Spatial Differentiation and Market Power in Input Procurement: Evidence from the Corn Market

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Abstract: We estimate the degree of spatial differentiation among downstream firms that buy corn from upstream farmers and examine whether such differentiation confers market power upon buyers, defined as the ability to pay a price for corn that is below its marginal value product. We estimate a structural model of spatial competition using corn procurement data from the U.S. State of Indiana over 2004-2014. We adopt a strategy that allows us to estimate firm-level structural parameters while using aggregate data. Our results return a transportation cost of 0.12 cents per bushel per mile (5% of the corn price under average distance traveled), which provides evidence of spatial differentiation among buyers. The estimated average markdown is \$0.80 per bushel (16% of average corn price in the sample), of which \$0.35 is explained by spatial differentiation and the rest by the fact that firms operated under binding capacity constraints. We also find that corn prices paid to farmers at the mill gate are independent of distance between the plant and the farm, indicating that firms do not engage spatial price discrimination. Finally, we evaluate the effect of a hypothetical merger on input markets and farm surplus. A merger between nearby ethanol producers eases competition and increases markdowns by \$0.14 or 20% and triggers a sizable reduction in farm surplus. In contrast, a merger between distant procurers has little effect on competition and markdowns.

Keywords: Buyer Power, Corn, Merger Price Discrimination, Spatial Differentiation, Transportation Costs.

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

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Many markets are characterized by spatially differentiated firms where agents must pay transportation costs to purchase goods. Seminal theoretical contributions have shown that transportation costs and spatial differentiation can have significant effects on competition and welfare (see Hotelling (1929), Salop (1979), and Anderson and de Palma (1988)). Empirical studies provide evidence that spatial differentiation and transportation costs can soften competition and increase market power, having an effect on prices and surpluses (see Porter and Zona (1999), Inderst and Valletti (2009), and Miller and Osborne (2014)). Spatial differentiation formed the center of many policy debates and attracted much attention among antitrust authorities. Most empirical studies devoted their attention to measuring the competitive effect in downstream markets, such as the retail gasoline markets, the cement market, and the automotive market, among others. Until now, however, little work has focused on spatial differentiation and competition in input markets or agricultural procurement markets, where downstream firms may exert market power when buying inputs from upstream sellers.

This study focuses on agricultural procurement markets; markets in which downstream firms purchase products from upstream farmers to use as inputs in their production processes. These markets are characterized by large and spatially dispersed processors purchasing farm products from small, uniformly distributed farmers. Moreover, transportation from the farms to the plants is costly due to the bulky and/or perishable nature of farm products. These features of agricultural procurement markets have led researchers to routinely assert, despite scant empirical evidence, that spatial differentiation among agricultural processors may soften competition, possibly allowing firms to price inputs below their marginal value product; in other words, allowing firms to engage in input price markdown (e.g. Rogers and Sexton 1994; Graubner et al. 2011; Richards et al. 2013; Durham and Sexton 1992). The extent to which buyer power, markdowns, and surpluses are determined by transportation costs and the degree of spatial differentiation among buyers of farm products is an empirical question, which we address in our study.

We consider a market in which oligopsonistic downstream firms buy corn from farmers. The downstream firms are spatially differentiated such that, all else constant, farmers find it more convenient to sell to nearby firms because of reduced transportation cost. We empirically examine whether spatial differentiation allows firms to suppress corn prices below a competitive benchmark (the input's value of marginal product net of processing cost). A further aspect we address in our study is whether transportation costs and spatial differentiation allows downstream firms to discriminate among farmers. For example, a corn buyer could pay a much lower corn price to a farmer that is closely located to its own plant, since it requires the farmer to pay a low transportation cost. If the farmer delivered a more distant competitor's plant it had to pay a higher transportation cost. The additional transportation cost that a farmer had to pay to serve the more distant plants can serve a reference point for the nearby plant to engage in price discrimination and offer a low mill price. In this case, input prices are chosen as a function of geographic distance between sellers and buyers. Concerns regarding price discrimination in agricultural procurement markets percolated through regulatory interventions including the Robinson-Patman Act (O'Brien and Shaffer, 1994), and the Grain Inspection, Packers, and Stockyards Administration (GIPSA), among others.

We estimate a structural model that consists of downstream firms–i.e., corn processors including ethanol firms and wet-milling food producers–buying an input (corn) from upstream firms (farmers), while accounting for a competitive fringe comprised of livestock producers, dry-milling food processors, and exporters. Ethanol and wet-milling firms set input prices paid to farmers and farmers pay the transportation cost to ship the corn to buyers. Prices paid by buyers to different farmers will then be influenced by supply conditions, transportation cost, competition from other plants, and capacity constraints. The goal of our structural approach is to explicitly estimate transportation costs, firm-level production cost parameters and parameters of the residual supply faced by buyers, which are necessary for computation of price markdowns in the presence of spatial competition. We also conduct two counterfactual experiments to characterize the spatial differentiation aspect. First, we evaluate the effects of changes in market structure (through number of firms) on markdowns and surplus. Second, we evaluate the effects of two hypothetical *mergers* that differ in the distance between merging firms and therefore further explore the impact of spatial competition on prices, markdowns, and surplus.

The empirical estimation of parameters necessary to compute markdowns in our structural model is challenging since input prices paid by individual firms are privately negotiated and hardly 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 data. The estimation strategy consists of adopting firm-level optimization routines to compute predictions on plant-level, spatially explicit input prices and shipments. These predictions are aggregated to the level of data availability such that demand, and supply parameters can be estimated that rationalize the data.

In this study, we use aggregate (county-level) information on corn prices and production 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; i.e., a few large processors (oligopsonists) that purchase corn from a large number of producers who pay transportation cost to deliver products to the buyers. Second, large processors in Indiana are relatively insulated (more so than their counterparts in Illinois, Iowa, or Nebraska) from other large processors in neighboring states, though they are likely to compete among themselves (more so than their counterparts in Minnesota, Ohio, or Wisconsin). Finally, the corn market in Indiana has remained unaffected by mergers among corn processors compared to other states. This allows us to retrieve estimates that are unconfounded by merger activity and mostly identified by spatial competition.

Our data provide evidence for corn being shipped for up to 100 miles. The estimation results return a transportation cost of 0.12 cents per bushel per mile (5% of the corn price for average shipping distance), which provides evidence for spatial differentiation among buyers. This transportation cost softens competition and allows corn processors to exert a significant amount of buyer power and attain an input price markdown of $0.80 per bushel (16% of the corn price). Our results also show that firms often set prices under binding capacity constraints confirming the existence of Bertrand-Edgeworth competition. Once capacity constraints are binding, markdown increases. We also find that corn prices paid by buyers to farmers are independent of distance, which confirms that firms do not engage spatial price discrimination.

Finally, we conduct counterfactual experiments on consolidation among ethanol plants, a prominent trend in the industry in recent years. Our results indicate that a merger between nearby ethanol plants eases competition and increases markdowns attained by merging firms by $0.14 or

20%. We also find that the impact of the merger is not circumscribed to merging plants; the merger triggers anti-competitive spillovers that increase markdown by non-merging firms, though to a lesser extent than merging ones. Consequently, we find that mergers reduce farmers' surplus and it does so beyond a geographically confined area around the merging firms suggesting strong spatial spillovers. In contrast, a merger between distant ethanol plants has little effect on competition and markdowns. Our results clearly indicate that the market and welfare effects of a merger depend upon the degree of rivalry between merging firms, which is determined by their degree of spatial differentiation.

Our study is related to work on spatial differentiation in fast-food restaurants (Thomadsen 2005), movie theaters (Davis 2006), coffee shops (McManus 2007), and retail gasoline (Houde 2012). It also closely relates to Durham and Sexton (1992) in that it estimates residual supplies faced by agricultural processors but follows an estimation strategy similar to Miller and Osborne (2014) which allows estimation of firm-level parameters. Their work, however, concentrates on pricing in downstream markets, i.e., the cement industry. Other, prominent contributions that focus on buying power in the corn procurement market include Saitone, Sexton, and Sexton (2008) and Wang et al. (2019). The main differentiating attribute of our paper relative to these studies is that we do not *impose* buying power but rather estimate the degree of buying power based on a structural model. In this sense, our study contributes to a rich empirical literature on buying 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 estimates spatial differentiation as a source of buying power and examines the role of spatial competition in shaping anti-competitive behavior. Our findings are consistent, though much larger, than those from Bonnano and Lopez (2010), who estimate that Walmart pays an average markdown of 2 percent in labor markets.

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 the U.S. State of Indiana. We identify 4 market features that will constitute the foundation for our empirical structural model.

We use county-level corn prices that are purchased from Geo Grain. Geo Grain records corn prices at multiple elevator locations across the State. These data provide full coverage of the Indiana's territory. We use local cash corn price instead of basis (as it is common in other studies of spatial price patterns of corn) because our model does not generate a predicted forward price (e.g. Chicago Board of Trade) since it is instead, designed to model local conditions. We also use information on location, capacity, and ownership of large 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 large plants and county centroids. We also gathered data on supply shifters; including distance between exporting ports and county centroids, and corn requirements by the livestock and dry-milling sectors in each county.

We obtained data on corn production, corn storage, and livestock inventory from the National Agricultural Statistics Service of the United States Department of Agriculture (NASS, USDA). Information on corn exports and international prices are taken from the Economic Research Service (ERS), USDA and the Federal Reserve Bank of St. Louis (FRED), respectively. The information on ethanol plants' location, ownership, capacity, and year built comes from the Official Nebraska Government (ONG), the Renewable Fuel Association (RFA), the U.S.

Environmental Information Administration (EIA), and the Biofuel Atlas published by the National Renewable Energy Laboratory (NREL). Information on wet- and dry-milling food processors' capacities and locations is based on Hurt (2012) and personal communications with the author. Historical diesel and electricity prices are obtained from the EIA. Distances are calculated using Arc-GIS.

Information provided in Table 1 portrays an aggregate picture of the corn market in Indiana. The upper panel of Table 1 shows the presence of 5 destinations for Indiana corn: ethanol, wet-milling, dry-milling, livestock, exports, and storage. This panel reports the shares of corn supplied annually in Indiana sold to each of these sectors during our period of analysis (2004-2014). The middle panel of Table 1 describes the sources of corn supply in Indiana for each year. These figures show that most of corn supply in any given year, comes from production in that year. However, supply from storage can amount to up to 10% of total supply.

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

Corn farmers typically ship corn to their buyers in trucks (Denicoff et al., 2014; Adam and Marathon, 2015) since plants source corn locally and trucking is less costly than other forms of transportation within relatively short distances (i.e., below 500 miles). According to the Grain Truck and Ocean Rate (GTOR) report from USDA, the transportation rate of grains in the North

Central region[1] inclusive of Indiana on the 1st quarter of 2016 was 0.23 cents, 0.14 cents, and 0.11 cents per bushel-mile for 25, 100, and 200 miles, respectively.[2] At an average closing corn price of $3.5 per bushel in 2016, this means that transportation costs amounted to about 2 to 6% of price within these distances. This underscores the importance of transportation cost and suggests a possible geographical localization of corn procurement markets; i.e., plants tend to source corn locally.

Notwithstanding its importance in limiting the geographical boundaries of procurement markets, transportation cost is not by itself sufficient to soften competition. Rather, localization must occur in combination with the presence of a few dominant buyers with a large share of the local procurement market. Information reported in Table 2 reveals that ethanol plants and wet-milling processors are quite large, while individual livestock operations and dry-millers are not. On average, ethanol plants and wet milling plants are 4,000 times larger than an individual livestock operator and 6 to 10 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 indicate that most of these plants (88%) have an annual corn processing capacity larger than all the corn produced in the county where they are located. Ratios for many of these plants in several years 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 US (McNew and Griffith 2005) and Indiana in particular (Jung et al. 2019) found a positive effect of plant sitting on corn prices, but

[1] The North Central region in the GTOR report includes North and South Dakota, Nebraska, Kansas, Minnesota, Iowa, Missouri, Wisconsin, Illinois, Michigan, Indiana, Kentucky, Tennessee, and Ohio.
[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.

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 suppliers a price above their opportunity cost (best bid from other procurement sectors including livestock, dry millers, or exporting companies) to re-direct enough corn towards them. The dissipation of the price effect with distance is also consistent with geographically localized procurement markets. We summarize our discussion in:

> **Market Feature 1***: Ethanol and wet-milling plants purchase a large fraction of corn from farmers that are located in close proximity to them.*

The sheer size of these plants relative to local supply also suggests they have to travel considerable distances to procure enough input which likely results in spatial overlap of procurement regions, especially when plants are spatially clustered. Figure 1 shows the locational pattern of ethanol plants (yellow circles) and wet-milling plants (red circles), as well as the spatial pattern of corn productions in Indiana in 2014. This figure reveals substantial differences in spatial clustering of ethanol plants. As local market conditions for ethanol vary widely, so will 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). This leads to:

> **Market Feature 2:** *Ethanol and wet-milling firms are large buyers (oligopsonists), possibly exerting market power. Dry-milling firms, livestock operators, and the export sector are smaller buyers acting as a competitive fringe*.

Another important empirical feature of the corn procurement market is the nature of procurement channels. A portion of the corn produced is sold immediately after harvest, but another portion is stored in elevators and sold throughout the year. Processors buy corn both from farmers and commercial elevators. They also use a mix of spot and contracts. Contracts are usually signed during the growing season and specify a post-harvest delivery date, a quantity, and a per unit price. In addition, large processors may engage in private negotiations with suppliers regarding who pays for the cost of transporting corn to the plant (Hardy et al. 2006). This requires a trading model that can accommodate the whole range of spatial price discrimination (SPD), from free-on-board pricing (no SPD) whereby suppliers pay for the full cost to uniform delivered price (perfect SPD) where the plant fully absorbs transportation cost.

The composition of procurement channels matters because our estimation is based on spot market-level data; i.e. cash prices. Therefore, systematic and significant deviations of contract prices from spot markets, in combination with substantial procurement through contracts, would introduce significant measurement error in market-level prices which can introduce bias in our parameter estimates. We consider the use of spot prices to be reasonable for two reasons. First, a large fraction of corn procured by the processors is purchased in spot markets. Contracts are commonly used by processors 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 products storage (e.g., Schill (2016)).[3] Second, corn futures markets are highly liquid with efficient price discovery mechanisms which causes convergence, albeit partial, of forward prices to spot prices, limiting *systematic* deviations of contract prices from spot prices in subsequent months. This information is summarized by:

[3] According to Schill 2016, the use of hedging also reduces upside profit potential, which further limits the use of contracts.

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

We now turn our attention to market conditions under which oligopsonists sell their processed products. Regarding ethanol plants selling their product in gasoline markets, it is important to note that concentration by sales in the ethanol industry is small (as documented by the Federal Trade Commission's 2018 Report on Ethanol Market Concentration). Also, ethanol prices follow gasoline prices and the prices of byproducts produced by ethanol firms (called distillers grains with solubles or DDGS) follow corn prices. Therefore, ethanol producers have no market power downstream, either in the gasoline or byproduct markets. Turning to wet-milling firms, they sell their products to processed food and beverage companies, the meat industry, and a range of food and non-food consumers of corn starch. There is no evidence of market power exertion by wet-millers in selling their products (Coltrain et al., (2004); Hettinga et al., (2009)). Finally, corn buyers that belong to the competitive fringe (dry millers, livestock oeprators, and the export sector) are price-takers in corn procurement. These facts determine the following feature:

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

In Figure 3, we map the spatial structure of processing plants (yellow dots) and county-level corn prices (color brightness) in 2014, the last year in our sample. The map shows a positive correlation between the location of large processors (oligopsonists) and corn prices in each year. This pattern applies 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 prices of corn. Consistent with Market Feature 2, these areas are located close to exporting ports (plotted as green dots in Figure 3), which cause 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 consists of a set of equations that describe firms' selling and buying behavior. On the supply side, we consider farmers that sell corn for plant-specific prices to ethanol plants (among other alternatives). On the demand side, we consider ethanol plants that act as oligopsonists. Corn buyers offer specific prices to different farmers that are dependent on their locations. The corn buyers' profit optimality conditions characterize optimal corn prices that are specific to every corn seller and dependent on the distances between every corn buyer and corn seller. 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 county-level data. Our estimation algorithm returns optimally predicted corn prices and quantities at the ethanol-firm level, firm-level capacity utilization rates, and parameter estimates that characterize marginal processing costs. On the sellers' side, we estimate the transportation costs, which reflect spatial differentiation and competition.

The estimated structural parameters enable us to compute firms' markdowns and to evaluate the degree of spatial competition. Finally, we conduct counterfactual experiments in which we evaluate the effects of changes in market structure (through changes in number of firms and mergers) on prices and the corn sellers' surplus while taking the spatial aspect of the market into consideration.

Downstream Firms (Ethanol and Wet-Milling Firms)

The empirical model we develop here closely 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 oligoposonistic market in which large downstream firms (buyers) purchase from small upstream firms (sellers) and are spatially differentiated, such that buyers will source corn locally depending on transportation cost. In our model, oligopsonists compete with each other but also with a competitive fringe composed of dry-millers, livestock producers, and exports, as documented in *Market Feature 2*. We also model ethanol producers and wet-millers as price-setting firms and allow these firms to engage in spatial price discrimination by setting different prices to different sellers such that markdown may vary across sellers, closely mimicking *Market Feature 3*. Finally, and reflecting *Market Feature 4,* we assume ethanol plants and wet-millers do not exert market power downstream and operate under capacity constraints that may or may not be binding depending on market conditions.

Every oligopsonistic firm *(F)* may own multiple plants (j). The firm determines for every plant the corn price p_{ijt}^{c} (the superscript *C* refers to corn and the subscript *t* refers to the time period) that is paid to suppliers (farmers) located in county i=1,…,92 in Indiana.[4] The firm-specific vector

[4] For notational simplicity, we drop the time subscript.

of corn prices $\boldsymbol{p_F^c}$ contains as its elements the county-specific corn prices p_{ij}^c that are offered by every plant to every county. The quantity of corn demanded and processed by 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 every county i, $\boldsymbol{x}_i$ is a vector of demand shifters that captures procurement from the competitive fringe, and $\boldsymbol{\beta}$ is a vector of parameters to be estimated.

Oligopsonists maximize profits every period while determining the optimal corn prices offered by every plant to famers in every county:

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

$$\sum_{j \in IN_F^P} FC_j - \sum_{j \in IN_F^P} \int_0^{Q_j^h} mc\left(Q; \boldsymbol{w}_j, \boldsymbol{\xi}\right) dQ \qquad (1)$$

subject to

$$\alpha^h \sum_{i \in IN^C} q_{ij}^c(\boldsymbol{p}_i^c; \boldsymbol{x}_i, \boldsymbol{\beta}) \leq CAP_j \qquad \forall j \in IN_F^P \qquad (2)$$

$$\sum_{j \in IN^P} q_{ij}^c(\boldsymbol{p}_i^c; \boldsymbol{x}_i, \boldsymbol{\beta}) \leq RSUP_i \qquad \forall i \in IN^C \qquad (3)$$

The first term in the first line of equation (1), $(P^h * \alpha^h * \sum_i \sum_j q_{ij}^c(\boldsymbol{p}_i^c; \boldsymbol{x}_i, \boldsymbol{\beta}))$, is the firm's revenue from selling the processed products denoted by h ($h = eth$ for ethanol, or $h = wm$ for wet millers' 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.

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

The second through fourth terms in the right-hand side of equation (1) represent cost components. The second term, $(\sum_i \sum_j p_{ij}^c q_{ij}^c(\boldsymbol{p}_i^c; \boldsymbol{x}_i, \boldsymbol{\beta}))$, represents the firm's total costs from buying corn as an input. The third term in equation (1), $\sum_{j \in IN_F^P} FC_j$, are the annualized costs of construction or installation and are summed across plants owned by that firm.

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

Note that our model also allows for capacity constraints, which is a distinctive feature of corn processors. We specify the marginal processing cost function as:

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

Equation (4) allows marginal processing cost to depend on capacity utilization $\frac{\alpha^h \sum_i q_{ij}^c(p_i^c; \boldsymbol{x}_i, \boldsymbol{\beta})}{CAP_j}$. If γ is positive (negative) plants display economies (diseconomies) of capacity utilization, and if γ is zero plants operate under constant marginal processing cost.

Inequality (2) ensures that production by plant *j* is not higher than what is technologically possible to produce in any given year (CAP_j denotes capacity of plant *j*). Finally, inequality (3) ensures that corn purchased by all plants does not surpass the available amount of corn from a county (production plus storage minus demand from the fringe). $RSUP_i$ refers to the residual corn supply from farmers in each county, i.e., it is the sum of annual corn production and the stock of corn in storage minus demand from fringe.

The solution to the optimization problem, as shown in equations (1)-(3), consists of a system of Karush-Kuhn-Tucker conditions fully characterized in Appendix B.

Upstream Firms (Farmers)

We consider corn supply sold to each county in equilibrium. Total corn supply in each period is determined by production and inventories carried over from previous years. Inventories are shaped by previous season's weather and production is determined by planted acres and growing season weather. Planted acres are largely driven by world market conditions that determine expected price of corn relative to other crops, which we do not model but take as given. While oligopsonists' pricing may have an effect on local planted acres (e.g., Wang et al. 2019), its relation to production is much weaker due to the mediating role of growing season weather. In addition, modeling firms' internalization of the effect of pricing on future planted acres and supply would greatly increase the mathematical and computational burden in our analysis. It would require modeling and solving a large dynamic pricing game, possibly rendering a solution intractable. We abstract away from such considerations and focus on a model of shipments and short-run supplies.

Our model predicts corn supplied by each country to each procurement firm. It builds on two premises: First, suppliers can sell corn to one of three sectors: oligopsonists, local competitive fringe (dry-millers and livestock producers), and exports. Second, sectors other than oligopsonists do not exert market power. Both of these premises are motivated by *Market Feature 1*. Previous studies have documented that corn demand from the local competitive fringe can be quite inelastic, especially from its larger source, livestock operators (Suh and Moss, 2017). Therefore, we simply subtract that from 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 in 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 and price discrimination.

Suppliers obtain value from selling corn to plant j, where $j = 1, \dots, J$ if the plant is owned by an oligopsonist firm, and $j = J + 1$ if the plant is an exporting port. The corn price for exports is determined by the international price. The suppliers have to pay the transportation cost. In terms of exports, the transportation cost is determined by the distance from the county's centroid to the closest exporting port. The value function of supplier n in county i, associated with selling her corn to plant j is given as:

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

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

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

$$S_{ij}(\boldsymbol{p}_i^c; \boldsymbol{x}_i, \boldsymbol{\beta}) = Prob(Y_n = j) = \frac{\exp(\boldsymbol{x}_i'\boldsymbol{\beta})}{\sum_{j=1}^{J+1}\exp(\boldsymbol{x}_i'\boldsymbol{\beta})}, \tag{6}$$

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:

$$q_{ij}^c(\boldsymbol{p}_i^c; \boldsymbol{x}_i, \boldsymbol{\beta}) = S_{ij}(\boldsymbol{p}_i^c; \boldsymbol{x}_i, \boldsymbol{\beta}) * RSUP_i \tag{7}$$

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

We turn to explaining the estimation strategy.

Estimation Strategy

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

We employ a multinomial logit system for estimation of the farmers' supply equation (6), which has several advantages. 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 suppliers' responses to prices making the aggregate supply response smooth to changes in corn prices. Otherwise, small changes in price 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 pre-determined radius. This is important in our study since plants purchase corn from distant sellers (beyond 100 miles in some cases).

Next, we use the multinomial logit supply (as shown in equation (6)) and the oligopsonists' profit maximization objective (as shown in equations (1)-(3)) to generate price predictions based on the set of candidate parameters. Those are closely matched with the observed prices applying a Minimum Distance Estimator while iterating over parameters: [6]

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

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

where Θ is a compact parameter space, and $\boldsymbol{C}_t^{-1}$ is an identity matrix, which is not only a positive definite matrix, but also includes uniformly weights equations defined in the vector $\boldsymbol{p}_t^c - \widetilde{\boldsymbol{p}}_t^c(\boldsymbol{\theta}; \boldsymbol{Y}_t)$. We denote the vector of observed county-level prices in period t by $\boldsymbol{p}_t^c$. We denote the predicted, county-level prices by $\widetilde{\boldsymbol{p}}_t^c(\boldsymbol{\theta}; \boldsymbol{X}_t)$, where $\boldsymbol{\theta} = [\,\boldsymbol{\alpha}, \boldsymbol{\beta}]'$ is a vector of parameter values, and $\boldsymbol{X_t}$ is a vector of 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 solves for the prices and quantities given the candidate parameters and exogenous variables. It does so by generating a vector of *firm-level* Karush-Kuhn-Tucker conditions in the Mixed Complementarity Problem structure. The outer loop minimizes the distance between the observed and predicted equilibria by iterating over the candidate parameters in $\boldsymbol{\theta}$. The iterative estimation algorithm is relegated to *Appendix A*. We use the MPEC modeling strategy, as suggested by Su and Judd (2012)[7], and implement the double loop structure in the General Algebraic Modeling System (GAMS) software.[8] This increases ease of computation preventing common nonconvergence and infeasibility issues.

Identification

We consider 92 counties in Indiana over a 11- year time horizon, such that equation (8) includes 92x11=1,012 aggregated equilibrium predictions. Identification proceeds based on these 1,012

[7] We summarize the economic model of MPEC in *Appendix B*.
[8] The GAMS programming code is available from authors upon request.

non-linear conditions stacked in equation (8). The solution to the oligopsonists' optimization problem, equations (1)-(3), is characterized by the Karush-Kuhn-Tucker conditions in Appendix B and constitutes the inner loop. It generates *JxN* predictions of *firm-level* equilibrium prices $\tilde{\boldsymbol{p}}_{i,t}^{c}(\boldsymbol{\theta}; \boldsymbol{X}_t)$ (a price offered by each plant to each county in each period), which are functions of data and candidate parameters.

The corn prices offered by all plants to each county are weighted using the corresponding procurement shares (which are endogenously determined in equilibrium) such that an aggregate, predicted county-level price $\tilde{\boldsymbol{p}}_{t}^{c}(\boldsymbol{\theta}; \boldsymbol{X}_t)$ is obtained. We compare the aggregated equilibrium predictions to the empirical analogs in the dataset. These comparisons yield total annual deviations between predicted market outcomes and their empirical analogs. The Minimum Distance Estimator minimizes the sum of squared errors. Therefore, 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 vector $\boldsymbol{\theta}$ contains parameters in farmers' supply equation ($\boldsymbol{\beta}$), along with the parameters characterizing marginal cost of processing corn ($\boldsymbol{\alpha}$).

The price coefficient β^p is, as revealed by Karush-Kuhn-Tucker conditions in Appendix B, achieved primarily based on the correlation between county-level prices and the joint variation of ethanol 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. Both of these vary cross-sectionally and over time. The parameter β^e is identified by the correlation between distance to exporting port and corn prices. The former varies only cross-sectionally, so this parameter is identified based on cross-sectional variation.

Marginal cost parameters included in vector $\boldsymbol{\alpha}$ are determined by the correlation between natural gas price and corn price (α_{ng}), electricity price and corn price (α_{el}), and finally time and corn price (α_t). As noted in our description of the industry (Figure 4), 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 4 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 of corn price until 2012 with a reversal afterwards.

Estimation Results

In this section, we present the results of the famers' and the oligopsonists' estimation equations and compute derived statistics that govern our market and surplus predictions. We validate these results based on their ability to generate observed data, and against other estimates previously available from the literature.

The Upstream Firms (Farmers)

Parameter estimates of the corn residual supply, characterized in equation (7), are reported in the upper panel of Table 4.[9] The positive coefficient on the export dummy variable implies that proximity to an exporting port causes an upward shift in the farmers' supply; in other words, exports present a significant shifter in residual supply, consistent with our discussion of Figure 3.[10]

[9] All standard errors, as shown in Table 4, are bootstrapped.

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

The estimated coefficient for corn price (β^p) is significant and positive. The positive and statistically significant coefficient is indicative of a "business stealing" effect, whereby a firm can divert corn away from its competitors and towards itself by offering a higher price to farmers. The negative estimated coefficient for transportation distance (β^d) shows that, all else constant, farmers supply less to plants located farther away. This is expected since a larger distance makes it more costly for farmers to deliver corn, and the famers' opportunities to deliver to alternative competing ethanol plants increases.

The transportation cost, a derived statistic which can be computed as the ratio between the parameters (β^d/β^p), is equal to 0.12 cents per bushel per mile. Under average predicted distance traveled and average predicted price paid by plants in our model, this amounts to about 5% of corn price. It should be noted that our estimated corn transportation cost is very close to the average cost estimate (within 200 miles) of 0.16 cents as reported by GTOR. The GTOR estimate is an average for the entire North-Central region, which may explain the small deviations from our transportation costs that are specific to Indiana. One potential explanation is that road infrastructure and diesel prices in the North-Central region States differ from Indiana.

Transportation cost forces firms to raise the price they offer for corn to secure larger amounts. This results in oligopsonists facing upward sloping residual corn supplies. Our parameter estimates translate into a firm-level residual indirect supply elasticity of 0.065 (significant at the 1% level). This is calculated as the average of elasticities 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 would increase by about 30 cents at the plant's gate (from \$5/bushel to about \$5.30/bushel, or 6.5%).[11]

The Downstream Firms (Ethanol and Wet-Milling Firms)

Parameter estimates of the cost structure of ethanol and wet-milling firms', characterized in equation (4), are reported in the middle panel of Table 4. The coefficients for natural gas prices (α^{ng}) and electricity prices (α^{elec}) suggest these are important cost shifters; i.e. an increase in input prices rises marginal processing cost, especially for natural gas which is consistent with the fact that expenditures on natural gas are larger as a share of total cost than expenditures on electricity. The negative estimated coefficient for the time trend (α^{time}) shows that plants have become more efficient over time. Our cost parameter estimates combine to generate an average processing cost of \$1.62 per gallon, which falls within the range of estimates (around \$1.35 per gallon) reported in Perrin et al. (2009) and Irwin (2018).

Finally, parameter γ measures the change in marginal processing cost per unit of unutilized capacity. The estimate is not statistically significantly different from zero, which suggests a constant marginal processing cost. Constant marginal processing cost is consistent with widely held assumptions in the literature (e.g. Gallagher et al 2005; Perrin et al. 2009) but differ from findings in Sesmero et al. (2016).[12] Our estimated capacity utilization ratio amounts to 0.98, which is close to the ratios reported by Dale and Tyner (2006). In general, our empirical model predicts

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

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

revenues and profits of ethanol plants that are within the range published in financial reports (e.g., Green Plains Renewable Energy) and other independent reports (see Irwin (2018)).

Validation of our results against available anecdotal or statistical evidence, lends credence to our parameter estimates. But since identification is based on matching between predicted and observed equilibrium prices, perhaps the most important validation exercise is related to our estimated model's ability to generate accurate price predictions. Figure 5 shows the predicted and observed farm-gate prices across counties and over time. Each dot represents a combination of a price observed in a specific county in a given year, and the price predicted by our model in that county for that same year. Dots fragment into clusters due to the fact that prices differ substantially across years. The figure illustrates that our structural model does a remarkable job of generating observed data. In fact, the correlation between predicted and observed prices is close to 0.99. The high correlation supports our model's goodness of fit. It should be noted that our empirical model appears to slightly over-predict prices when observed prices are uncharacteristically low or high in our sample. This is less of a concern in our case, however, since we conduct counterfactual experiments around mean conditions, where our model seems to perform best.

Corn Prices and Markdowns over Time

In the following, we predict plant-county pair prices paid by ethanol and wet-milling plants and compare these to the VMP of corn (net of marginal processing cost) to calculate markdown. Figure 6 portrays a substantial average price markdown over the study period. The average markdown is around $0.80 per bushel, or 16% of the average corn price (approximately $5/bushel). To put this markdown in context, we note that plants' fixed cost is typically around $0.60 per bushel (see Irwin 2018). Therefore, while, on average, corn price markdown may have allowed plants to push average variable cost below output price during this period, they are likely to have experienced economic losses in some periods once fixed costs are considered. This is especially true in years like 2012 where a historical drought pushed $RSUP_i$s down (i.e. pushed inverse residual supplies upwards) increasing corn purchase cost for all firms.

As it is also clear from Figure 6, average markdown levels vary widely over time (they drop significantly from 2006 to 2012 and then recover). Fluctuations over time are mostly explained by macroeconomic factors affecting the price of corn, and largely absorbed by $RSUP_i$s in our model. Nevertheless, conditional on residual supply, our model also finds substantial variation of markdown across plants within a year, as suggested by minimum and maximum markdown curves in Figure 6. The difference between largest and smallest markdown in a year averages 50 cents per bushel over the study period but varies from almost no variation in 2012 to $1 in 2009. Other derived statistics estimated and reported in Table 4 shed light on the factors underpinning variation of markdown across firms.

In our context, variation of markdown across firms may be explained by spatial differentiation (which causes firms to face an upward sloping input residual supply, creating a wedge between marginal factor cost and input supply) or by binding capacity constraints (which create a wedge between value of marginal product and input supply). Our results indicate oligopsonists do face an upward sloping residual input supply as indicated by a positive and statistically significant elasticity of residual corn supply reported in Table 4. But our results also reveal that most firms operate at full capacity during most of the study period, as indicated by a high average capacity utilization rate (0.98), also reported in Table 4.

Therefore, a salient feature of this market is that the trading environment implied by our estimates is consistent with a Bertrand-Edgeworth oligopsony with spatially differentiated downstream buyers. In Figure 7, we provide a graphical representation of markdown for an individual firm in this context. A profit-maximizing oligopsonist will operate at the level of production for which the value of marginal product is equal to marginal factor cost. Markdown is equal to the distance between value of marginal product and residual supply. However, if capacity is smaller than the profit-maximizing production quantity, then the plant will operate at capacity and markdown is determined by the distance between value of marginal product and residual supply at capacity. By construction, this distance is larger than the wedge between marginal factor cost and residual supply. Therefore, if the value of marginal product of corn is sufficiently low relative to residual supply (e.g. due to a reduction in ethanol price or a bad corn crop), then markdown is determined by spatial differentiation. On the other hand, if marginal product of corn is sufficiently high relative to residual supply, markdown would be driven by capacity constraints. Which situation prevails must be determined empirically.

Our results indicate that, on average, capacity constraints prevail, and markdowns are determined by the distance between value of marginal product and residual supply at capacity. Therefore, as depicted in Figure 7, markdowns are larger than they would be in the absence of those constraints. Specifically, for the average observation in our sample (average across firms and over time), the wedge between value of marginal product and residual supply at capacity is $0.8, while the wedge between supply and marginal factor cost at capacity is $0.34.

Spatial Price Discrimination

An additional concern in our context is whether oligopsonists vary markdown by distance, i.e. whether they engage in spatial price discrimination, which would add another source of deviation from the competitive benchmark. In the absence of spatial price discrimination, the buyer pays the same plant-gate price to all sellers, regardless of their location. Therefore, the price received from a plant by suppliers at the farm-gate (county centroid in our analysis) would decrease linearly with distance from the plant. On the other hand, under spatial price discrimination, buyers pay different mill prices–and consequently achieve different markdowns–to farmers located at varying distances from the plant. Farmers located in close proximity to the plant are paid a lower mill price than (i.e. markdown increases) more distant farmers. Hence, under spatial price discrimination, farmers in close proximity to buyers are paid a farm gate price that lies below the linearly declining price-distance gradient.

Figure 8 displays the predicted price-distance gradient (farm-gate prices received by suppliers located at varying distances from these plants), as well as the linear price-distance gradient for a selected plant. The plant we selected operates under rather average conditions in all important dimensions: ratio of capacity to local supply, and distance to the nearest exporting port and competitors. Our analysis reveals that the firm does not engage in spatial price discrimination, as demonstrated by the absence of deviation of predicted farm-gate prices from the linear price-distance gradient. We have computed these gradients for all firms in our sample, and our finding on the absence of price discrimination, holds for all of them. This indicates that firms to do not price-discriminate regardless of their size, distance to competitors and exporting ports, or conditions under which they operate (livestock and local supply).

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

Spatial Purchase Patterns by Downstream Firms

We examine how corn purchases by ethanol plants evolve with distance, and how competition affects such spatial patterns of procurement. Figure 9 shows the share of total corn purchased by the plant that is bought from farmers located at varying distances. Conditional on parameter estimates, the spatial pattern of purchases is influenced by capacity, geographical distribution of corn production, and local competition. Since these conditions vary across firms, purchases by distance vary across firms. Therefore, we report the purchase-distance relationship for two plants for which operating conditions closely mimic "average" conditions; i.e. the plants display a ratio of capacity to local (county) corn supply close to 2. Moreover, these plants vary over competition intensity which allows us to illustrate the effect of competition on the plants' spatial pattern of procurement. The plant in Cass county faces no nearby competitors, while the plant in Randolph county faces a close competitor.

The figure suggests that ethanol plants procure most of their corn within a distance of 50 miles (as revealed by calculating the area below procurement curves) but likely purchase corn at greater distances. The predicted procurement patterns coincide with previous descriptions of procurement regions under similar corn density conditions (e.g. Kang et al. (2010)). This finding further validates our parameter estimates and lends credence to our analysis. These procurement patterns also support our choice of the logit supply specification. The logit specification allows for overlapping regions, but by imposing that competition is global (all plants purchase a positive amount from all counties), it may lead to over-prediction of competition. However, our estimated model predicts that very little corn is typically sourced from distances farther than 100 miles, suggesting that the risk of over-prediction of competition is limited.

Next, we investigate how competition shapes the spatial pattern of corn purchases. Differences across firms reported in Figure 9 show that the plant facing more competition (there is a competitor in close proximity) are forced to travel greater distances (in the direction of their uncontested markets) to source corn. We note that an increase in plant size relative to local corn supply (which could be explained by plant's expansion, a bad crop, or growth in corn demand shifters like livestock) would have an effect on these curves similar to competition. These factors would then expand the geographical area where farmers are benefited by demand from large processors.

Counterfactual Experiments: Mergers, Markdowns, and Farm Surplus

A key factor underpinning markdowns and farm surplus in our context is the position and slope of the corn residual supply faced by each firm. The residual supply critically depends upon the degree to which firms internalize price externalities. In the following, we evaluate the effects of mergers between ethanol firms.

A change in ownership structure on the downstream market via mergers, can have significant effects on corn demand, prices, and production. The evaluation of mergers is interesting for several reasons. First, merger effects are critically dependent on the spatial distance between the merging ethanol plants. One of the reasons is that ethanol plants determine their input demand and price dependent on the spatial competition (i.e., the distance to their competitors in combination with transportation cost) as well as the counties' residual supply of corn. Since predictions in our model are based on our own structural estimation of transportation cost and spatial differentiation, a merger counterfactual perfectly fits our model environment. Second, large corn processors do not have opportunities to relocate plants (because of prohibitively high costs) and seldom expand capacity, therefore, changes in the ownership structure are popular expansion strategies. In fact, a wave of consolidations virtually doubled the sales-based Herfindahl-Hirschman Index from 260 to 500 in the period 2013-2018, as indicated in the Federal Trade Commission's 2018 Report on Ethanol Market Concentration. But while mergers have been a pervasive feature of the industry in recent years, they have not taken place among plants in Indiana. Consequently, Indiana offers an unconfounded market place for merger simulations, which seem particularly timely given recent trends in other States.

A merger between plants j and k allows the merging firm to internalize competitive externalities that would have not been otherwise internalized. In our model, mergers are simulated by introducing changes in the structure of the ownership matrix $\boldsymbol{\Omega}(\boldsymbol{p}^c)$, a critical element of firms' first order conditions as shown in equation (b3), appendix B.[13] If plant k increases its corn price to county i, it accounts for the shift in the residual supply of corn from that county to plant j, represented by the cross-price effect $\frac{\partial q_{ij}^c(\boldsymbol{p}_i^c;\boldsymbol{x}_i,\boldsymbol{\beta})}{\partial p_{ik}}$ in the ownership matrix. If the firm that owns plant k does not own plant j, then the corresponding element in the ownership matrix is zero. As indicated in the Karush-Kuhn-Tucker conditions in Appendix B, this change in the ownership structure will result in a different Nash equilibrium of the pricing game.

The cross-price effect governing the impact of mergers depends upon spatial differentiation between plants k and j which, in our context, is determined by the distance between plants, transportation cost, and spatial pattern of corn supply. Since merger effects are likely dependent

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

on the degree of spatial differentiation across ethanol plants, we compare the effects of two merger scenarios that differ by the geographical proximity between merging firms. In one scenario, Poet purchases the plant in Randolph county, which is located in close proximity to its other plants in Jay county and Shelby county. In another scenario, Poet purchases a plant in Cass county, which is somewhat near Poet's plant in Wabash county, but isolated from its other plants. Figures 11.a and 11.b show, respectively for each scenario, Poet-owned plants with yellow dots surrounded by red circles. They also show the plant purchased by Poet with a red dot.

Figure 10 reports changes in markdown under both merger scenarios previously described. Our analysis reveals that, all else equal, consolidation with a nearby plant results in substantial increase in markdown. Based on structural parameter estimates, we predict that plants owned by merging firms will increase markdown, on average, by $0.14 or almost 20% of markdown 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 rather by a downward shift in corn residual supply faced by each firm due to internalization of the competitive externalities.

While consolidation between nearby ethanol plants increases markdown by the consolidated firms, it may also trigger competitive spillovers into 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; i.e. non-consolidating firms also attain higher markdown due to the fact that mergers soften competition. In fact, as reported in Figure 10, a non-consolidating firm located 49 miles away of Poet plants increases markdown by

$0.12, and a non-consolidating firm located 103 miles away from Poet plants increases markdown by $0.07.

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 11.a. Lighter colors denote larger reductions in farm surplus due to weaker competition. Some of the largest reductions take place in close proximity to merging firms. But adverse effects on farm surplus extend well beyond the geographical confines of merging plants, revealing strong competitive spillover effects of mergers. Reductions in farm surplus across Indiana vary between $0 and $8 million per county, amounting to roughly a total of $300 million at the State level.

Turning to consolidation of Poet's plants with a distant competitor, this merger has a much smaller effect on markdown by merging firms as reported in Figure 10. A comparison between this and the effects of a merger with a nearby competitor, clearly indicates that the magnitude of the downward shift in corn residual supplies as a result of a merger depends upon the degree of rivalry in procurement between consolidating firms; i.e. depends upon their degree of spatial differentiation. In line with these smaller price effects we find that a merger with a distant competitor results in much smaller effects on farm surplus across the State, as reported in Figure 11.b.

Conclusion

This study conducts an empirical investigation of the existence of spatial oligopsonistic market power and spatial price discrimination in the corn procurement market. We implement a 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, common in our setting. Therefore, our extended framework can accommodate a model of Bertrand competition with differentiated inputs, or a model of Bertrand-Edgeworth competition with binding capacities. While the literature has devoted some attention to models of spatial differentiation in output markets, there is a remarkable lack of empirical evidence on spatial differentiation in input markets. This is particularly relevant for agriculture, since market power exertion by processors buying from farmers, in combination with high cost to transport products from farms to plants, has long concerned researchers and policy makers.

Our counterfactual simulations indicate that the effect of mergers among corn procurement oligopsonists (particularly in the corn ethanol industry, where mergers seem increasingly common) depend 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 non-consolidating, nearby 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. On the other hand, a merger between plants located far apart (farther than 70 miles) is much less consequential for markdown and farm surplus. This suggests that assessment of mergers between corn ethanol firms should explicitly consider the location of plants owned by merging firms. While our primary focus is consolidation counterfactuals, our structural model can be used to also simulate counterfactual scenarios on expansion, entry, and policies. We plan to extend our analysis in these directions.

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 pre-merger equilibrium prices and quantities (i.e. that would offset increased market power effect) after the merger takes place (e.g. Werden-Froeb index) and would thus be acceptable from a regulatory point of view. Our analysis suggests the need for the development of such an index in agricultural procurement markets, which display two distinct features: 1) spatial differentiation, and 2) possibly binding capacity constraints. The development of a regulatory index of this nature seems like a potentially relevant research for both scientists and policy makers.

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Tables

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[1]	3.85	4.00	3.97	10.06	21.15	32.71	34.82	38.46	65.48	38.65	37.86
Wet Milling	21.58	22.44	22.26	19.81	22.61	20.72	21.94	23.33	32.52	19.36[2]	18.97[2]
Livestock[3]	16.72	17.70	18.39	17.30	20.06	18.29	19.46	20.81	29.31	16.73	16.38
Dry Milling	2.84	2.95	2.93	2.60	2.97	2.72	2.88	3.07	4.27	2.55	2.49
Corn Export[4]	17.63	16.12	19.02	18.35	20.29	15.43	15.84	16.41	12.70	5.52	16.26
Others (Storage, ship outside IN)	37.39	36.78	33.44	31.87	12.91	10.13	5.06	-2.08	-44.28	17.19	8.03
Total Corn Supply[6]	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Annual Production7	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[8]	5.88	6.32	11.70	8.74	7.22	9.14	7.52	8.00	8.85	6.18	3.38

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

1. Estimated based on the information of ethanol plants capacities
2. Assume to stay constant from 2012 (Hurt, 2012)
3. Estimated based on the livestock inventory data (NASS, USDA). This is converted to the annual amount fed based on the assumption of 11.6 bushels of corn per head of a hog over its lifespan (4 months), 50 bushels of corn per head of a cattle over its lifespan (18 months), 0.62 bushels of corn per head of poultry over its lifespan (10 weeks).
4. State Export Data (ERS, USDA) and Survey Data for global price of corn (FRED, Federal Reserve Bank of St. Louis).
5. Total corn supply in Indiana is the sum of the corn production harvested in the crop year and the corn stock from the previous crop year.
6. Survey Data (2015), Quick Stats. NASS, USDA for both Hurt (2012) and author
7. Extremely low due to drought
8. This is the corn stock from the previous *crop year of corn*.

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

Note: Capacity measured in Million Bushels per Year

[1] Source: Official Nebraska Government (2015), The Biofuel Atlas of NREL, Hurt (2012), NASS, USDA

[2] 2,823 for hog, 14,106 for cattle, 2,347 for poultry (NASS, USDA)

[3] To estimate this we divide the total corn demand from livestock operators by the total number of livestock operators in Indiana, due to the lack of data for individual operators. On the other hand, mean capacity for other sectors are 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
Ethanol Plants	The Andersons Clymers Ethanol, LLC	Cass	2.49
	Grain Processing Corp.	Daviess	0.61
	Central Indiana Ethanol, LLC	Grant	1.42
	Iroquois Bio–Energy Company, LLC	Jasper	0.56
	POET Bio-refining	Jay	2.41
	POET Bio-refining	Madison	1.73
	Valero Renewable Fuels Company, LLC	Montgomery	2.08
	Abengoa Bioenergy Corp.	Posey	3.59
	POET Bio-refining	Putnam	3.79
	Cardinal Ethanol	Randolph	2.61
	Noble Americas South Bend Ethanol LLC	St. Joseph	3.38
	POET Bio-refining	Wabash	2.12
	Green Plains Renewable Energy	Wells	3.58
Wet Millers	Tate & Lyle	Tippecanoe	5.43
	Cargill	Lake	6.93
	Grain Processing Corp.	Daviess	2.89
	Ingredion	Marion	24.31
	Below 1[1]		2
	Above 1[2]		15

Note: All counties have 1 ethanol plant but Posey county with 2 ethanol plants.
* Source: Official Nebraska Government (2017), Renewable Fuel Association (2017) and The Biofuel Atlas, NREL
* Note: Status over the previous periods, 2004 through 2013, is available on authors' request.
1. The number of counties that ethanol plants demand less corn than produced among counties where at least one ethanol plant is located.
2. The number of counties that ethanol plants demand more corn than produced among counties where at least one ethanol plant is located.
3. Grain Processing Corp. (GPC) operates an ethanol plant and a wet-milling plant in Daviess county.

Table 4. Parameter Estimates and Derived Statistics

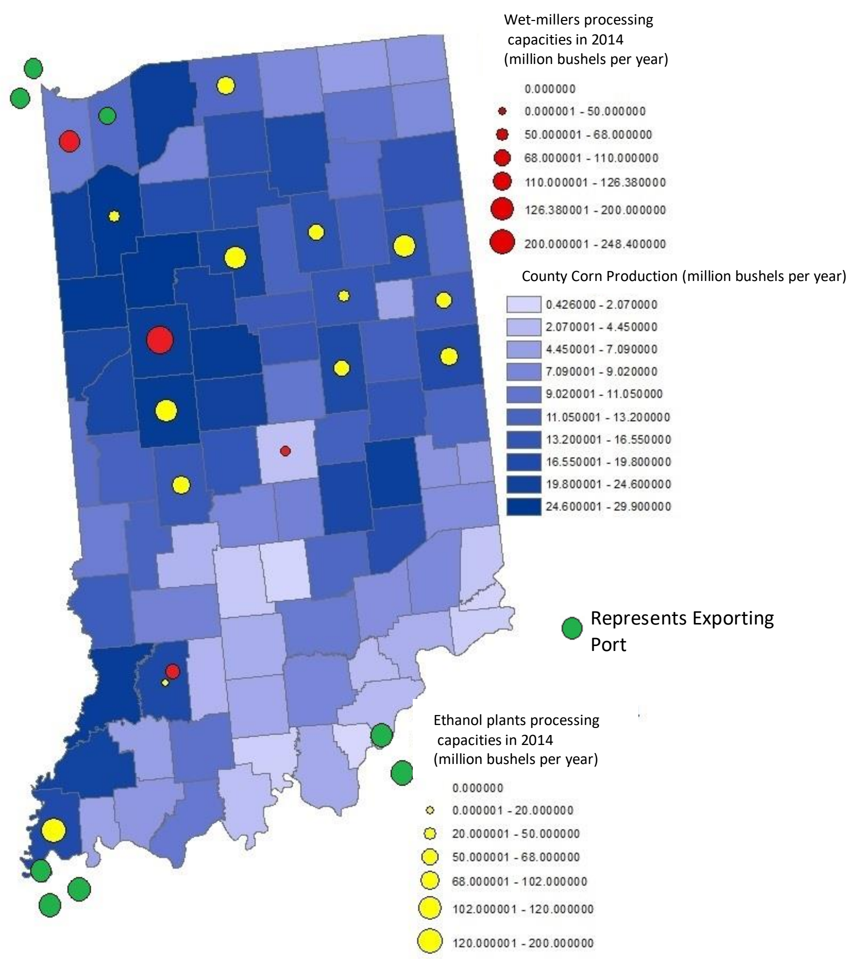
Variables	Parameters	Parameter Estimates	Std.Err	
Residual supply				
Corn price	β^p	3.408***	0.71	
Distance	β^d	-0.004***	1.9e-5	
Export dummy	β^e	0.309***	0.0005	
Marginal costs				
Natural gas price	α^{ng}	0.132***	0.005	
Electricity price	α^{elec}	0.051***	0.0015	
Time trend	α^{time}	-0.185***	0.02	
Extra costs per unit of unutilized capacity	γ	1.58e-4	2.8e-4	
Derived statistics	*Previous Studies*	*Our Estimates*		
		Parameter	Std.Err	
Transportation cost ($ per bu-mile)	0.0016[1]	0.0012***	9.3e-6	
Cap. utilization ratio	0.95[2]	0.98***	0.007	
Marg. processing cost (per gallon)	1.35[3]	1.62***	0.16	
Firm elasticity of residual indirect corn supply[4]		0.065***	0.016	

*Note: Statistical significance at the 10%, 5%, and 1% are denoted as *, **, and ***, respectively.

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

Figures

Figure 1. Oligopsonists Locations and Corn Production in Indiana Counties in 2014



* Source: Renewable Fuel Association (2017), Geo Grain, Official Nebraska Government (2017)

Figure 2. Structure of choices for corn suppliers in our empirical model

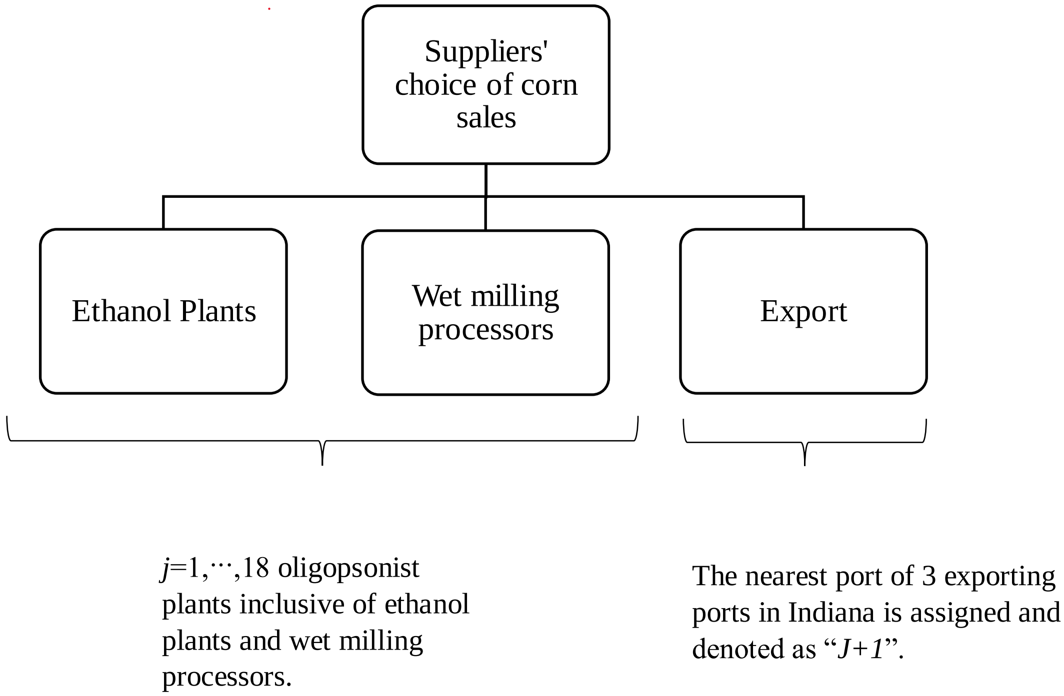


Figure 3. Oligopsonists Locations and Corn Prices in Indiana Counties in 2014

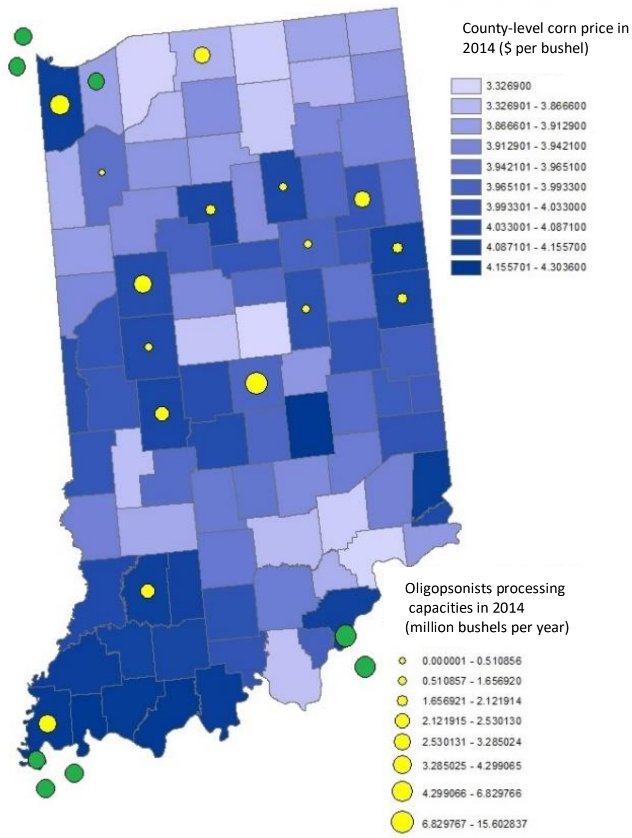


Figure 4. Evolution of relevant prices in the corn market

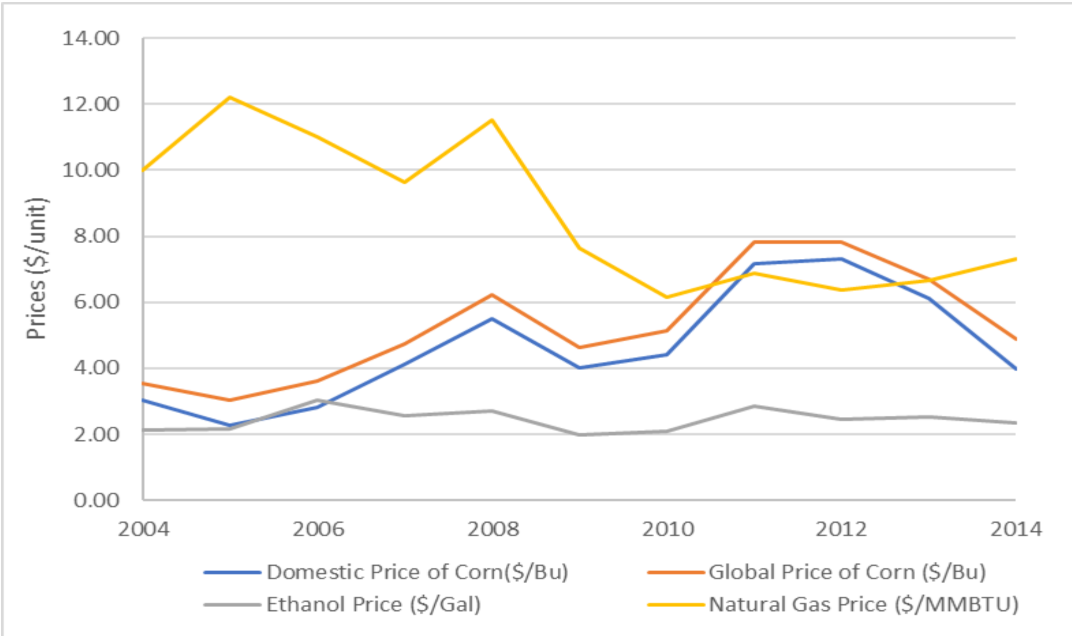


Figure 5. Predicted versus Observed farm-gate prices

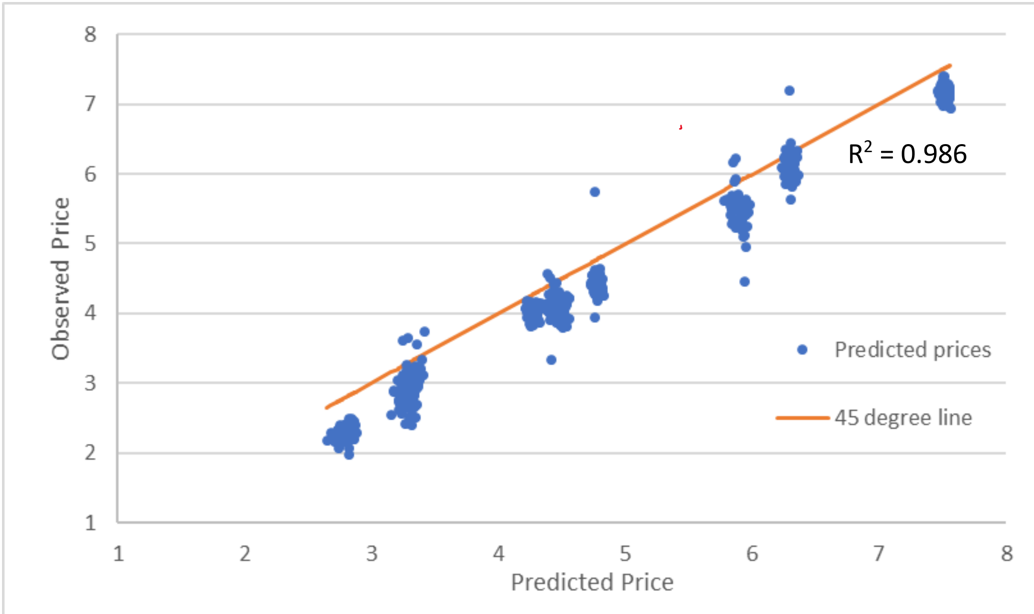


Figure 6. VMP, Predicted Corn Prices, and Markdown

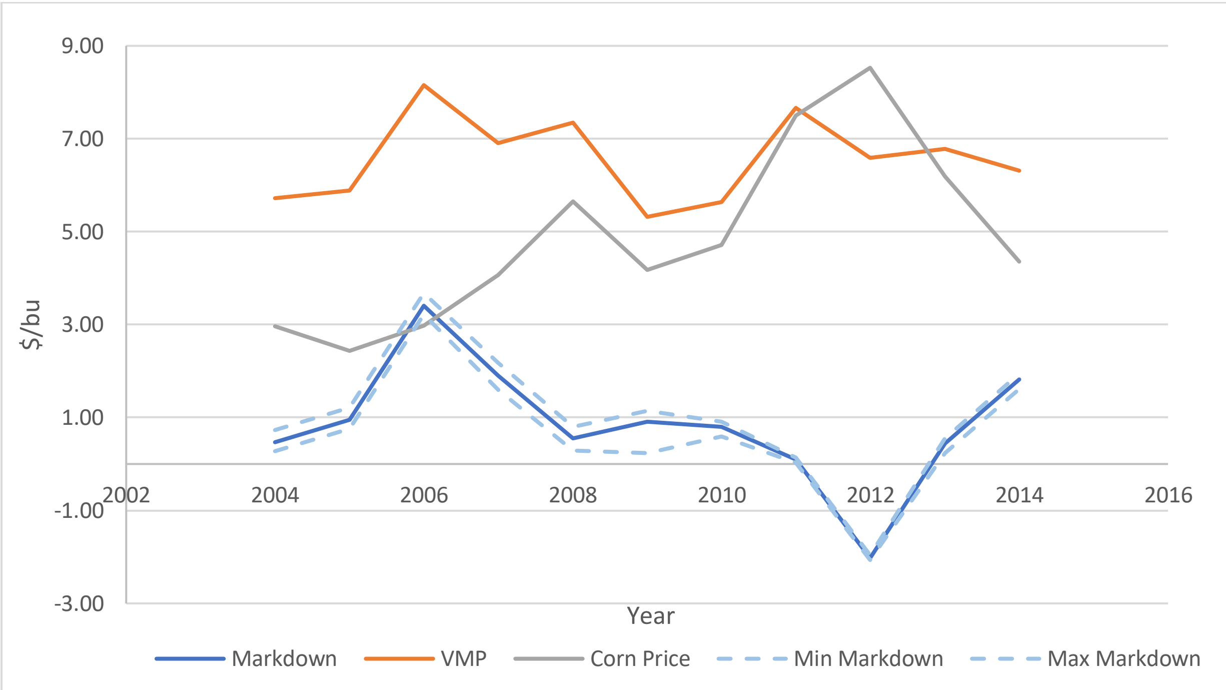


Figure 7. Sources of Markdown for Average Plant in our Sample

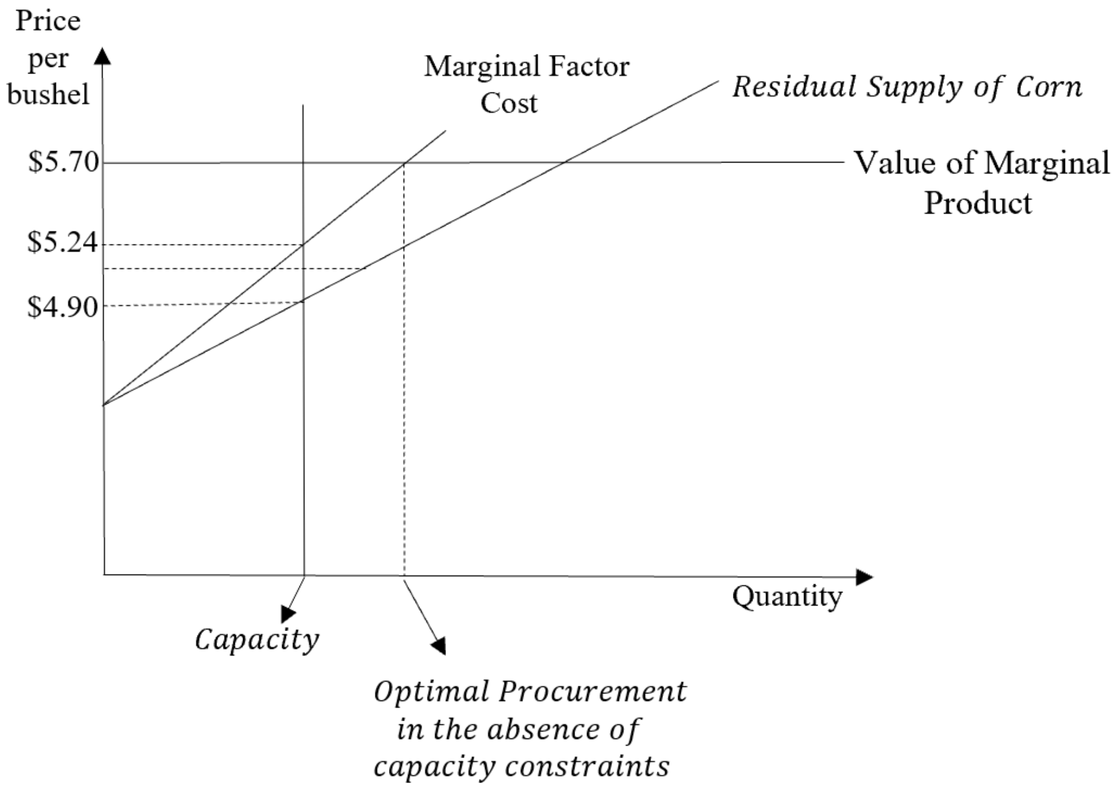
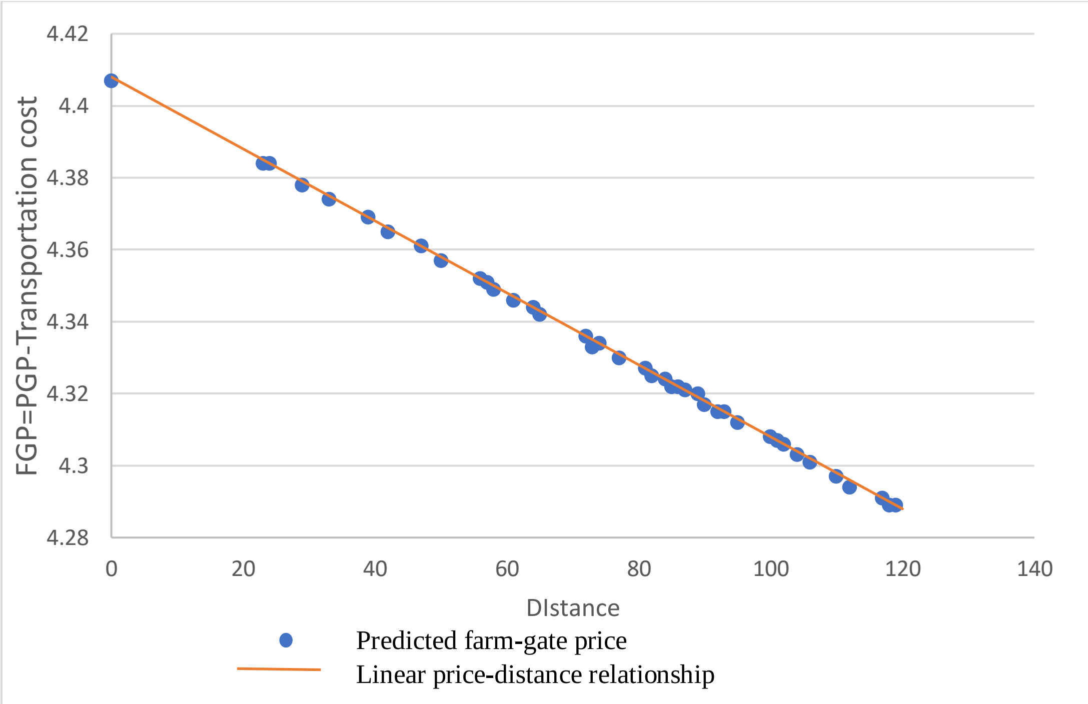
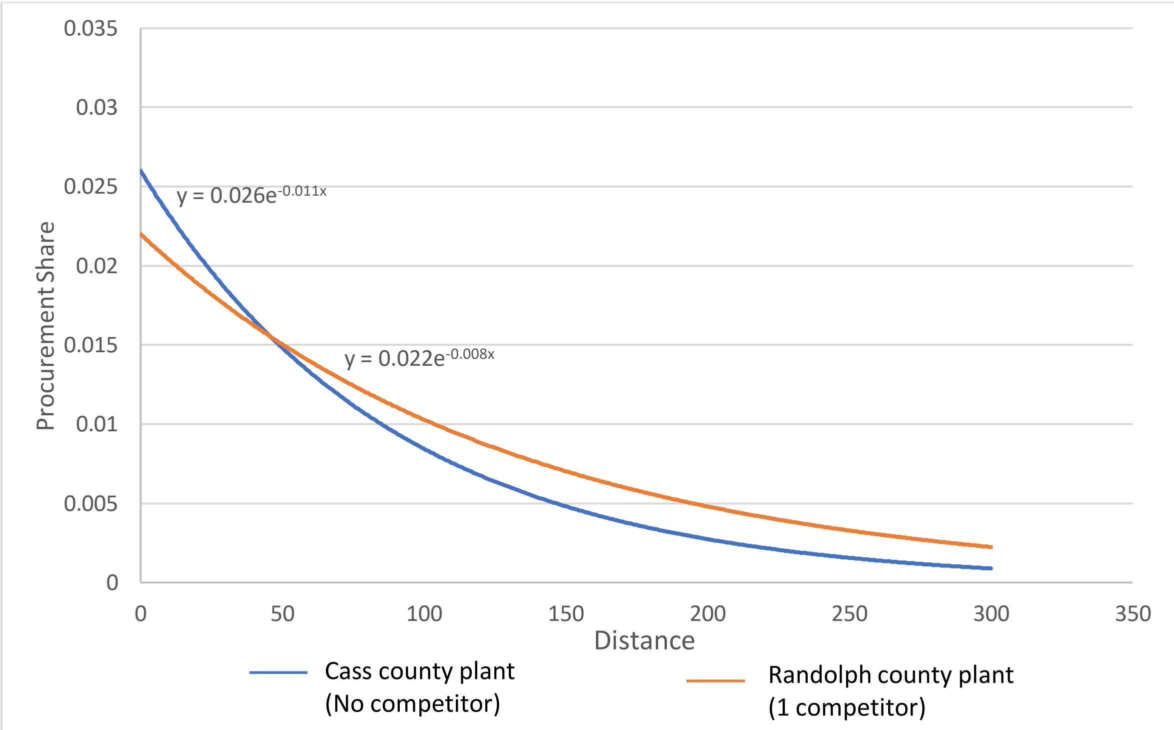


Figure 8. Spatial Price Discrimination for a Selected Plant in our Sample [a]



[a] Ratio of Plant Capacity to County Corn Supply is 2 for all three plants/counties. This makes plants comparable and allows us to tease out the effect of competition on spatial pattern of corn purchases.

Figure 9. Predicted Corn Purchases by Distance for Selected Plants in our Sample [a]



[a] Ratio of Plant Capacity to County Corn Supply is 2 for all three plants/counties. This makes plants comparable and allows us to tease out the effect of competition on spatial pattern of corn purchases.

Figure 10. Spatial Pattern of Consolidation and Change in Markdown

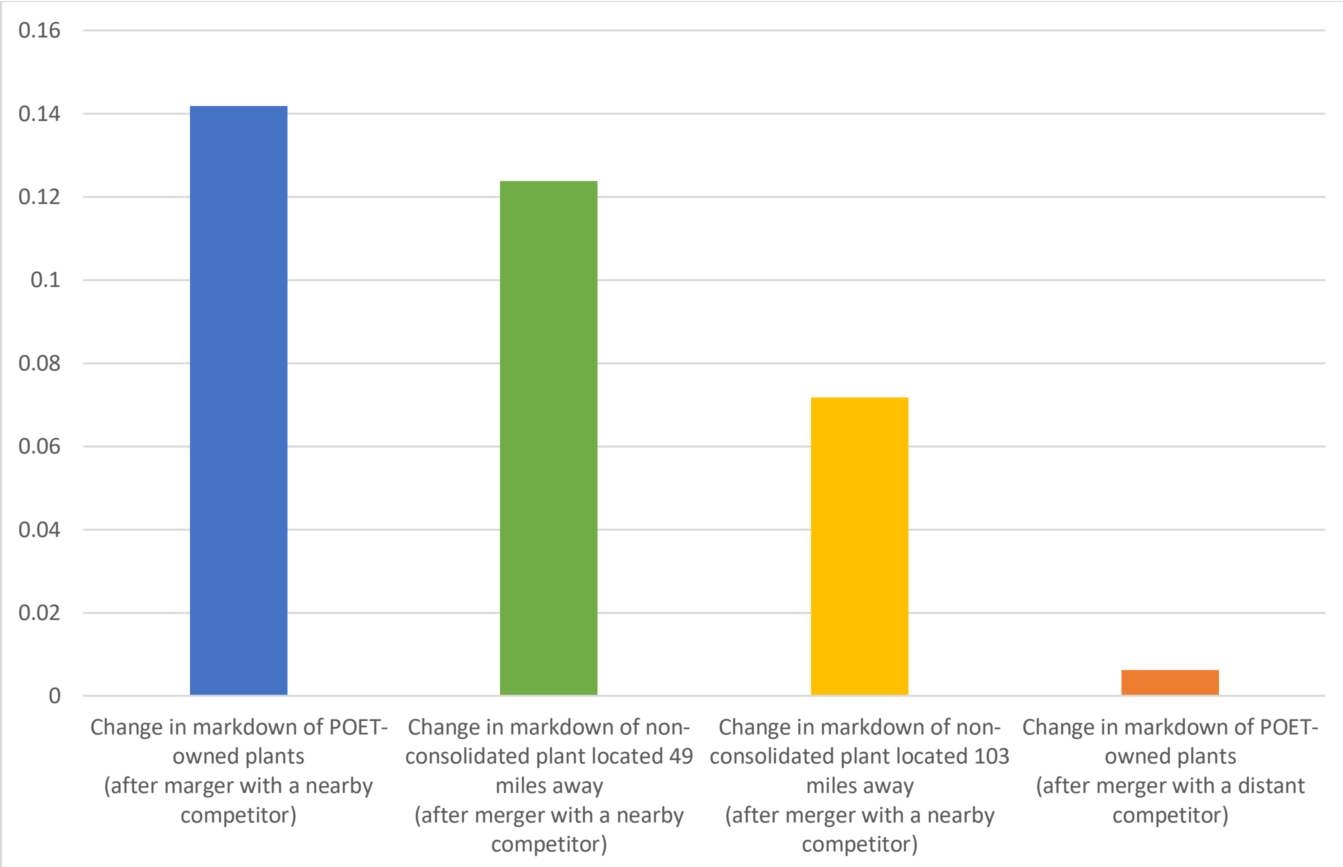


Figure 11. Change in producer surplus for consolidation counterfactuals

Figure 11.a. Changes in producer surplus after merger with nearby plant

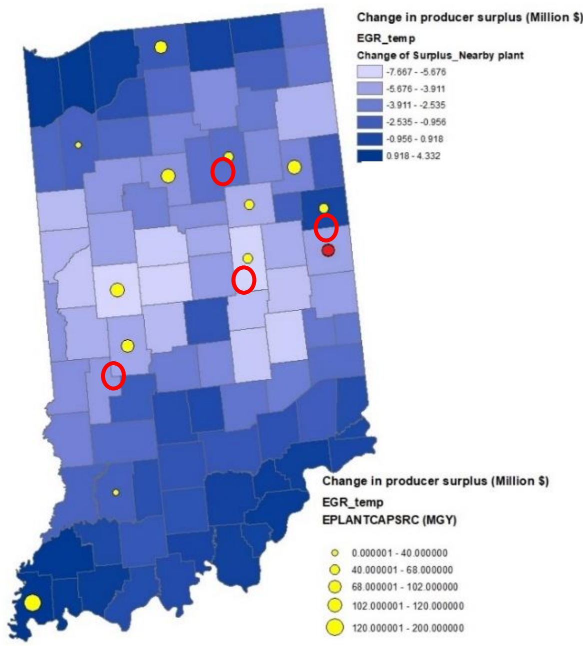
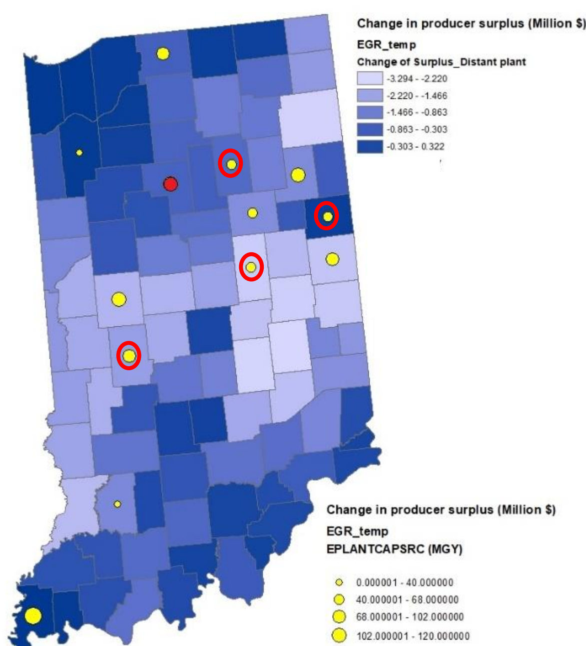
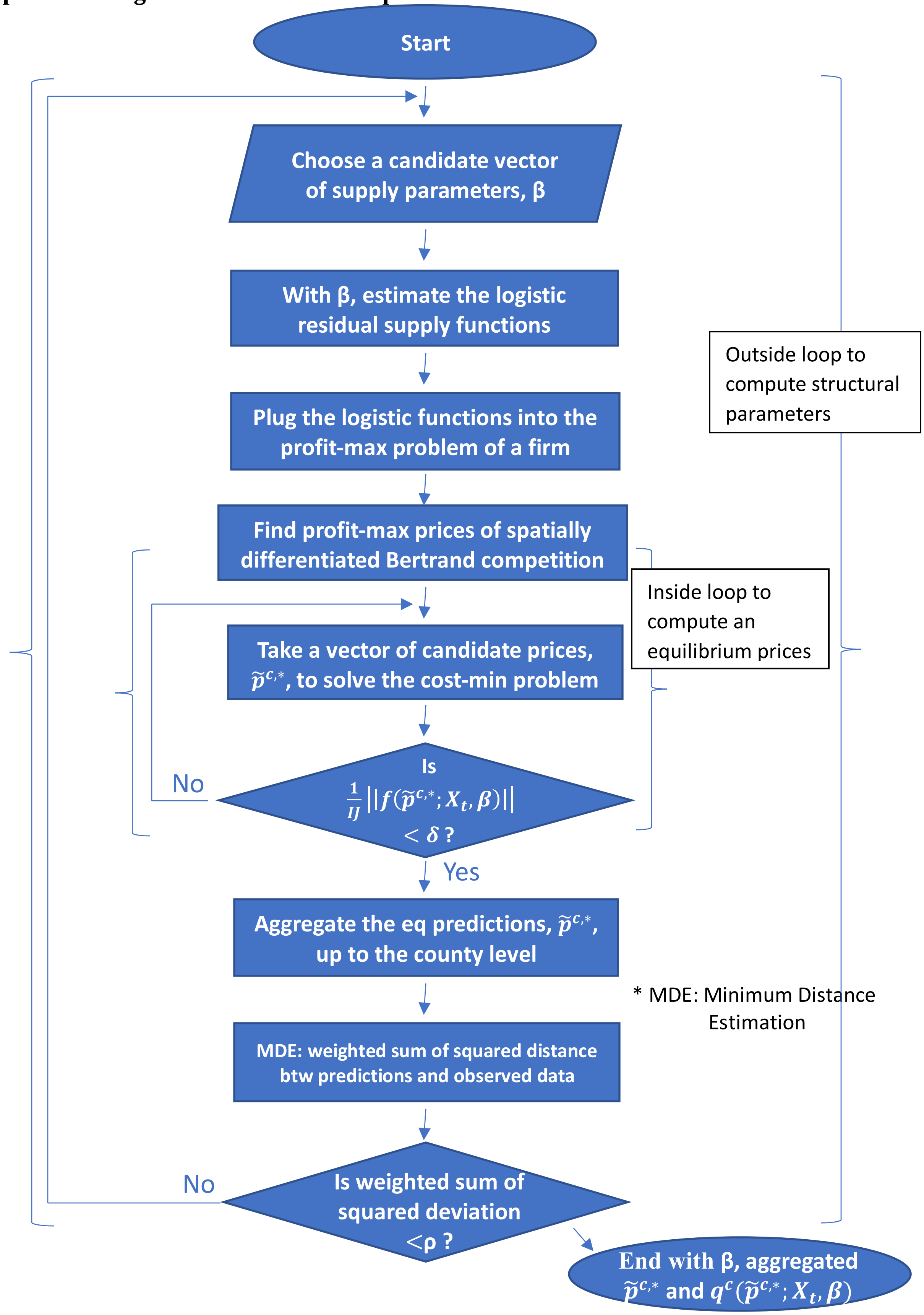


Figure 11.b. Changes in producer surplus after merger with distant plant



Appendix A. Algorithm of the iterative parameter estimation



Appendix B. Detailed Estimation Strategies

a. First order conditions of firm's profit maximization. In this Appendix, we provide detailed information of how ……. First order conditions of the Lagrangian function take the form

$$\frac{\partial \mathcal{L}_F(\cdot)}{\partial \boldsymbol{p}_F^c} = -\boldsymbol{q}^c(\boldsymbol{p}^c;\boldsymbol{\beta}) + \boldsymbol{\Omega}(\boldsymbol{p}^c)\{\boldsymbol{\Gamma} - \boldsymbol{p}_F^c - \mathbf{M} - \boldsymbol{\Lambda}\} = \mathbf{0} \ \ \forall\, i \in IN^C, j \in F \qquad \text{(a1)}$$

$$\frac{\partial \mathcal{L}_F(\cdot)}{\partial \lambda_j^c} = -\alpha_j^h \sum_{i\in IN^C} q_{ij}^c(\boldsymbol{p}_i^c;\boldsymbol{x}_i,\boldsymbol{\beta}) + CAP_j = 0 \ \ \forall\, i \in IN^C, j \in F \qquad \text{(a2)}$$

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 dominant plants in Indiana.

$$\Omega_{jk}^i(\boldsymbol{p}_i^c;\boldsymbol{\beta}) = \begin{cases} \dfrac{\partial q_{ij}^c(\boldsymbol{p}_i^c;\boldsymbol{x}_i,\boldsymbol{\beta})}{\partial p_{ik}} & if\ plants\ j\ and\ k\ have\ the\ same\ owner \\ 0 & otherwise \end{cases} \qquad \text{(a3)}$$

The elements of each submatrix include information of substitution patterns in each county i. 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 only $\boldsymbol{p}_i^c$, independent of $\boldsymbol{p}_{-i}^c$. In summary, $\boldsymbol{\Omega}(\boldsymbol{p}^c)$ is constructed based on two premises; (i) farmers in one area chooses among all J dominant plants in Indiana and (ii) corn supply in one county i is unaffected by plant gate price in other counties, $-i$. In addition, the elements of each submatrix reflect the extent to which firms internalize the externalities from pricing decisions in each plant. Each plant j sources corn from multiple counties. If firm F owns multiple plants, then it will internalize pricing externalities across its plants. In other words, if plant 1 increases its corn bid to county i (an increase in p_{i1}), it will reduce the residual supply of corn from that county faced by plant 2 (all else constant, it will reduce q_{i2}^c); i.e. a business stealing effect. If the same firm owns both plants, it will fully internalize this negative externality, $\frac{\partial q_{i2}^c(\boldsymbol{p}_i^c;\boldsymbol{x}_i,\boldsymbol{\beta})}{\partial p_{i1}}$. Otherwise, the plant would not internalize the externality and $\frac{\partial q_{i2}^c(\boldsymbol{p}_i^c;\boldsymbol{x}_i,\boldsymbol{\beta})}{\partial p_{i1}}$ would take a value of zero. Therefore, common ownership is the reason why $\boldsymbol{\Omega}(\boldsymbol{p}^c)$ has a block diagonal structure.

$\boldsymbol{\Gamma}$ is a vector of $P^h * \alpha_j^h$s which are from revenue of each plant. $\mathbf{M}$ is a vector of $\alpha_j^h * mc\left(Q_j^h;\boldsymbol{w}_j,\boldsymbol{\xi}\right)$s which are from extra cost of low capacity utilization of each plant, and $\boldsymbol{\Lambda}$ is a vector of Lagrangian multiplier, $\lambda_j^{\boldsymbol{c}}$.

Equation (a1) cannot have an analytic solution and should be solve numerically using non-linear equation solver. Then, finally, a vector of prices that solves the system of Equations (a1) and (a2) will be a Bertrand-Nash equilibrium. Plant-county prices are then aggregated to a single county-level price *prediction* (weighting plant-specific prices by the plant's share on total corn purchases) (equation (a4)) and compared to the *observed* data for MDE estimation.

$$\widetilde{\boldsymbol{p}}_i^c(\boldsymbol{\beta},\boldsymbol{Y_t}) = \sum_{\boldsymbol{j\in IN^P}}\left[\left\{\frac{q_{ij}^{c,*}(\boldsymbol{p}_i^{c,*};\boldsymbol{x}_i,\boldsymbol{\beta})}{\sum_{\boldsymbol{j\in IN^P}} q_{ij}^{c,*}(\boldsymbol{p}_i^{c,*};\boldsymbol{x}_i,\boldsymbol{\beta})}\right\} p_{\boldsymbol{ij}}^{\boldsymbol{c},*}\right] \tag{a4}$$

b. Summary of the economic modeling in MPEC structure. Applying MPEC modeling strategy, we can implement all the loop structure at once in the General Algebraic Modeling System (GAMS) software[14] by using appropriate model structure and algorithm solver developed by Dirkse and Ferris (1998) exclusively for solving MPEC. By incorporating M&O estimation strategy as MPEC structure into GAMS, we can avoid computational burden, nonconvergence, and infeasibility

[14] GAMS code is available upon request.

issues that are possibly involved in their loop procedure. Putting the MDE and Bertrand-Nash equilibrium together, our economic model can be summarized as below in MPEC structure.

$$\min_{\boldsymbol{\theta}\in\Theta}\frac{1}{T}\sum_{t=1}^{T}[\boldsymbol{p}_t^c-\widetilde{\boldsymbol{p}}_t^c(\boldsymbol{\theta};\boldsymbol{X}_t)]'\boldsymbol{C}_t^{-1}[\boldsymbol{p}_t^c-\widetilde{\boldsymbol{p}}_t^c(\boldsymbol{\theta};\boldsymbol{X}_t)] \tag{b1}$$

subject to

$$RSUP_i-\sum_{j\in IN^P}q_{ij}^c(\boldsymbol{p}_i^c;\boldsymbol{x}_i,\boldsymbol{\beta})\geq 0 \tag{b2}$$

$$-\frac{\partial\mathcal{L}_F(\cdot)}{\partial\boldsymbol{p}_F^c}=\boldsymbol{q}^c(\boldsymbol{p}^c;\boldsymbol{\beta})-\boldsymbol{\Omega}(\boldsymbol{p}^c)\{\boldsymbol{\Gamma}-\boldsymbol{p}_F^c-\mathbf{M}-\boldsymbol{\Lambda}\}\geq\mathbf{0}\quad\perp\quad\boldsymbol{p}_F^c \tag{b3}$$

$$CAP_j-\alpha_j^h\sum_{i\in IN^C}q_{ij}^c(\boldsymbol{p}_i^c;\boldsymbol{x}_i,\boldsymbol{\beta})\geq 0\quad\perp\quad\lambda_j \tag{b4}$$

Equation (b3) and Equation (b4) is Mixed Complementary Program (MCP) structure or Karush-Kuhn-Tucker (KKT) first order conditions for each firm as it is supposed to be for equilibrium constraints for MPEC. Equation (b2) is for supply constraints for each county that total supply of corn in one county cannot exceed the residual supply of that county. This is global constraints not exclusive for each firm but for each county. We apply a bootstrap method to compute standard errors of each parameter.

Appendix C. Graphical analysis of oligopsony market