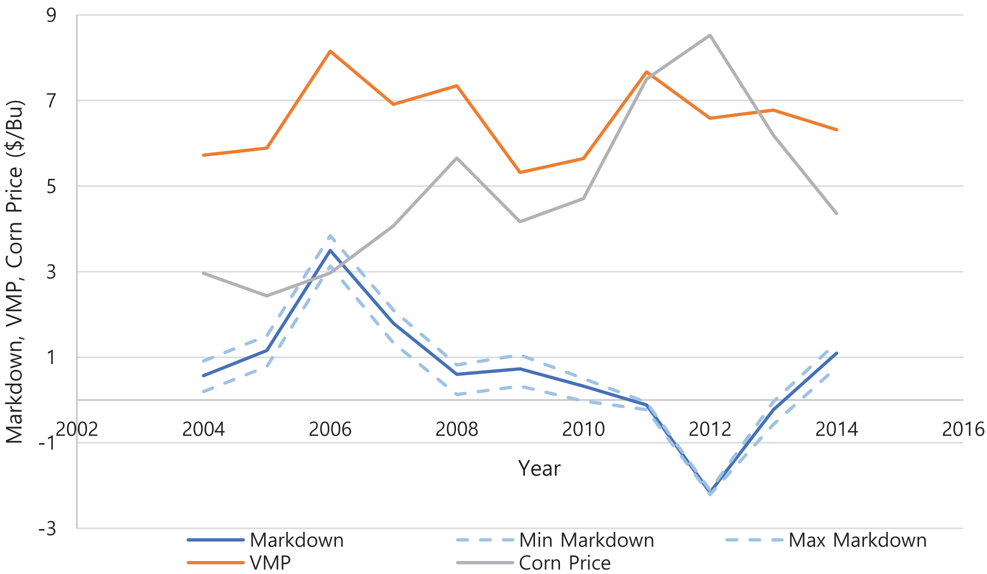


Figure 5. VMP, Predicted corn prices, and markdown

and calculate markdowns, defined as the difference between the value of marginal product (VMP) of corn net of marginal processing cost and the predicted prices of corn at the plant gate. Figure 5 portrays a substantial average price markdown. The average markdown is around $0.67 per bushel, or 13% 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: although markdowns enabled oligopsonist-owned plants to push the average variable cost below the output price overall, the plants likely experienced tight margins or even losses in some periods.

Figure 5 shows that 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. In 2006 the international price of corn was low and, simultaneously, the price of ethanol was high, boosted by government policies. In 2012 a historical drought pushed the residual corn supplies from farmers ($RSUP_i$s) down (i.e., pushed the inverse residual supplies upward), increasing corn procurement cost for all oligopsonist firms. The year 2012 seems like an outlier when compared with other years in our sample. To examine the robustness of our estimates, we have re-estimated the model excluding 2012. Our results remain virtually unchanged. With this in mind, we believe inclusion of 2012 in our baseline specification is preferable for two reasons. First, there were years after 2014 where conditions were highly unfavorable as in 2012. Second, inclusion of the 2012 year does not affect our model's goodness of fit. In fact, our model is capable of predicting 2012 prices, as well as prices in other years as revealed in figure 4.

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 5. The difference between the largest and smallest markdowns in a year averages $0.57 per bushel over the study period but varies from almost no variation in 2012 to $0.79 in 2007. Between-firm variability in markdowns stem from the fact that individual firms face different input supplies.

Our estimates in table 4 point to two forces underlying firms' markdowns. The first factor relates to the spatial differentiation aspect and the fact that oligopsonistic firms face an upward-sloping residual input supply (as indicated by the positive elasticity of the inverse input supply), which creates a wedge between marginal factor cost and input supply. The second factor relates to our finding that many firms operate at full capacity, with an average capacity utilization rate of 0.97. This creates a wedge between the VMP and

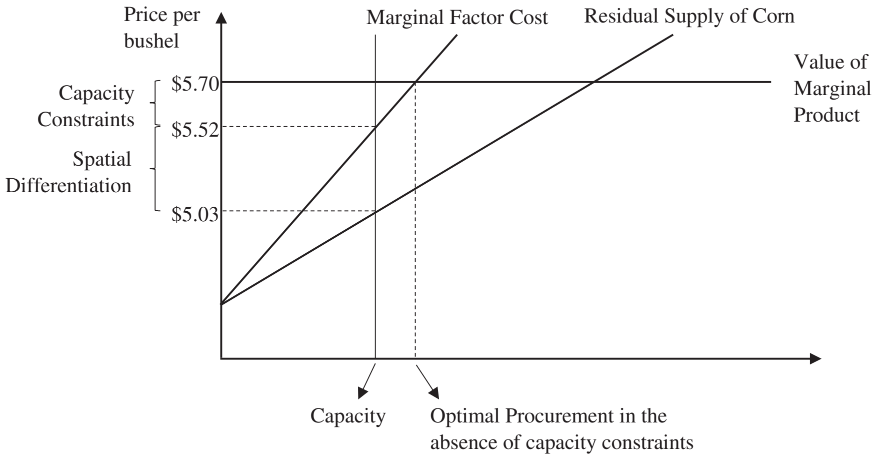


Figure 6. Sources of markdown for average plant in our sample

marginal factor cost. 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 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 VMP is equal to the (residual) marginal factor cost. Markdown then is equal to the distance between the VMP and residual supply at the profit-maximizing procurement quantity. However, if capacity is smaller than the profit-maximizing quantity, then the plant will operate at capacity and markdown is the distance between the VMP and residual supply at capacity. By construction, this distance is larger than the wedge between marginal factor cost and residual supply. Therefore, if the VMP 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).

Our results indicate that capacity constraints often prevail, and markdowns are determined by the distance between the VMP and residual supply at capacity. Therefore, as depicted in figure 6, markdowns are larger than they would be in the absence of those constraints. For the average (across firms and over time) observation in our sample, the wedge between the VMP and residual supply at capacity is $0.67, whereas the wedge between supply and marginal factor cost at capacity is $0.49. These findings are consistent with Bertrand-Edgeworth competition, a setting in which binding capacity constraints deliver a stronger degree of market power to otherwise spatially differentiated Bertrand-pricing buyers (Kreps and Scheinkman 1983; Benassy 1989; Canoy 1996; Somogyi 2020).

Our finding that plants tend to operate at high levels of capacity utilization seems hard to reconcile with the fact that no new plants entered the market since 2014. One possibility is that plants do not collude on pricing conditional on capacity but collude to not expand capacity, thereby bolstering buying power. However, there are good reasons to not expand capacity that do not stem from collusion. Construction of new plants or expansion of existing ones are hindered by large sunk costs, asset specificity, and uncertainty (Schmit et al. 2011). As a result, investors tend to require a high expected profitability (higher than the one that would push incumbents to operate at full capacity) before they commit. Profitability has been inhibited since 2011 by the “blending wall” (a technical barrier to inclusion of ethanol in liquid fuels) and an overall reduction in support through public policies (removal of subsidies and tariffs protecting corn ethanol).

We should note that oligopsonists cannot pay a price to farmers that is below their reservation price; that is, the price they can get from the competitive fringe. Our model accommodates this by: (*a*) subtracting corn demand from the local competitive fringe from local supply, and (*b*) 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.

We further explore the relationship between spatial differentiation and procurement patterns. Based on our estimated parameters, we compute how the quantity of corn purchased by oligopsonistic firms depends on the distance between their plants and farmers. We find that plants procure most of their corn within a distance of fifty miles. The predicted procurement patterns coincide with previous descriptions of procurement regions under similar corn supply conditions (e.g. Kang et al. 2009). This finding further validates our estimates and lends credence to our analysis. We also find that, all else constant, plants facing more spatial competition (there is a competitor in close proximity) are forced to travel greater distances (in the direction of their uncontested markets) to procure corn.

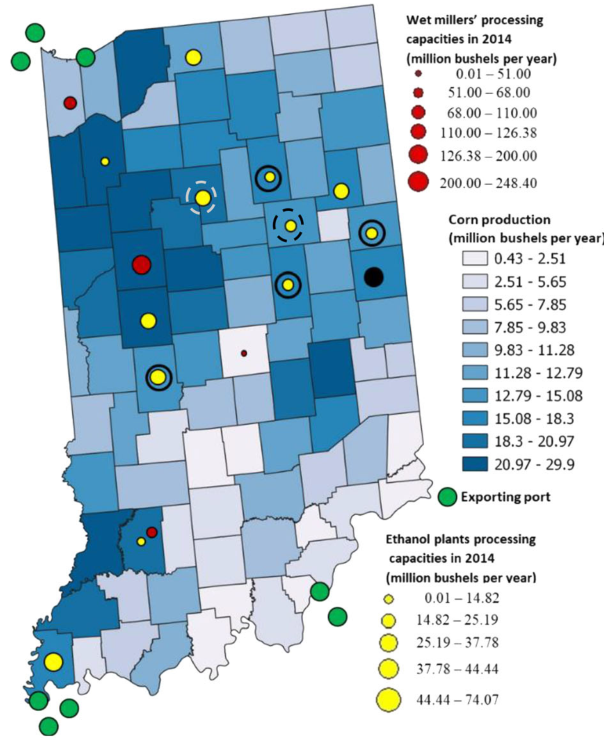
Counterfactual Experiments: Mergers, Markdowns, and Farm Surplus

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. We now evaluate the effect of different types of mergers between ethanol plants. Mergers among corn ethanol firms have been ubiquitous over the last few years (FTC 2018). This is not entirely surprising given the nature of corn ethanol production. Large corn processors do not 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* (FTC 2018). But although mergers have been a pervasive feature of the ethanol industry in recent years, they have not taken place in Indiana. Hence, Indiana offers an unconfounded marketplace for merger simulations, which seem particularly timely given recent trends in other states.

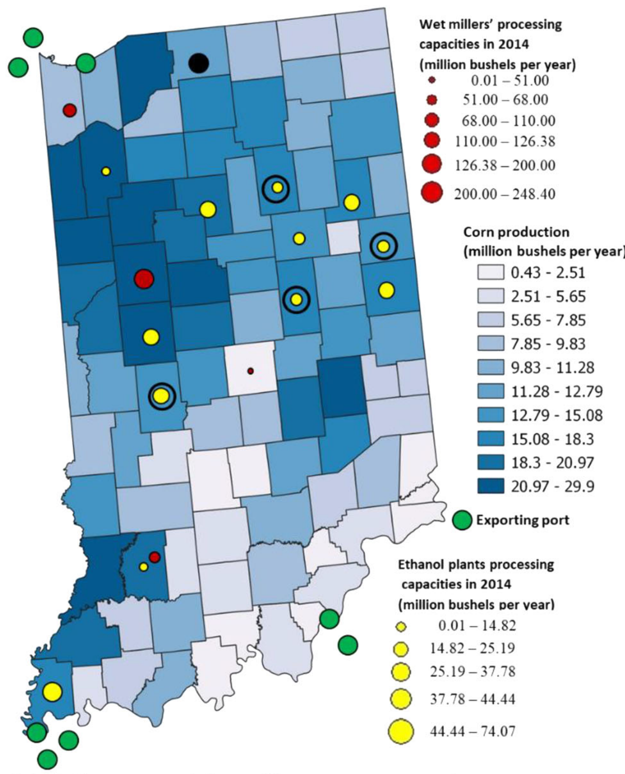
Understanding the efficiency and distributional effects of mergers is of key importance for antitrust authorities. But antitrust agencies have long recognized that mergers between firms that purchase close substitutes (input supplies with large cross-price elasticities) tend to harm efficiency and concentrate surplus more than those that take place between firms that purchase weak substitutes. 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. To attain a deeper understanding of this, we simulate mergers that are characterized by varying distances between merging partners. We include a detailed description of how a merger is technically implemented in our empirical model in Appendix C.

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 (26 miles away from the nearest Poet plant), which is located close to two of its other plants in Jay County and Madison County. Figure 7a shows the 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. The second merger describes a case in which Poet purchases a much more distance and isolated plant in St. Joseph County (90 miles away from the nearest Poet plant). Figure 7b shows the 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.

For 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 $0.20 (18% 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



(a) **Merger with a nearby competitor**



(b) **Merger with a distant competitor**

Figure 7. Merging and non-merging plants in counterfactual simulations

Notes: (a) Merger with a nearby competitor. (b) Merger with a distant competitor

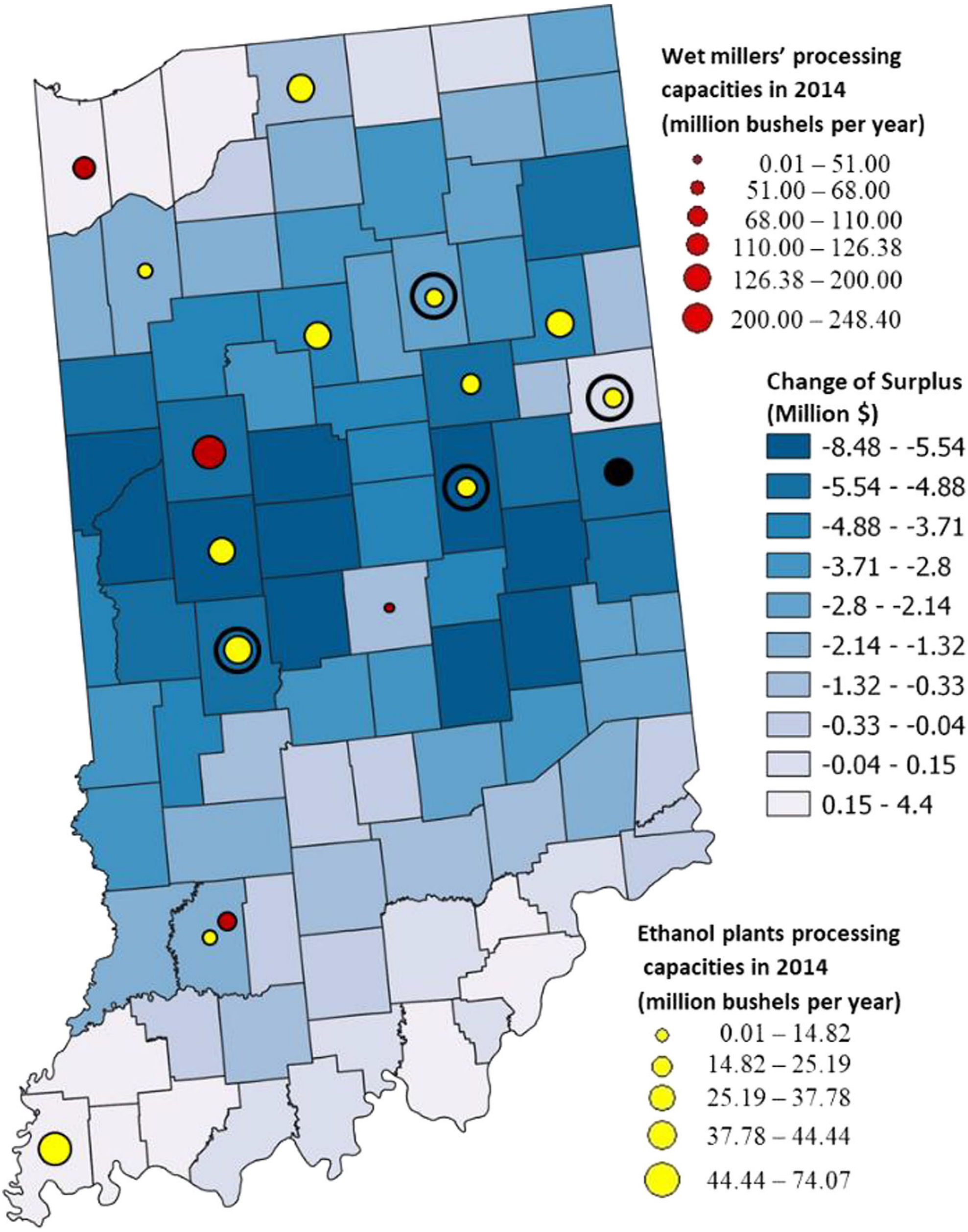


Figure 8. Change in producer surplus (million dollars) due to merger with nearby plant

by each firm due to internalization of the competitive externalities. For the second merger case, in which Poet merges with a distant competitor, we do not find increases in markdown. A comparison across mergers 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 close spatial substitutes and, consequently, are likely to have high cross-price elasticities.

Although 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. We find that a non-consolidating firm located in the middle of four plants owned by Poet (indicated in figure 7a with a black dashed circle) increases markdown by \$0.19 after the merger, and a non-consolidating firm facing only one Poet's plant (indicated in figure 7a with a grey dashed circle) increases markdown by \$0.14. Therefore, although mergers can also increase markdown of non-consolidating firms, the effect also seems to dissipate with distance and competition intensity.

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 8. 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 vary from \$0 to \$8 million per county, amounting to roughly a total of \$230 million at the state level.

There are three key takeaways from our merger simulations. First, modern antitrust guidelines give increasingly more weight to cross-price elasticities between merging firms, as opposed to the overall level of concentration in the industry. Results from our merger simulations confirm this is the right approach in our setting and, furthermore, that a key factor behind cross-price elasticities is the distance between merging firms. Second, when deciding on which mergers to allow, antitrust authorities tend to weigh efficiency gains against increase in market power from the merger. Our merger simulation contributes to computation of the latter because it provides a quantitative assessment of how the merger increases markdown of both consolidating and non-consolidating firms and how it decreases farm surplus throughout the state. Finally, and perhaps more importantly, we find that the merger does not result in reduction in corn procurement because firms operate at high capacity utilization before and after the merger. Therefore, we show that mergers would have important distributional implications but limited efficiency implications.

Conclusion

This study conducts an empirical investigation of the existence of spatial oligopsonistic market power and counterfactual simulations for consolidation in the corn procurement market. Although 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. Therefore, our extended framework can accommodate a model of Bertrand competition with differentiated inputs and a model of Bertrand-Edgeworth competition with binding capacities. We find evidence that spatial differentiation allows corn buyers to engage in input price markdown.

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 locations of merging firms' plants.

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). Our analysis suggests that if such an index is developed for agricultural procurement markets, it should accommodate two distinct features: (*a*) spatial differentiation, and possibly (*b*) binding capacity constraints. The development of a regulatory index of this nature seems relevant for both scientists and policy makers.

Finally, previous studies of agricultural procurement have argued that spatial price discrimination–whereby buyers vary markdown by distance–has emerged or is likely to emerge in fruits and vegetables (Durham, Sexton, and Song 1996), livestock, dairy (Alvarez et al. 2000; Graubner et al. 2011), and pulpwood (Löfgren 1985) markets to name a few. This is consistent with theoretical predictions of spatial price discrimination (Zhang and Sexton 2001; Graubner et al. 2011; Fousekis 2011a). Spatial price discrimination is an important topic that warrants further attention in future studies.

Supplementary Material

Supplementary material are available at American Journal of Agricultural Economics *online.*

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Appendix A. Estimation Strategy

a. 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:

$$\text{(A1)}\quad \begin{aligned}\frac{\partial \mathcal{L}_F(\cdot)}{\partial \boldsymbol{p}_F^c} &= -\boldsymbol{q}^c(\boldsymbol{p}^c;\boldsymbol{\beta}) \\ &+ \boldsymbol{\Omega}(\boldsymbol{p}^c)\left\{\boldsymbol{\Gamma} - \boldsymbol{p}_F^c - \boldsymbol{M} - \boldsymbol{\Lambda}\right\} \\ &\geq \boldsymbol{0}, \boldsymbol{p}_F^c \geq \boldsymbol{0}, \boldsymbol{p}_F^c\left\{\frac{\partial \mathcal{L}_F(\cdot)}{\partial \boldsymbol{p}_F^c}\right\} \\ &= 0 \forall i \text{ and } j \in F.\end{aligned}$$

$$\text{(A2)}\quad \begin{aligned}\frac{\partial \mathcal{L}_F(\cdot)}{\partial \lambda_j} &= -\alpha_j^h \sum_{i \in IN^C} q_{ij}^c(\boldsymbol{p}_i^c;\boldsymbol{x}_i,\boldsymbol{\beta}) \\ &+ CAP_j \geq 0, \lambda_j \geq 0, \lambda_j\left\{\frac{\partial \mathcal{L}_F(\cdot)}{\partial \lambda_j^c}\right\} \\ &= 0 \forall j \in F,\end{aligned}$$

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:

$$\text{(A3)}\quad \Omega_{jk}^i(\boldsymbol{p}_i^c;\boldsymbol{\beta}) = \begin{cases} \dfrac{\partial q_{ij}^c(\boldsymbol{p}_i^c;\boldsymbol{x}_i,\boldsymbol{\beta})}{\partial p_{ik}} & \textit{if plants } j \textit{ and } k \textit{ have the same owner} \\ 0 & \textit{otherwise} \end{cases}.$$

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^c_{i2})—which is the business stealing effect. If the same firm owns both plants, it will fully internalize this negative externality, $\frac{\partial q^c_{i2}\left(\boldsymbol{p}^c_i;\boldsymbol{x}_i,\boldsymbol{\beta}\right)}{\partial p_{i1}}$. Otherwise, the plant would not internalize the externality, and $\frac{\partial q^c_{i2}\left(\boldsymbol{p}^c_i;\boldsymbol{x}_i,\boldsymbol{\beta}\right)}{\partial p_{i1}}$ 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 $P^h * \alpha^h_j$. $\boldsymbol{M}$ is a vector of $\alpha^h_j * mc\left(Q^h_j;\boldsymbol{w}_j,\boldsymbol{\alpha},\gamma\right)$, which represents the change in marginal processing cost associated with producing below capacity, and $\boldsymbol{\Lambda}$ is a vector of Lagrangian multipliers $\lambda^{\boldsymbol{c}}_j$.

There is no analytical solution to the system (A1)–(A2), 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:

$$\text{(A4)} \quad \tilde{\boldsymbol{p}}^{\boldsymbol{c}}_{\boldsymbol{i}}(\boldsymbol{\beta},\boldsymbol{X_t}) = \sum_{j\in F}\left[\left\{\frac{q^{c,*}_{ij}\left(\boldsymbol{p}^{c,*}_i;\boldsymbol{x}_i,\boldsymbol{\beta}\right)}{\sum_j q^{c,*}_{ij}\left(\boldsymbol{p}^{c,*}_i;\boldsymbol{x}_i,\boldsymbol{\beta}\right)}\right\} p^{\boldsymbol{c},*}_{\boldsymbol{ij}}\right].$$

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

b. 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:

$$\text{(A5)} \quad \min_{\boldsymbol{\theta}\in\Theta} \frac{1}{T}\sum_{t=1}^{T}\left[\boldsymbol{p}^c_t - \tilde{\boldsymbol{p}}^c_t(\boldsymbol{\theta};\boldsymbol{X}_t)\right]' \boldsymbol{C}^{-1}_t \left[\boldsymbol{p}^c_t - \tilde{\boldsymbol{p}}^c_t(\boldsymbol{\theta};\boldsymbol{X}_t)\right]$$

subject to

(A1)

(A2)

$$\text{(A6)} \quad RSUP_i - \sum_j q^c_{ij}\left(\boldsymbol{p}^c_i;\boldsymbol{x}_i,\boldsymbol{\beta}\right) \geq 0 \forall i.$$

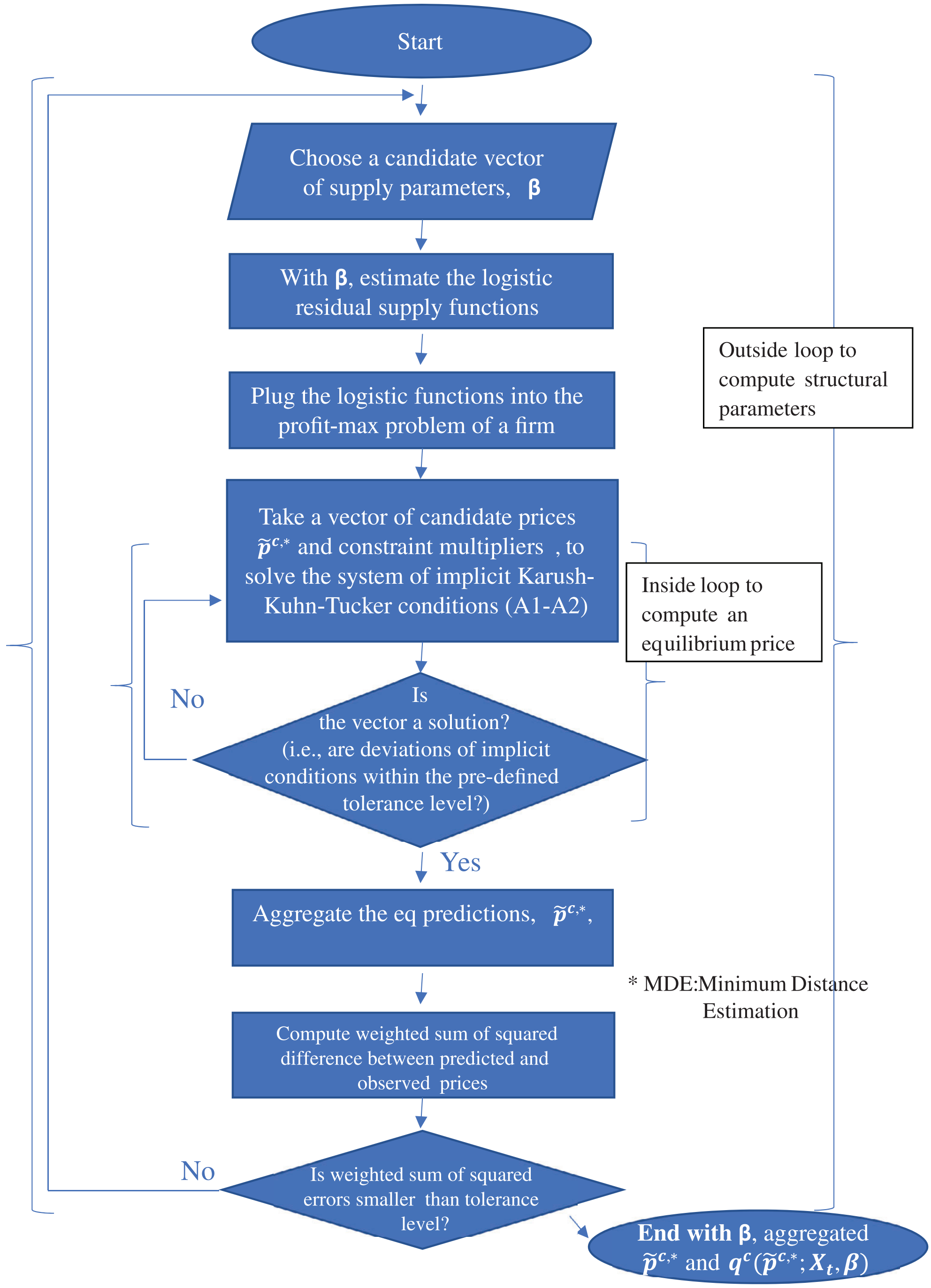
Constraints (A1) and (A2) guarantee that predicted prices are computed based on Nash equilibrium plant-county prices calculated as a mixed complementary program (MCP). Therefore, the problem above has a Mathematical Programming with Equilibrium Constraints (***MPEC***) structure. Equation (A6) adds to 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[17] 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.

Appendix B. Algorithm of the Iterative Parameter Estimation

The estimation process involves an inner loop and an outer loop (see Figure below). The inner loop solves for the county–plant pairs of prices ($\tilde{\boldsymbol{p}}^c_{ij}$) and quantities ($\tilde{\boldsymbol{q}}^c_{ij}$) for all plants and all counties given the candidate parameters and exogenous variables. It does so in two steps. First, it generates a vector of *firm-level* Karush-Kuhn-Tucker (KKT) conditions

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



in the mixed complementarity problem structure that solves problem (1)–(3). Expressions for the KKT conditions are reported in Appendix A. 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, $\tilde{\boldsymbol{p}}^c_{ijt}(\boldsymbol{\theta}; \boldsymbol{X}_t)$, 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, $\tilde{\boldsymbol{q}}^c_{ijt}(\boldsymbol{\theta};\boldsymbol{X}_t)$. 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 $\tilde{\boldsymbol{p}}^c_{it}(\boldsymbol{\theta};\boldsymbol{X}_t)$ is obtained: $\tilde{\boldsymbol{p}}^c_{it}(\boldsymbol{\theta};\boldsymbol{X}_t) = \sum_j \left(\frac{\tilde{\boldsymbol{q}}^c_{ijt}(\boldsymbol{\theta};\boldsymbol{X}_t)}{\sum_j \tilde{\boldsymbol{q}}^c_{ijt}(\boldsymbol{\theta};\boldsymbol{X}_t)} \right) \tilde{\boldsymbol{p}}^c_{ijt}(\boldsymbol{\theta};\boldsymbol{X}_t)$. These county-level price predictions are then stacked in vector $\tilde{\boldsymbol{p}}^c_t(\boldsymbol{\theta};\boldsymbol{X}_t)$ of equation (8). The outer loop minimizes the distance between the observed prices and the predicted price equilibria by iterating over the candidate parameters in $\boldsymbol{\theta}$. The conditions are stacked, and the estimator (see equation (8)) compares the aggregated equilibrium predictions $\tilde{\boldsymbol{p}}^c_t(\boldsymbol{\theta};\boldsymbol{X}_t)$ to the empirical analogs in the dataset $\boldsymbol{p}^c_t$. These comparisons yield total annual deviations between predicted market outcomes and their empirical analogs. The minimum distance estimator minimizes the sum of squared errors.

Appendix C. Merger Simulation in our Empirical Model

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 $\frac{\partial q^c_{ij}(\boldsymbol{p}^c_i;\boldsymbol{x}_i,\boldsymbol{\beta})}{\partial p_{ik}}$ in the ownership matrix $\boldsymbol{\Omega}(\boldsymbol{p}^c)$, which is a critical element of firms' first-order conditions (as shown in equation (A3), Appendix A). Please see Appendix A for a detailed description of this matrix and its elements. 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, on the other hand, 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 corresponding element of the ownership matrix. Therefore, in our empirical model, a merger is captured by a change in the corresponding elements of the ownership matrix $\boldsymbol{\Omega}(\boldsymbol{p}^c)$ from 0 to 1. As indicated in the Karush-Kuhn-Tucker conditions in Appendix A, this change in ownership structure will induce the firm to consider the cross-price effect imposed upon other plants also owned by the firm. Because cross-price effects $\frac{\partial q^c_{ij}(\boldsymbol{p}^c_i;\boldsymbol{x}_i,\boldsymbol{\beta})}{\partial p_{ik}}$ are larger for plants located in close proximity, the change in equilibrium prices and shipments will be larger when merging plants are located in close proximity. This is the reason why the post-merger counterfactual equilibrium will vary depending on the distance (i.e., subject to the degree of spatial differentiation) between merging plants.