Jung, Jinho; Sesmero, Juan; Siebert, Ralph

Working Paper

Spatial Differentiation and Market Power in Input Procurement: Evidence from a Structural Model of the Corn Market

CESifo Working Paper, No. 8088

Provided in Cooperation with:
Ifo Institute – Leibniz Institute for Economic Research at the University of Munich

Suggested Citation: Jung, Jinho; Sesmero, Juan; Siebert, Ralph (2020) : Spatial Differentiation and Market Power in Input Procurement: Evidence from a Structural Model of the Corn Market, CESifo Working Paper, No. 8088, Center for Economic Studies and ifo Institute (CESifo), Munich

This Version is available at:
https://hdl.handle.net/10419/215090

CESifo WORKING PAPERS

8088
2020

February 2020

Spatial Differentiation and Market Power in Input Procurement: Evidence from a Structural Model of the Corn Market

Jinho Jung, Juan Sesmero, Ralph Siebert

CESifo

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
Editor: Clemens Fuest
www.cesifo-group.org/wp

An electronic version of the paper may be downloaded
· from the SSRN website: www.SSRN.com
· from the RePEc website: www.RePEc.org
· from the CESifo website: www.CESifo-group.org/wp

CESifo *Working Paper No. 8088*

Spatial Differentiation and Market Power in Input Procurement: Evidence from a Structural Model of the Corn Market

Abstract

We estimate the cost of transporting corn and the resulting degree of spatial differentiation among downstream firms that buy corn from upstream farmers and examine whether such differentiation softens competition enabling buyers to exert market power (defined as the ability to pay a price for corn that is below its marginal value product net of processing cost). We estimate a structural model of spatial competition using corn procurement data from the 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 $0.12 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 the average corn price in the sample), of which $0.34 is explained by spatial differentiation and the rest by the fact that firms operated under binding capacity constraints. We also find that corn prices paid to farmers at the mill gate are independent of distance between the plant and the farm, providing evidence that firms do not engage in spatial price discrimination. Finally, we evaluate the effect of hypothetical mergers on input markets and farm surplus. A merger between nearby ethanol producers eases competition, increases markdowns by 20%, and triggers a sizable reduction in farm surplus. In contrast, a merger between distant buyers has little effect on competition and markdowns.

JEL-Codes: D430, L110, L130, L430, Q110, Q130.

Keywords: corn procurement, transportation costs, spatial differentiation, buyer power, spatial price discrimination, merger.

*Jinho Jung**
Department of Agricultural Economics
Purdue University / West Lafayette / IN / USA
jung104@purdue.edu

Juan Sesmero
Department of Agricultural Economics
Purdue University / West Lafayette / IN / USA
jsesmero@purdue.edu

Ralph Siebert
Krannert School of Management
Purdue University / West Lafayette / IN / USA
rsiebert@purdue.edu

*corresponding author

Juan Sesmero would like to acknowledge financial support from USDA National Institute of Food and Agriculture through both a grant (Award # 2017-67023-26277) and Multi-State Hatch funding program (Accession number 1012188). In addition, we would like to thank several seminar participants for valuable feedback.

Introduction

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

When a farmer is located at a certain distance from the buyer, the price received by the farmer at the farm gate is lower than the price paid by the buyer at the plant gate. The difference between these prices is equal to transportation cost. Therefore, all else constant, farmers have incentives to sell to nearby buyers in order to avoid transportation cost and obtain a higher price. In a way this protects buyers from competition which may allow them to reduce the price offered to farmers, thereby increasing markdown. The buyer may even go as far as discriminating farmers based on their location, offering a lower plant-gate price to farmers located in close proximity to the plant and a higher plant-gate price to more distant farmers; i.e., buyers may engage in spatial price discrimination (see Graubner et al. 2011; Sesmero 2018).[1] Our goal is to examine empirically

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

whether spatial differentiation introduced by transportation cost allows buyers to engage in corn price markdown and spatial price discrimination.

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

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

buyers and sellers. The optimization approach returns optimal plant-level input prices and shipments. These predictions are then aggregated to the level of data availability such that demand and supply parameters that rationalize the data can be estimated.

In this study, we use county-level information on corn prices and supply in the 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). 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 more than 50 miles. The estimation results return a transportation cost of $0.12 per bushel per mile (5% of the corn price for average shipping distance), which provides evidence of spatial differentiation among buyers. This transportation cost softens competition and allows corn processors to exert buyer power, attaining an average input price markdown of $0.34 per bushel (7% of the corn price) derived from spatial differentiation. Our results also show that, over our study period, firms often set prices under binding capacity constraints, consistent with Bertrand-Edgeworth competition. Once capacity constraints are binding, markdown increases; on average, capacity constraints increase markdown by $0.46 per bushel, more than doubling the effect of spatial differentiation. We also find that the

corn prices buyers pay to farmers are independent of distance, which confirms that firms do not engage in spatial price discrimination.

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

Our study is related to work on spatial differentiation in fast food restaurants (Thomadsen 2005), movie theaters (Davis 2006), coffee shops (McManus 2007), and retail gasoline establishments (Houde 2012). It also relates to Durham and Sexton (1992) in that it estimates residual supplies faced by agricultural processors. However, unlike Durham and Sexton (1992), our study follows an estimation strategy proposed by Miller and Osborne (2014) that will enable us to estimate firm-level structural parameters from market-level outcomes. Other prominent contributions that focus on buying power in the corn procurement market include Saitone, Sexton, and Sexton (2008) and Wang et al. (2019). The main differentiating attribute of our paper relative to these studies is that we do not *impose* buyer power, but *estimate* it. In this sense, our study

contributes to a rich empirical literature on buyer power in input markets, as reviewed by Azzam (1996), Sexton (2000), McCorriston (2002), Sexton (2013), Sheldon (2017), and Merel and Sexton (2017), among others. In contrast to these studies, however, our paper explicitly considers the relationship between spatial differentiation and competition. We also estimate the degree of spatial competition and identify it as a source of buying power.

The Corn Market in Indiana and the Data

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

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

We obtained data on corn production, corn storage, and livestock inventory from the National Agricultural Statistics Service of the United States Department of Agriculture (NASS, USDA). Information on corn exports and international prices is taken from the Economic Research

Service (ERS) of the USDA and the Federal Reserve Bank of St. Louis (FRED), respectively. The information on ethanol plant location, ownership, capacity, and year built comes from the government of Nebraska, the Renewable Fuel Association (RFA), the 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 the authors' own personal communications. Historical diesel and electricity prices are obtained from the EIA. 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 producers purchase a substantial fraction of corn supplied within relevant market boundaries, and market boundaries can be confined by transportation costs. Therefore, all else constant, concentration will increase with transportation cost and with the size of a purchasing firm. We now turn our attention to these two aspects.

Corn farmers typically use trucks to ship corn to their buyers (Denicoff et al. 2014; Adam and Marathon 2015) since plants source corn locally and trucking within relatively short distances (i.e., below 500 miles) is less costly than other forms of transportation. According to the Grain

Truck and Ocean Rate (GTOR) report from the USDA, the transportation rate of grains in the North Central region[2] 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.[3] 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, while individual livestock operations and dry millers are not. On average, ethanol plants and wet-milling plants are 4,000 times larger than the average individual livestock operator and 6 to 10 times larger than dry millers. Table 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 sitting on corn prices, but they also indicate that the price effect dissipates with distance. The positive price effect is

[2] 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.
[3] 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.

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 redirect enough corn toward them. The dissipation of the price effect with distance is also consistent with procurement markets that are geographically localized due to transportation costs. In summary:

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

Notwithstanding the geographically localized nature of procurement, the sheer size of these plants relative to localized supply also suggests that they have to travel considerable distances to procure enough input. This likely results in spatial overlap of these plants' procurement areas, especially when they are spatially clustered. Figure 1 shows the locational pattern of ethanol plants (yellow circles) and wet-milling plants (red circles), as well as the spatial pattern of corn production in Indiana in 2014. This figure reveals substantial differences in spatial clustering of ethanol plants. The variations in the local market conditions have an effect on the intensity of competition for corn procurement. But large processors (as indicated by larger circles in Figure 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 the procurement channels. A portion of the corn produced is sold immediately after harvest, but another portion is stored in elevators and sold throughout the year. Processors buy corn from both farmers and commercial elevators. They purchase corn both in the spot market and through contracts. Contracts are usually signed during the growing season and specify a post-harvest delivery date, a quantity, and a price. The composition of procurement channels matters because our estimation is based on elevator-level cash prices that are then aggregated to the county level. Therefore, measurement error in prices could arise if: (1) a large portion of corn is purchased directly from farmers and those prices differ from elevator prices; or (2) a large portion of corn is purchased through contracts and contract prices differ from cash prices.

We consider the use of elevator cash prices to be an adequate strategy in our context for two reasons. First, while buyers often bypass elevators and purchase directly from farmers, elevator prices do not deviate substantially and systematically from farm prices. As for the second potential source of measurement error, a substantial fraction of corn procured by the processors is purchased in spot markets. Processors use contracts for hedging and protecting profitability during periods of thin margins, but hedging opportunities are limited by illiquid futures markets on the output side due to limited ethanol and food product storage (see Schill 2016).[4] Moreover, corn

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

futures markets are highly liquid, with efficient price discovery mechanisms, which causes convergence, albeit partial, of forward prices to spot prices.[5]

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

We summarize the information on procurement channels and pricing by:

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

We now turn our attention to market conditions under which oligopsonists sell their processed products. If oligopsonist-owned plants exerted market power downstream, the output price would be a function of quantity processed and supplied, which would itself be a function of corn price. This would add a layer of complexity to our analysis. Beyond a residual input supply, an additional output residual demand function faced by each plant would have to be estimated. However, it is unlikely that individual oligopsonistic plants exert market power downstream for

[5] 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.

two reasons. There are close substitutes in the market for the main outputs from both ethanol as well as wet-milling firms. The price of ethanol mostly followed the price of gasoline during our study period according to data from the state of Nebraska's website (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 2019) and wet-milling plants (Porter and Spence 1982) is typically very high, which limits the role of output price on the procurement decision. These facts determine the following feature:

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

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

exporting ports (plotted as green dots in Figure 2) 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 consists of a set of equations that describes upstream firms' selling behaviors and downstream firms' buying behaviors. On the demand side, we consider ethanol and wet-milling plants that act as oligopsonists. On the supply side, we consider farmers in counties that sell corn to oligopsonists for plant-specific prices and to the competitive fringe.

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

Downstream Firms (Ethanol and Wet-Milling Firms)

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

Turning to our empirical model, we allow oligopsonistic firms *(F)* to own multiple plants (j). The firm determines for every plant *j* the corn price p_{ijt}^{c} (the superscript *C* refers to corn, and the subscript *t* refers to the time period) that is paid to suppliers (farmers) located in county i=1,…,92 in Indiana. Since the structure of the problem is the same in all periods, and for notational simplicity, we drop the time subscript *t*. The firm-specific vector of corn prices $\boldsymbol{p_F^c}$ contains as its elements the county-specific corn prices p_{ij}^{c} that are offered by every plant *j* owned by firm *F* to every county *i*. The quantity of corn shipped from county *i* to plant *j* is denoted by $q_{ij}^{c}(\boldsymbol{p_i^c}; \boldsymbol{x_i}, \boldsymbol{\beta})$,[6] 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

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

shifters that captures procurement by the competitive fringe from county *i*, and $\boldsymbol{\beta}$ is a vector of parameters to be estimated.

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

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

subject to

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

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

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 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, $(\sum_j \int_0^{Q_j^h} mc\left(Q; \boldsymbol{w}_j, \boldsymbol{\alpha}\right) dQ)$ refers to the total processing cost of producing ethanol and wet-milling products, where Q_j^h refers to the corresponding production quantities, *mc* denotes marginal cost, Q is the amount of corn processed, $\boldsymbol{w}_j$ is a vector of cost shifters (natural

gas and electricity prices) and a time trend to capture technological and/or efficiency change, and $\boldsymbol{\alpha}$ is a vector of corresponding parameters.

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

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

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

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

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

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[7] carried over from

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

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

Our model predicts corn supplied by each county to each procurement firm. It builds on two premises. First, suppliers can sell corn to one of three sectors: oligopsonists, local competitive fringe (dry millers and livestock producers), and exports competitive fringe. Second, sectors other than oligopsonists do not exert market power. Both of these premises are motivated by *Market Feature 1*. Previous studies have documented that corn demand from the local competitive fringe can be quite inelastic, especially from its larger source, livestock operators (Suh and Moss 2017). Therefore, we simply subtract that from the total supply. In contrast, export prices are determined in the international market and are not influenced by individual exporting firms. A competitive exporting sector implies exporting firms procure excess supply at their marginal value product. This is consistent with the stylized fact that exports are highly (and positively) correlated with production, as revealed by a relatively constant share of exports over time (see table 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 oligopsonistic firm and $j = J + 1$ if the plant is an exporting port. Since there are 18 oligopsonistic plants in our sample (14 ethanol plants and four wet-milling plants), $J = 18$. The corn price for exports is determined by the international price. The suppliers have to pay the transportation cost. In terms of exports, the transportation cost is determined by the distance from the county's centroid to the closest exporting port. The value function of supplier n in county i, associated with selling their corn to plant j is given as:

$$v_{ij}^n = \beta^p p_{ij}^c + \beta^d d_{ij} + \beta^e e_j + \varepsilon_{ij}^n = \boldsymbol{x_i'\beta} + \varepsilon_{ij}^n, \tag{5}$$

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), and e_j is a dummy variable that is set to 1 if plant j is an exporting port ($j = J + 1$).

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

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

where $\boldsymbol{x}_{ij}' = [p_{ij}^c, d_{ij}, e_j]$ 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) $$q_{ij}^c(\boldsymbol{p}_i^c; \boldsymbol{x}_i, \boldsymbol{\beta}) = S_{ij}(\boldsymbol{p}_i^c; \boldsymbol{x}_i, \boldsymbol{\beta}) * RSUP_i,$$

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.

Estimation Strategy

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

For estimation of the farmers' supply equation (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 suppliers' responses to prices, making the aggregate supply response smooth to changes in corn prices. Otherwise, small price changes would result in corner solutions at the county level and generate discontinuities in supply behavior. Third, it does not artificially constrain farmers to sell corn within a predetermined radius. This is important in our study since plants purchase corn from distant sellers (well beyond 50 miles in some cases).

Next, we use the multinomial logit supply (as shown in equation (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:[8]

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

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

The inner loop solves for the county-plant pairs of prices ($\widetilde{\boldsymbol{p}}_{ij}^c$) and quantities ($\widetilde{\boldsymbol{q}}_{ij}^c$) for all plants and all counties given the candidate parameters and exogenous variables. It does so in two steps. First, it generates a vector of *firm-level* Karush-Kuhn-Tucker (KKT) conditions in the Mixed Complementarity Problem structure that solves problem (1)-(3). Expressions for the KKT

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

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*, $\widetilde{\boldsymbol{p}}_{ijt}^{c}(\boldsymbol{\theta}; \boldsymbol{X}_t)$, which are functions of candidate parameters and data. Along with these prices, the inner loop also generates $J \times N$ equilibrium predictions of firm-county quantity pairs in period *t*, $\widetilde{\boldsymbol{q}}_{ijt}^{c}(\boldsymbol{\theta}; \boldsymbol{X}_t)$. The corn prices offered by all plants to each county are weighted using the corresponding procurement shares such that an aggregate, predicted county-level price $\widetilde{\boldsymbol{p}}_{it}^{c}(\boldsymbol{\theta}; \boldsymbol{X}_t)$ is obtained: $\widetilde{\boldsymbol{p}}_{it}^{c}(\boldsymbol{\theta}; \boldsymbol{X}_t) = \sum_j \left(\frac{\widetilde{\boldsymbol{q}}_{ijt}^{c}(\boldsymbol{\theta}; \boldsymbol{X}_t)}{\sum_j \widetilde{\boldsymbol{q}}_{ijt}^{c}(\boldsymbol{\theta}; \boldsymbol{X}_t)} \right) \widetilde{\boldsymbol{p}}_{ijt}^{c}(\boldsymbol{\theta}; \boldsymbol{X}_t)$. These county-level price predictions are then stacked in vector $\widetilde{\boldsymbol{p}}_{t}^{c}(\boldsymbol{\theta}; \boldsymbol{X}_t)$ of equation (8).

The outer loop minimizes the distance between the observed and predicted equilibria by iterating over the candidate parameters in $\boldsymbol{\theta}$. The conditions are stacked, and the estimator (see equation (8)) compares the aggregated equilibrium predictions $\widetilde{\boldsymbol{p}}_{t}^{c}(\boldsymbol{\theta}; \boldsymbol{X}_t)$ to the empirical analogs in the dataset $\boldsymbol{p}_t^c$. These comparisons yield total annual deviations between predicted market outcomes and their empirical analogs. The Minimum Distance Estimator minimizes the sum of squared errors.

The iterative estimation algorithm is relegated to Appendix B. We model this problem as a Mathematical Programming with Equilibrium Constraints (**MPEC**) as suggested by Su and Judd (2012)[9] and implement the double-loop structure in the General Algebraic Modeling System

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

(GAMS) software.[10] This strategy increases ease of computation, preventing common nonconvergence and infeasibility issues.

Identification

We consider 92 counties in Indiana over an 11-year time horizon, such that equation (8) includes 92x11=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 ($\boldsymbol{\alpha}$).

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

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

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

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 pay special attention to estimating markdowns and evaluating the degree of spatial competition in the market. We validate these results based on their ability to generate observed data and against estimates from previous studies.

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.[11] The estimated coefficient for corn price (β^p) is statistically significant and positive. The coefficient shows that the price of corn increases in the amount of corn sold to downstream firms. The positive effect is indicative of a "business-stealing" effect, whereby a downstream firm diverts corn away from its competing firms by offering a higher corn price.

The negative estimate on the coefficient for transportation distance (β^d) shows that farmers supply less corn to oligopsonistic plants that are located farther away. This result is expected since

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

farmers have to pay the transportation cost for corn and a long-distance delivery becomes costly. Selling corn to other more closely located plants becomes an attractive alternative. The transportation cost, as computed by the ratio ($-\beta^d/\beta^p$), amounts to \$0.12 per bushel per mile. It should be noted that our estimated transportation cost is very close to the \$0.16 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 small deviations from our transportation costs, which are specific to Indiana. The small deviations could be explained by road infrastructure and diesel prices being different between the North Central region states and Indiana.

Evaluating the transportation costs at the average distance of corn delivery and the average corn price paid by oligopsonist-owned plants, our model predicts an average transportation cost of 5% of the corn price. The corn price that farmers receive from plants (after subtracting transportation costs) declines in distance between farmers and plants. Hence, our results show that the presence of transportation costs has an effect on corn price received by the farmers, providing evidence for spatial differentiation being an important aspect to consider.

The transportation costs and the resulting decline in the corn price received by farmers also provide evidence that oligopsonistic firms face upward-sloping residual corn supplies. Our parameter estimates return a firm-level residual indirect average supply elasticity (calculated across plants and time periods) of 0.065.[12] 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 at the plant's gate (it increases from \$5 per bushel to about \$5.30 per bushel, an equivalent of 6.5%).[13]

[12] The elasticity is significant at the 1% level.
[13] This is, of course, an oversimplification since such an increase in size would trigger an equilibrium displacement that would tend to make that price increase higher. This value should then be interpreted as a lower bound to the price effect.

Finally, the positive coefficient on the export dummy variable implies that proximity to an exporting port causes an upward shift in the farmers' supply; in other words, exports cause a significant shift in residual supply, consistent with our discussion of figure 2.[14]

The Downstream Firms (Ethanol and Wet-Milling Firms)

We now focus on the estimation results of the marginal processing costs of the downstream firms (ethanol and wet-milling firms), as characterized in equation (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 exceed those on electricity. The negatively estimated coefficient for the time trend (α^{time}) shows that plants have become more efficient over time, which is consistent with findings from Hettinga et al. (2009). Our estimated cost parameters predict an average processing cost of \$1.62 per gallon, which is close to the cost estimates (around \$1.35 per gallon) reported in Perrin et al. (2009) and Irwin (2018).

The γ parameter measures the change in marginal processing cost per unit of unutilized capacity. The estimate is not statistically significantly different from zero, providing evidence that the marginal processing cost is constant. Constant marginal processing cost is consistent with widely held assumptions made in the literature (see, for example, Gallagher et al. 2005; Perrin et al. 2009), but differs from findings in Sesmero et al. (2016).[15] Our estimated capacity utilization

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

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

ratio amounts to 0.98, which is close to the ratios reported by Dale and Tyner (2006). In general, our empirical model predictions for revenues and profits of ethanol plants fall within the range published in financial reports (see, for example, Green Plains Renewable Energy 2017) and other independent reports (see also Irwin 2018).

It is important to note that our estimation results generate predictions that closely match anecdotal or statistical evidence, and this lends credence to our parameter estimates. A further important validation exercise relates to our model's ability to generate accurate price predictions, which forms the center of our identification strategy in the empirical model. Figure 4 shows the predicted and observed farm-gate prices across counties and over time periods. Each dot represents a combination of an observed price (in a county and a year) and the corresponding predicted price. The dot patterns fragment into clusters because prices differ substantially across years. The correlation between predicted and observed prices is close to 0.99, which supports our model's goodness of fit. The figure illustrates that our structural model does a remarkable job of predicting close to observed prices. It should be noted, however, that our empirical model appears to overpredict prices slightly when observed prices are uncharacteristically low or high. This is less of a concern in our case, however, since we conduct counterfactual experiments around mean conditions, where our model seems to perform best.

Corn Prices and Markdowns over Time

In the following, we predict plant-county pair prices paid by ethanol and wet-milling plants and compare these to the value of marginal product of corn (net of marginal processing cost) to calculate markdowns. Figure 5 portrays a substantial average price markdown. The average markdown is around $0.80 per bushel, or 16% of the average corn price. To put this markdown in

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

Figure 5 shows that the markdowns vary widely over time (they drop significantly from 2006 to 2012 and then recover). Fluctuations over time are explained mostly by macroeconomic factors affecting the price of corn, and they are largely absorbed by $RSUP_i$s in our model. Nevertheless, conditional on residual supply, our model also finds substantial markdown variation across plants within a year, as suggested by the minimum and the maximum markdown curves in figure 5. The difference between the largest and smallest markdowns in a year averages $.50 per bushel over the study period but varies in magnitude from almost no variation in 2012 to $1 in 2009.

To explain the variation of markdowns across firms, we refer to the derived statistics reported in Table 4. The statistics emphasize two potential explanatory factors. The first factor relates to the spatial differentiation aspect and the fact that oligopsonistic firms face an upward-sloping residual input supply, which creates a wedge between marginal factor cost and input supply. The second factor relates to our finding that most firms operate at full capacity, with an average capacity utilization rate of 0.98. This creates a wedge between the value of marginal product and input supply. Therefore, our estimation results reveal a salient feature of the corn market—namely that spatially differentiated oligopsonistic firms 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 value of marginal product is equal to the marginal factor cost. Markdown is equal to the distance between the value of marginal product and residual supply. However, if capacity is smaller than the profit-maximizing production quantity, then the plant will operate at capacity, and markdown is determined by the distance between the value of marginal product and residual supply at capacity. By construction, this distance is larger than the wedge between marginal factor cost and residual supply.

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

Our results indicate that, on average, capacity constraints prevail, and markdowns are determined by the distance between the value of marginal product and residual supply at capacity. Therefore, as depicted in figure 6, markdowns are larger than they would be in the absence of those constraints. Specifically, for the average observation in our sample (average across firms and over time), the wedge between the value of marginal product and residual supply at capacity is $0.80, while the wedge between supply and marginal factor cost at capacity is $0.34. These findings are consistent with Bertrand-Edgeworth competition (a setting in which binding capacity constraints deliver a certain degree of localized market power to otherwise Bertrand-pricing buyers of spatially differentiated inputs).

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

Spatial Price Discrimination

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

In the absence of spatial price discrimination, the corn buyer pays the same mill price (before transportation costs) to all sellers, regardless of their locations. Consequently, the farm-gate prices lie on the linear price-distance gradient, as shown in figure 7. In the presence of spatial discrimination, however, corn buyers pay mill prices such that markdowns are higher for corn supplies from nearby farmers. In this case, the farm-gate prices received by farmers located close to the corn buyers would lie below the linear price-distance gradient depicted in figure 7. The rationale is as follows: The corn buyer accounts for the sellers' alternative selling options. The corn sellers that are close to the purchasing plant are presumably far from other plants, which makes it more costly to transport corn to them. The additional transportation cost is considered as a reference point and subtracted from the purchasing price, so corn sellers located in close

proximity to the buyer are paid a lower mill price. This enables the ethanol plant to set higher markdowns to closely located farmers.

Figure 7 displays the predicted price-distance gradient (farm-gate prices received by suppliers located at varying distances from these plants), as well as the linear price-distance gradient for a selected plant. The plant we selected operates under rather average conditions in all important dimensions: ratio of capacity to local supply and distance to the nearest exporting port and competitors. Our analysis shows that the firm does not engage in spatial price discrimination, as demonstrated by the absence of deviations of predicted farm-gate prices from the linear price-distance gradient. We have computed these gradients for all the firms in our sample, and our finding on the absence of price discrimination holds for all of them. This indicates that firms do not price discriminate, regardless of their size, distance to competitors and exporting ports, or conditions under which they operate (livestock and local supply).

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

Spatial Purchase Patterns by Downstream Firms

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

The spatial pattern of corn purchases is determined by many factors, including capacity, geographical distribution of corn production, and local competition. Since we are especially interested in evaluating the spatial competition effect on the plants' spatial pattern of procurement, we report the purchase-distance relationship for two plants that differ in the degree of spatial competition they face, but are similar otherwise (i.e., the plants display a ratio of capacity to local corn residual supply close to 2, and they are located far away from exporting ports). Figure 8 compares the spatial procurement patterns for two plants. The first plant faces no nearby competitors and is located in Cass County. The second plant faces a close competitor plant, and it is operating in Randolph County. The figure shows that these plants procure most of their corn within a distance of 50 miles (as revealed by calculating the area below procurement curves), but also likely purchase corn at greater distances. The predicted procurement patterns coincide with previous descriptions of procurement regions under similar corn supply conditions (e.g., Kang et al. 2010). This finding further validates our estimates and lends credence to our analysis.[16]

Next, we turn to the relationship between spatial competition and corn procurement. Figure 8 shows that the plant facing more spatial competition (there is a competitor in close proximity) is forced to travel greater distances (in the direction of their uncontested markets) to procure corn. It

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

should be recognized that, given a certain level of spatial competition, plant size relative to local corn supply (which could be explained by plant expansion, a bad crop, or growth in corn demand shifters like livestock) would shift the functions in figure 8 upward and exert a similar effect as local competition.

Counterfactual Experiments: Mergers, Markdowns, and Farm Surplus

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

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

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

among plants in Indiana. Consequently, Indiana offers an unconfounded marketplace for merger simulations, which 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 not have been otherwise internalized. Suppose plants *j* and *k* are owned by different firms, then the firms set their prices noncooperatively and do not account for any cross-price effects $\frac{\partial q_{ij}^c(\boldsymbol{p}_i^c;\boldsymbol{x}_i,\boldsymbol{\beta})}{\partial p_{ik}}$ in the ownership matrix $\boldsymbol{\Omega}(\boldsymbol{p}^c)$, which is a critical element of firms' first-order conditions (as shown in equation (A3), Appendix A).[17] Hence, the corresponding element in the ownership matrix is zero. The firm that owns plant *j* does not account for the effect that a price change by plant *j* has on the supply of corn to plant *k*.

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

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

In the first merger, Poet purchases the plant in Randolph County, which is located close to two of its other plants in Jay County and Shelby County. Figure 9a shows the plants owned by Poet before the merger as yellow dots surrounded by black circles; and the plant purchased by Poet

[17] See Appendix A for a detailed description of this matrix and its elements.

through the merger is highlighted by a black dot. In the second merger, Poet purchases a more isolated plant (the average distance between this plant and those owned by Poet before the merger is larger than the average distance between the plant in Randolph County and Poet-owned plants) in Cass County, also denoted as a black dot, but in figure 9b.

Figure 10 reports post-merger changes in markdowns for both merger cases. Focusing on the first merger case, in which Poet-owned plants merge with a nearby competing plant, we find substantial increases in markdowns. Based on our structural parameter estimates, we predict that plants owned by merging firms will increase markdown further, on average by $0.14 (which corresponds to a 20% increase in markdown for the average plant in our sample). Our analysis shows that under 2014 market conditions, consolidated plants operate at capacity before and after the merger. Therefore, the increase in markdown is not explained by reduced procurement, but by a downward shift in corn residual supply faced by each firm due to internalization of the competitive externalities.

Turning to the second merger case in which Poet merges with a distant competitor, this merger has a much smaller effect on markdown by merging firms, as reported in figure 10a. A comparison between this and the effect of a merger with a nearby competitor clearly indicates that the magnitude of the downward shift in corn residual supplies as a result of a merger depends upon the degree of spatial differentiation between consolidating firms. In other words, a merger is likely to increase markdown, but only if it takes place between firms that are not strongly spatially differentiated.

While consolidation between nearby ethanol plants increases markdown by the consolidated firms, it may also trigger competitive spillover effects to other, non-consolidating firms. As consolidating firms reduce corn prices due to internalization of competition externalities,

close competitors may benefit from weakened competition and reduce corn prices themselves. Our counterfactual simulation uncovers evidence of spillover effects; that is, non-consolidating firms also attain higher markdown due to the fact that mergers soften competition. In fact, as reported in figure 10b, a non-consolidating firm located 49 miles away from Poet's plants increases markdown by $0.12, and a non-consolidating firm located 103 miles away from Poet's plants increases markdown by $0.07.

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

Conclusion

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

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

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

More generally, our analysis indicates that assessment of mergers between spatial competitors in agricultural procurement markets should perhaps consider distance more explicitly. Previous studies have characterized efficiency gains associated with mergers that would restore

premerger equilibrium prices and quantities (i.e., that would offset increased market power effect) after the merger takes place (e.g., Werden-Froeb Index) and, thus, should not raise anticompetitive concerns. Our analysis suggests the need to develop such an index in agricultural procurement markets, which display two distinct features: (1) spatial differentiation; and possibly (2) binding capacity constraints. The development of a regulatory index of this nature seems relevant for both scientists and policy makers.

References

Adam, S. and Marathon N. 2015. Transportation of U.S. Grains: A Modal Share of Analysis. U.D. Department of Agriculture (USDA), Agricultural Marketing Service (AMS). Available at https://www.ams.usda.gov/sites/default/files/media/ModalJune2015.pdf

Agricultural Marketing Service (AMS), USDA. 2016. Grain Truck and Ocean Rate Advisory Quarterly Update. Transportation and Marketing Programs. Available at https://www.ams.usda.gov/services/transportation-analysis/gtor

Alvarez, A. M., Fidalgo, E. G., Sexton, R. J., and Zhang, M. 2000. Oligopsony power with uniform spatial pricing: theory and application to milk processing in Spain. *European Journal of Agricultural Economics*. 27 (3), 347-364.

Anderson, S. P., de Palma, A., and Thisse, J. –F. 1989. Spatial Price Policies Reconsidered. *Journal of Industrial Economics*. 38, 1-18.

Azzam, A. M. 1996. Testing the Monopsony-Inefficiency Incentive for Backward Integration. *American Journal of Agricultural Economics*. 78 (3), 585-590.

Azzam, A. M. and Schroeter, J. R. 1995. The Tradeoff Between Oligopsony Power and Cost Efficiency in Horizontal Consolidation: An Example from Beef Packing. Amer. J. Agr. Econ. 77, 825-836.

Berry, S. T. 1994. Estimating Discrete-Choice Models of Product Differentiation. The RAND Journal of Economics. 25(2), 242-262.

Blair, R. D. and Harrison, J. L. 1992. The measurement of monopsony power. *The Antitrust Bulletin/Spring, 1992. Federal Legal Publications, Inc.* 144-147.

Bonanno, A. and Lopez, R. A. 2012. Wal-Mart's monopsony power in metro and non-metro labor markets. *Regional Science and Urban Economics*. 46 (4), 569-579.

Coltrain, D., Dean, E., and Barton, D. 2004. Risk Factors in Ethanol Production. Available at https://fba.aiub.edu/Files/Uploads/AGB110011.pdf

Dale, R. T. and Tyner, W. E. 2006. Economic and Technical Analysis of Ethanol Dry Milling: Model Description. *Staff Paper (06-04), Dept. of Ag. Econ., Purdue University*.

Davis, P. 2006. Spatial competition in retail markets: Move theaters. *The Rand Journal of Economics.* 37, 964-982.

Denicoff, M. R., Prater, M. E., and Bahizi, P. 2014. Corn Transportation Profile. U.S. Department of Agriculture (USDA), Agricultural Marketing Service (AMS). Available at https://www.ams.usda.gov/sites/default/files/media/Corn%20Transportation%20Profile.pdf.

Durham, C. A., and Sexton, R. J. 1992. Oligopsony potential in agriculture: Residual supply estimation in California's processing tomato market. *American Journal of Agricultural Economics*. 74 (4), 962-972.

Durham, C. A., Sexton, R. J., and Song, J. H. 1996. Spatial Competition, Uniform Pricing, and Transportation Efficiency in the California Processing Tomato Industry. *American Journal of Agricultural Economics*. 78 (1), 115-125.

e-Education Institute, EGEE 439; Alternate Fuels from Biomass Sources. Pennsylvania State University. Available at https://www.e-education.psu.edu/egee439/node/672.

Edwards, William. 2017. Estimating Grain Transportation Cost. *Iowa State University Extension, Ag Decision Maker File A3-41.* Available at https://www.extension.iastate.edu/agdm/crops/html/a3-41.html.

Eidman, V. T. 2007. Ethanol Economics of Dry Mill Plant, Chapter 3. In R. J. Hauser, ed. *Corn-Based Ethanol in Illinois and the U.S.: A Report. Department of Agriculture and*

Consumer Economics, University of Illinois, November. Available at http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.520.5515&rep=rep1&type=pdf

Environmental Information Administration (EIA).

Fackler, P. L., & Goodwin, B. K. (2001). Spatial price analysis. In Handbook of Agricultural Economics, Volume 1 (pp. 971-1024). Amsterdam, Netherlands: Elsevier

Fousekis, P. 2011. Spatial Price Competition Between Cooperatives Unver Hotelling-Smithies Conjectures. *Agricultural Economics Review*. 12 (2), 5-15.

FRED. Federal Reserve Bank of St. Louis. FRED Economic Data for the Global Price of Corn. Available at https://fred.stlouisfed.org/series/PMAIZMTUSDM.

Gallagher, P., Wisner, R., and Brubacker, H. 2005. Price Relationships in Processors' Input Market Area: Testing Theories for Corn Prices Near Ethanol Plants. *Canadian Journal of Agricultural Economics*. 53, 117-139.

Graubner, M., Balmann, A., Sexton, R. J. 2011. Spatial Price Discriminations in Agricultural Product Procurement Markets: A Computational Economics Approach. *Amer. J. Agr. Econ.* 94(4), 949-967.

Green Plains Renewable Energy. 2017 Annual Report. Available at http://investor.gpreinc.com/static-files/789f73f1-c8e9-4ddf-acd1-421970d5a2cf.

Hettinga, W. G., Junginer, H. M., Dekker, S. C., Hoogwijk, M., McAloon, A. J., Hicks, K. B. 2009. Understanding the Reductions in US Corn Ethanol Production Cost: An Experience Curve Approach. *Energy Policy*. 37, 190-203.

Hotelling, H. 1929. Stability in Competition. *Economic Journal*. 39, 41-57.

Houde, J.-F. 2009. Spatial differentiation and vertical contracts in retail markets for gasoline. Available at http://ssrn.com/abstract=1417506

Hueth, B. and Taylor, C. W. 2013. Spatial Competition in Agricultural Markets: A Discrete-Choice Approach. *Agricultural & Applied Economics Association (AAEA) 2013 AAEA & CAES Joint Annual Meeting. Washington DC.*

Hurt, C. 2012. Ethanol Transforms Indiana Corn Uses. *Purdue Agriculture Economics Report, Purdue Extension, Purdue University*. Available at https://ag.purdue.edu/agecon/Documents/PAER_June%202012.pdf.Indiana Corn. 2012. Available at http://www.incorn.org/index.php/market-development/ethanol/ethanol-facts

Inderst, R. and Valletti, T. 2009. Price Discrimination in Input Markets. *The Rand Journal of Economics*. 40 (1), 1-19.

Irwin, S. 2018. What Happened to the Profitability of Ethanol Production in 2017? *Farmdoc Daily*. 8, 45.

Jung, J., Sesmero, J. P. and Siebert, R. 2019. Using Pre- and Post-Entry Data to Identify the Effect of Ethanol Expansion on the Spatial Pattern of Corn Prices: A Study in Indiana. *Agricultural and Applied Economics Association (AAEA) 2019 Annual Meeting. Atlanta, GA*.

Kang, S., Önal, H., Ouyang, Y., Scheffran, J., and Tursun, Ü. D. 2009. Optimizing the Biofuels Infrastructure: Transportation Networks and Biorefinery Locations in Illinois. *Handbook of Bioenergy Economics and Policy, Springer Link*. 33, 151-173.

Kreps, D. M. and Scheinkman, J. A. 1983. Quantity Precommitment and Bertrand Competition Yield Counot Outcomes. *The Bell Journal of Economics*. 14(2), 326-337.

MacDonald, J. M. and Korb, P. 2011. Agricultural Contracting Update: Contracts in 2008. *Washington DC: U.S. Department of Agriculture, Economic Information Bulletin No. EIB 72, February*.

McCorriston, S. 2002. Why should imperfect competition matter to agricultural economists? *European Review of Agricultural Economics*. 29(3), 349-371.

McManus, B. 2007. Nonlinear pricing in an oligopoly market: the case of specialty coffee. *RAND Journal of Economics*. 38(2), 512-532

McNew, K. and Griffith, D. 2005. Measuring the Impact of Ethanol Plants on Local Grain Prices. *Applied Economic Perspectives and Policy.* 27(2), 164-180.

Meral, P. and Sexton, R. J. 2017. Buying Power with Atomistic Upstream Entry: Can Downstream Consolidation Increase Production and Welfare? *International Journal of Industrial Organization*. 50, 259-293.

Miller, N. H. and Osborne, M. 2010. Competition among Spatially Differentiated Firms: An Empirical Model with an Application to Cement. *Economic Analysis Group Discussion Paper, Antitrust Division, U.S. Department of Justice.*

Miller, N. H. and Osborne, M. 2011. Competition among Spatially Differentiated Firms: An Estimator with an Application to Cement. Available at https://ideas.repec.org/p/bea/wpaper/0072.html.

Miller, N. H. and Osborne, M. 2014. Spatial Differentiation and Price Discrimination in the Cement Industry: Evidence from a Structural Model. *RAND Journal of Economics.* 45(2), 221-247.

NAMA (North America Miller's Association). Corm Milling Process. Available at https://www.namamillers.org/education/corn-milling-process/.

NASS (National Agricultural Statistics Service), USDA. Indiana Field Office. 2014. 2014 STATE AGRICULTURE OVERVIEW for Indiana. Available at

http://www.nass.usda.gov/Quick_Stats/Ag_Overview/stateOverview.php?state=INDIANA

NREL (National Renewable Energy Laboratory). The Biofuels Atlas. Available at https://maps.nrel.gov/biofuels-atlas/#/?aL=TxrT7x%255Bv%255D%3Dt&bL=groad&cE=0&lR=0&mC=39.67759833072648%2C-83.880615234375&zL=7

O'Brien, D. 2010. Updated Trends in U.S. Wet and Dry Corn Milling Production. *AgMRC Renewable Energy Newsletter, February*.

O'Brien, D. P. and Shaffer, G. 1994. The Welfare Effects of Forbidding Discriminatory Discounts: A Secondary Line Analysis of Robinson-Patman. Journal of Law, Economics, & Organization. 10 (2), 296-318.

Nebraska Department of Environment & Energy. 2015. Ethanol Facilities and Capacity by State and Plant. Available at http://www.neo.ne.gov/statshtml/122.htm

Perrin, R. K., Fretes, N. F., and Sesmero, J. P. 2009. Efficiency in Midwest US Corn Ethanol Plants: A Plant Survey. *Energy Policy*. 37(4), 1309-1316.

Porter, M. E. and Spence, A. M. 1982. The Capacity Expansion Process in a Growing Oligopoly: The Case of Corn Wet Milling. *The Economics of Information and Uncertainty, University of Chicago Press.* Available at https://www.nber.org/chapters/c4438.pdf

Porter, R. H. and Zona, J. D. 1999. Ohio School Milk Markets: An Analysis of Bidding. *Rand Journal of Economics*. 30, 263-288.

Renewable Energy Policy Network (REN). 2016. Renewables 2016 Global Status Report. Available at http://www.ren21.net/wp-content/uploads/2016/06/GSR_2016_Full_Report.pdf

Renewable Fuel Association (RFA). 2016. Ethanol Industry Outlook. Available at http://www.ethanolrfa.org/resources/industry/statistics/#1454099788442-e48b2782-ea53

Report on ethanol market concentration. 2018. Federal Trade Commission. Available at https://www.ftc.gov/system/files/documents/reports/federal-trade-commission-report-congress-ethanol-market-concentration/p063000_2018_ethanol_report.pdf

Richards, T. J., Allender, W. J., Hamilton, S. F. 2013. Rivalry in Price and Location by Differentiated Product Manufacturers. *Amer. J. Agr. Econ*. 95(3), 650-668.

Rogers, R. T. and Sexton, R. J. 1994. Assessing the Importance of Oligopsony Power in Agricultural Markets. *Amer. J. Agr. Econ*. 76(5), 1143-1150.

Saitone, T. L, Sexton, R. J, and Sexton, S. E. 2008. Market Power in the Corn Sector: How Does It Affect the Impacts of the Ethanol Subsidy? *Journal of Agricultural and Resource Economics*. 33(2), 169-194.

Salop, S. 1979. Monopolistic Competition with Outside Goods. Bell Journal of Economics. 10, 141-156.

Sesmero, J. P. 2018. Spatial Pricing in Uncontested Procurement Markets: Regulatory Implications. *Journal of Agricultural & Food Industrial Organization*. 16(1).

Sesmero, J. P., Perrin, R., and Fulginiti, L. 2016. A Variable Cost Function for Corn Ethanol Plants in the Midwest. *Canadian Journal of Agricultural Economics*. 64, 565-587.

Sexton, R. J. 2000. Industrialization and Consolidation in the U.S. Food Sector: Implications for Competition and Welfare. *Amer. J. Agr. Econ*. 82(5), 1087-1104.

Sexton, R. J. 2013. Market Power, Misconceptions, and Modern Agricultural Markets. *Amer. J. Agr. Econ*. 95(2), 209-219.

Sheldon, I. M. 2017. The Competitiveness of Agricultural Product and Input Markets: A Review and Synthesis of Recent Research. *Journal of Agricultural and Applied Economics*. 49(1), 1-44.

Su, C-L. and Judd, K. L. 2012. Constrained Optimization Approaches to Estimation of Structural Models. *Econometrica*. 80(5), 2213-2230.

Suh, D. H. and Moss, C. B. 2017. Decompositions of corn price effects: implications for feed grain demand and livestock supply. Agricultural Economics. 00, 1-10.

Thomadsen, R. 2005. The Effect of Ownership Structure on Prices in Geographically Differentiated Industries. *The Rand Journal of Economics*. 36 (4), 908-929.

Tirole, J. 2015. Market Failures and Public Policy. *The American Economic Review*. 105(6), 1665-1682.

Wang, Y., Delgado, M. S., Gramig, B., and Sesmero J. P. 2018. Impact of Ethanol Plant Spatial Competition on Local Corn Production: A Spatially Explicit Analysis. Available at http://web.ics.purdue.edu/~wang1551/land_use_012018.pdf.

Williams, O. and Bessler, D. A. 2010. Cointegration: implications for the market efficiencies of the high fructose corn syrup and refined sugar markets. *Applied Economics*. 29 (2), 225-232.

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 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[6]	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Annual production[7]	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

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

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 one ethanol plant, except for Posey County, which has two ethanol plants. Status over the previous periods, 2004 through 2013, is available from authors.
Source: Renewable Fuel Association (2016) and the Biofuels Atlas, NREL.
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 in which 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
Residual supply		
Corn price	β^p	3.408***
		(0.71)
Distance	β^d	-0.004***
		(1.9e-5)
Export dummy	β^e	0.309***
		(0.0005)
Marginal costs		
Natural gas price	α^{ng}	0.132***
		(0.005)
Electricity price	α^{elec}	0.051***
		(0.0015)
Time trend	α^{time}	-0.185***
		(0.02)
Extra costs per unit of unutilized capacity	γ	1.58e-4
		(2.8e-4)
Derived statistics	*Previous Studies*	*Our Estimates*
Transportation cost ($ per bu-mile)	0.0016[1]	0.0012***
		(9.3e-6)
Cap. utilization ratio	0.95[2]	0.98***
		(0.007)

Table 4. Continued

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: Standard errors are computed by bootstrapping and reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels are denoted as *, **, and ***, respectively.

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

Figures

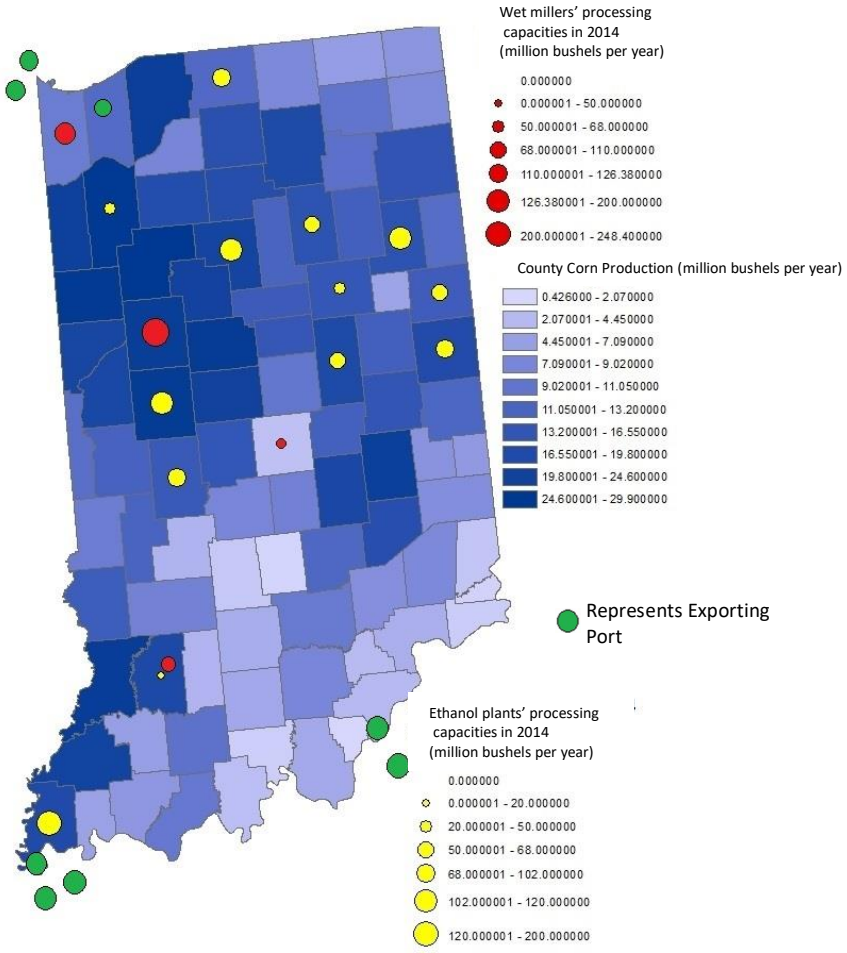

Figure 1. Oligopsonists' locations and corn production in Indiana counties in 2014

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

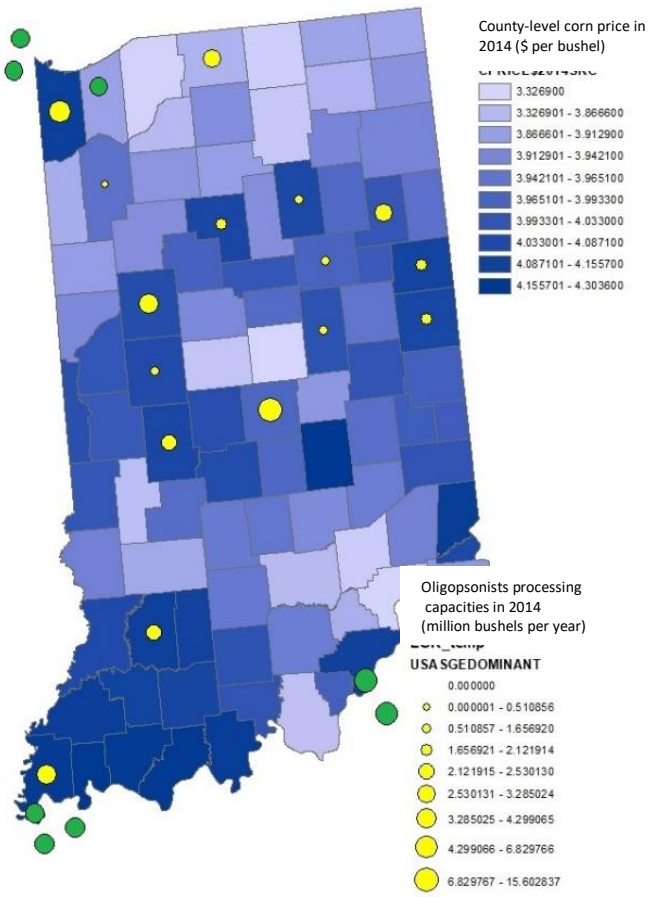

Figure 2. Oligopsonists' locations and corn prices in Indiana counties in 2014

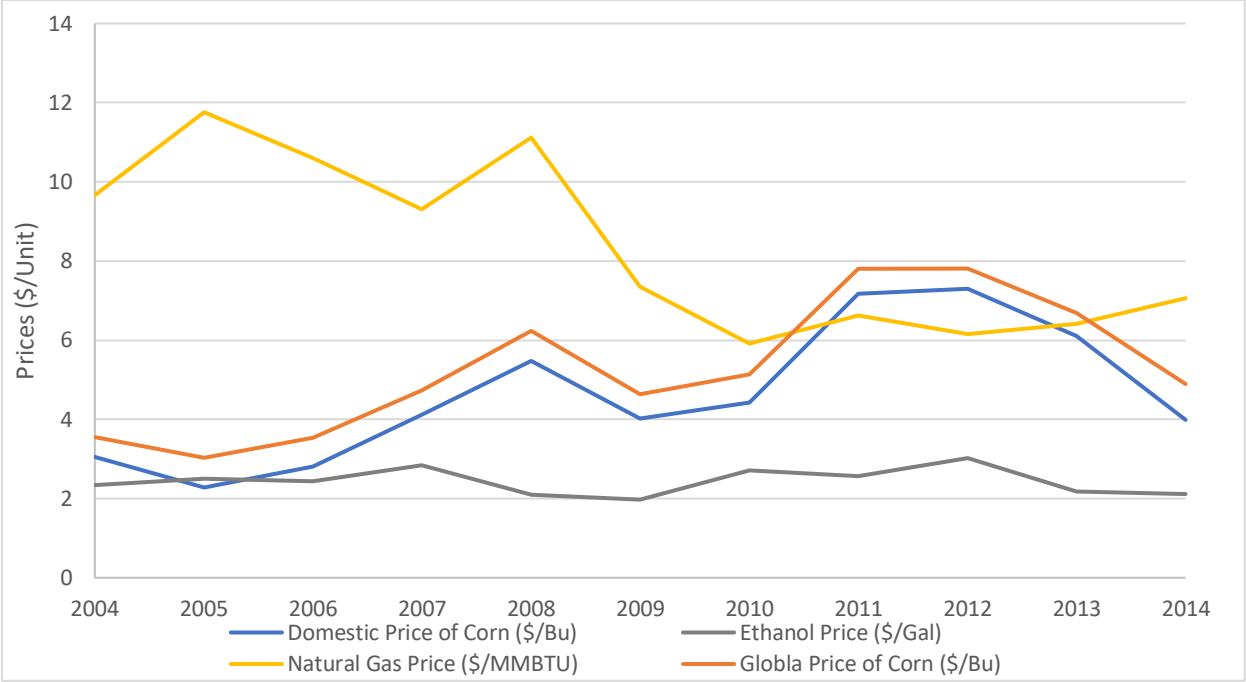

Figure 3. Evolution of relevant prices in the corn market

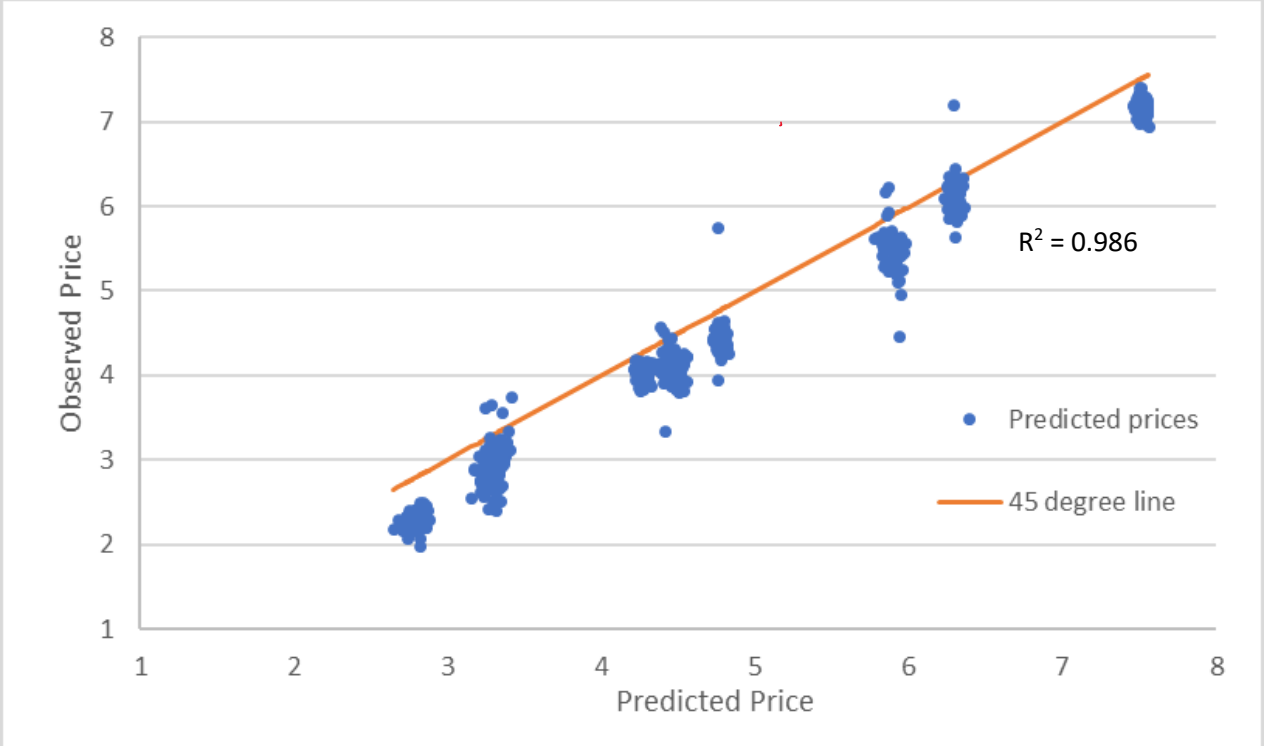

Figure 4. Predicted versus observed farm-gate prices

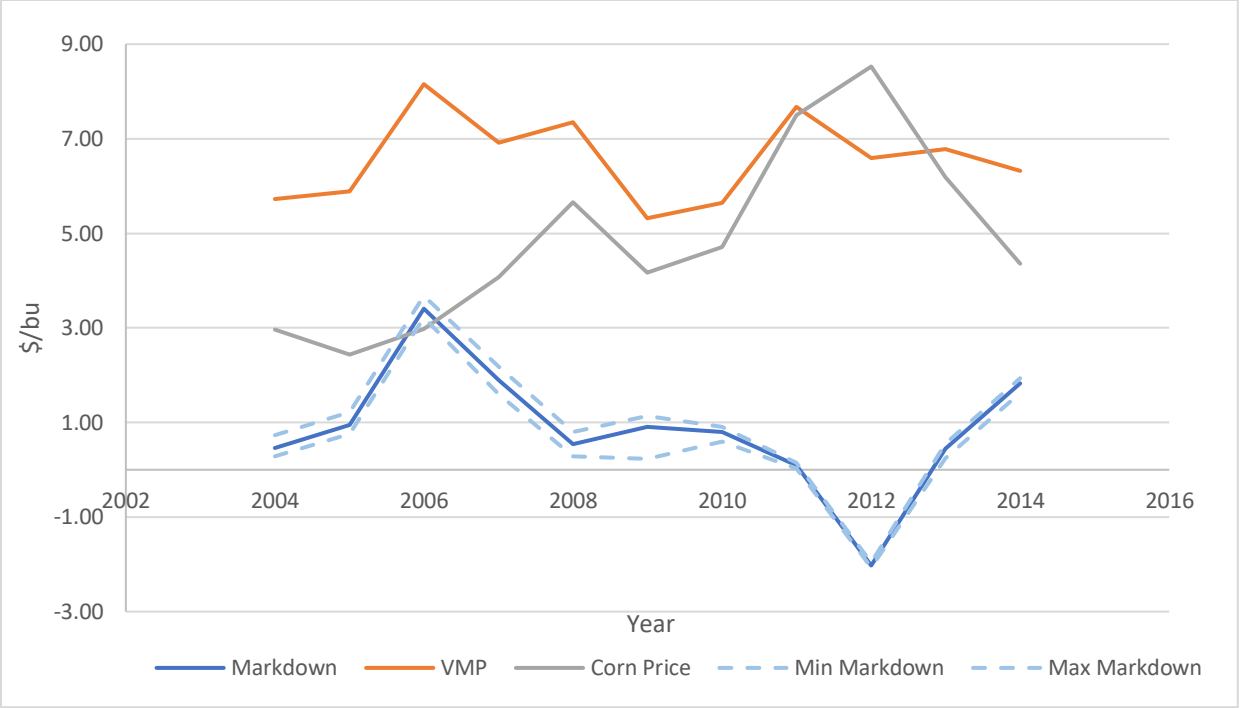

Figure 5. VMP, Predicted corn prices, and markdown

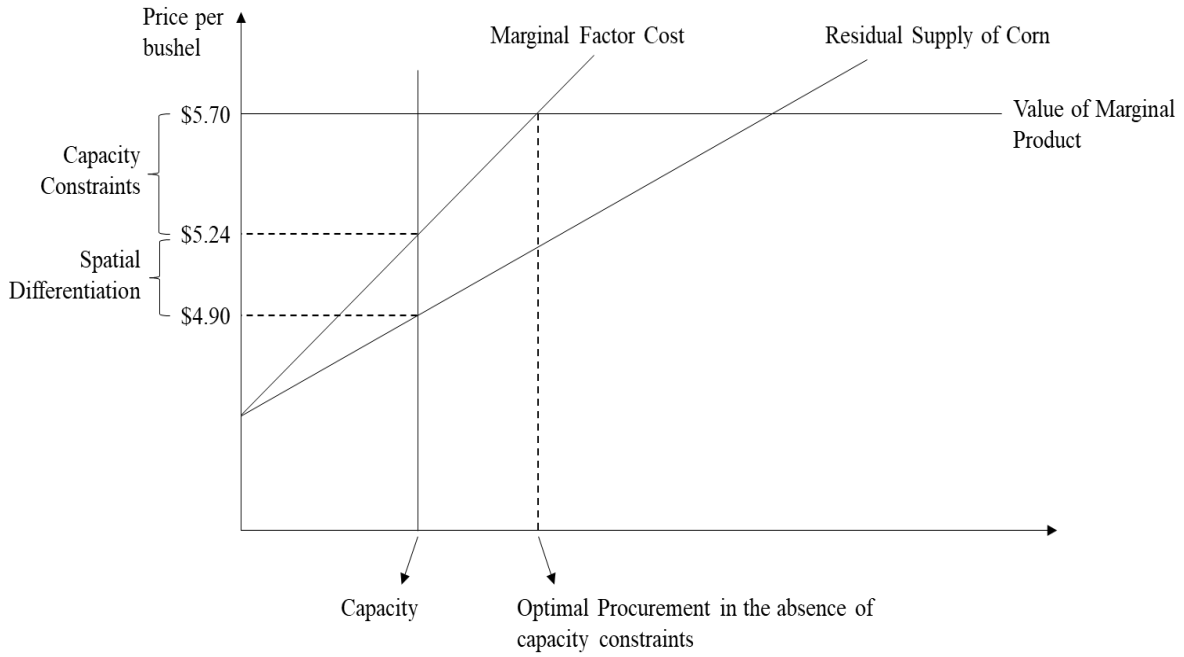

Figure 6. Sources of markdown for average plant in our sample

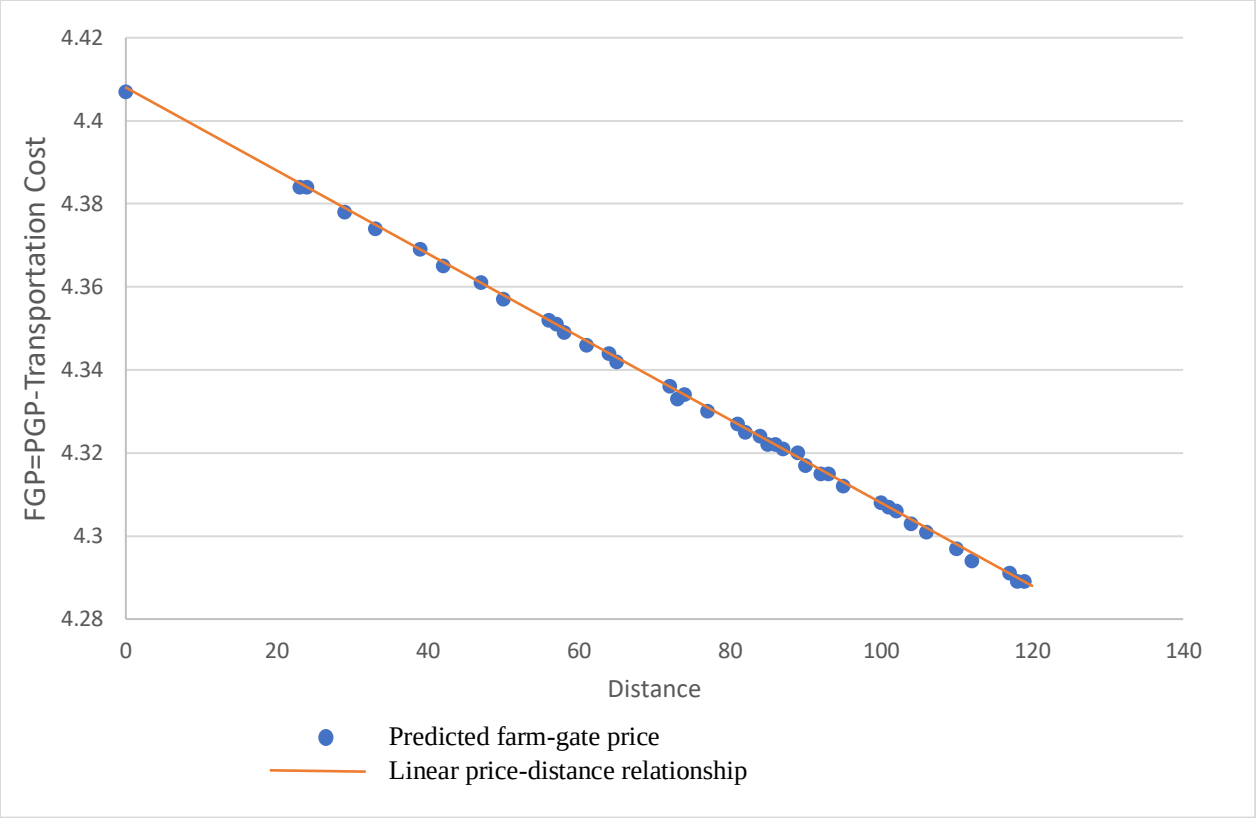

Figure 7. Spatial price discrimination for a selected plant in our sample [a]

[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 the spatial pattern of corn purchases.

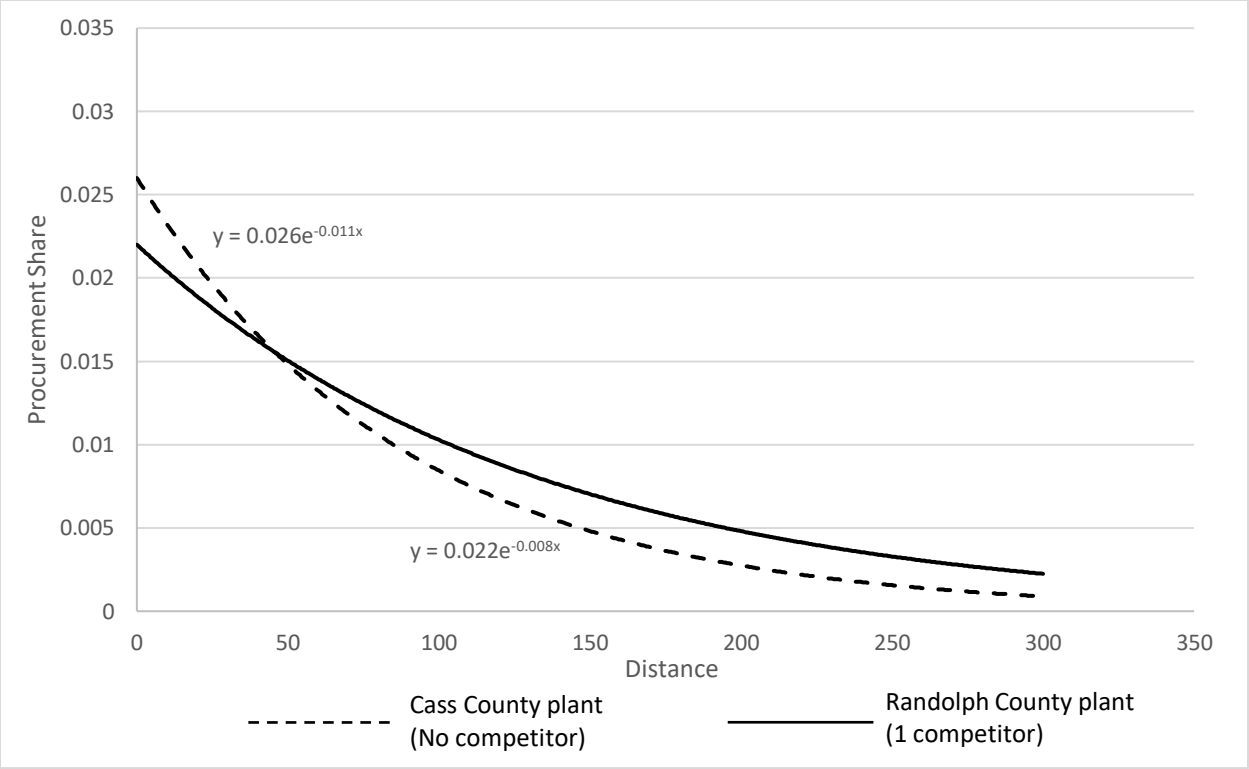

Figure 8. Predicted corn purchases by distance for selected plants in our sample [a]

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

Figure 9. Merging and non-merging plants in counterfactual simulations

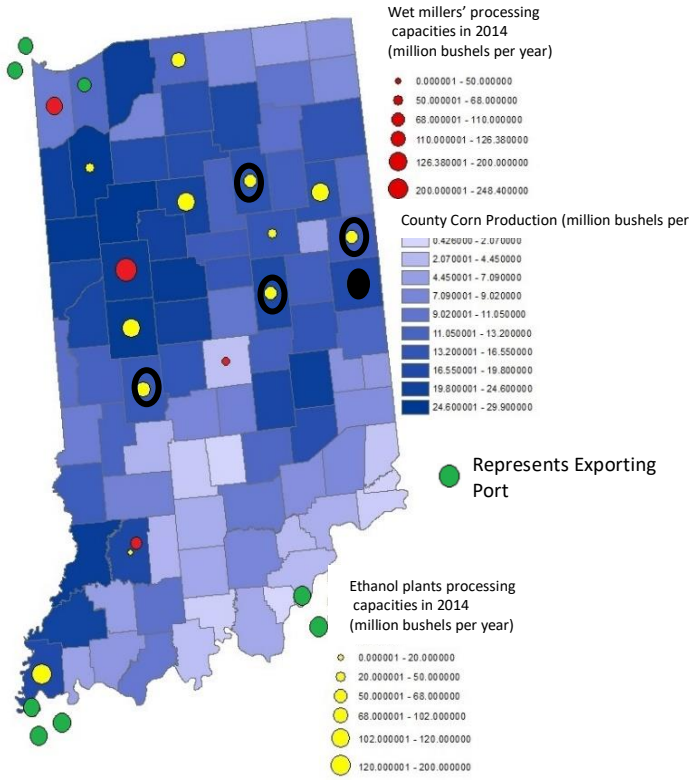

Figure 9a. Merger with a nearby competitor

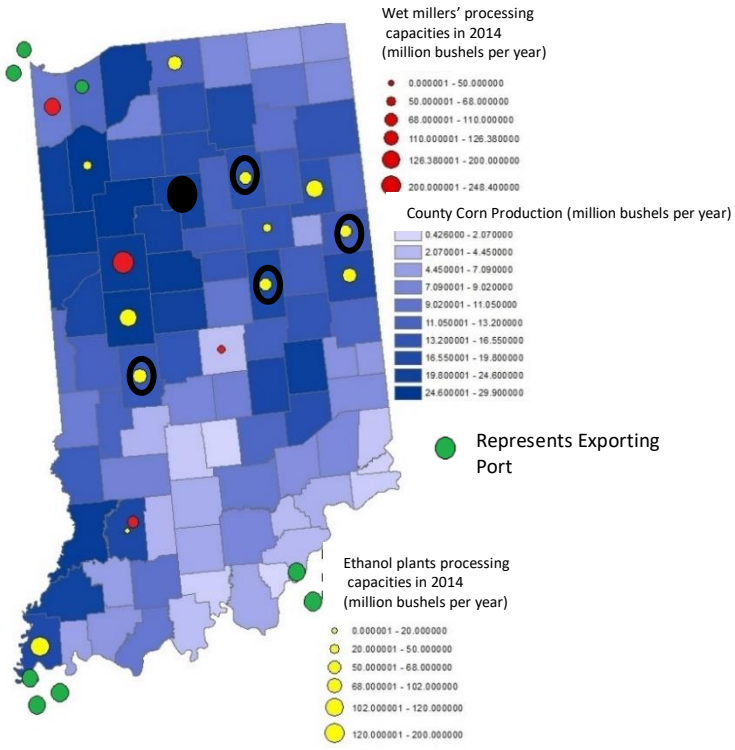

Figure 9b. Merger with a distant competitor

Figure 10. Spatial pattern of consolidation and change in markdown

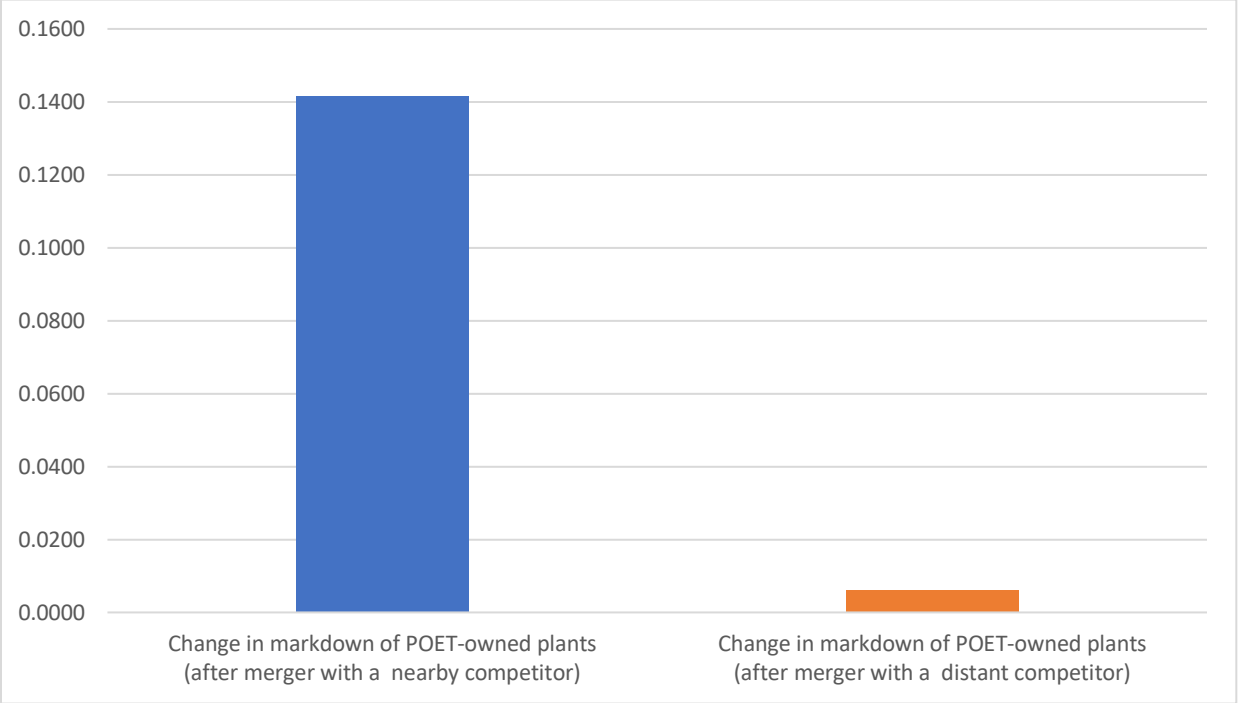

Figure 10a. Comparison between the merger with a nearby and a distant competitor

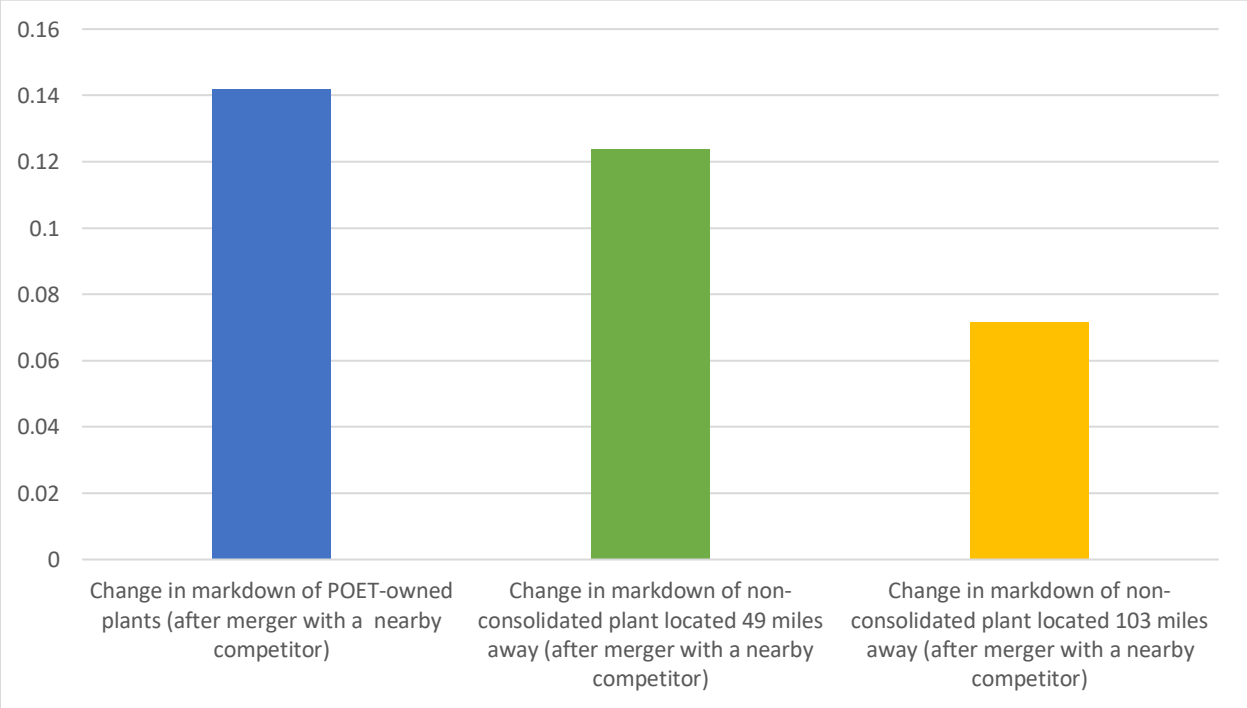

Figure 10b. Spillover effect of the merger with a nearby competitor

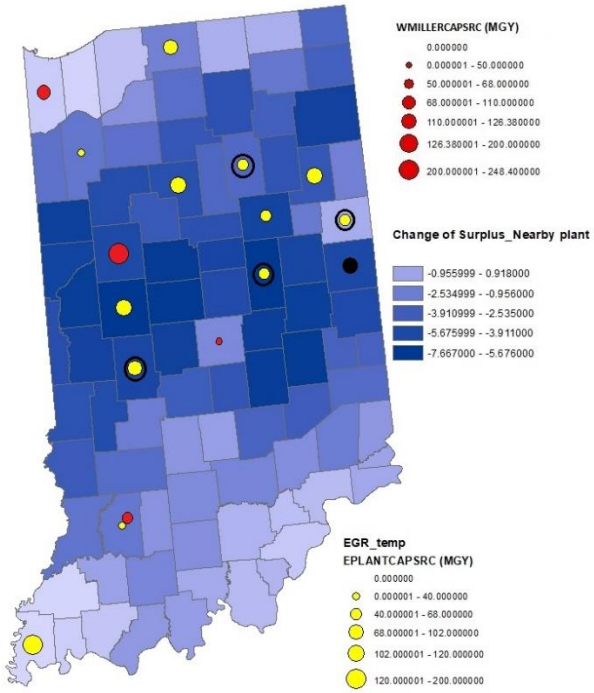

Figure 11. Change in producer surplus due to merger with nearby plant

Appendix A. Detailed Estimation Strategies

a. Firms' profit maximization. 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:

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

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

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

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

The reason that $\boldsymbol{\Omega}(\boldsymbol{p}^c)$ is a block diagonal structure is that $q_{ij}^c(\boldsymbol{p}_i^c;\boldsymbol{x}_i,\boldsymbol{\beta})$ is a function of prices offered to that county by all plants $\boldsymbol{p}_i^c$, but independent of prices offered by those plants to other counties $\boldsymbol{p}_{-i}^c$. Therefore, $\boldsymbol{\Omega}(\boldsymbol{p}^c)$ is constructed based on two premises: (1) farmers in one area choose among all J oligopsonist plants in Indiana; and (2) corn supply in one county i is unaffected by prices received by farmers in other counties, $-i$.

Moreover, the elements of each submatrix reflect the extent to which a plant internalizes competition externalities imposed on another plant in the sample. Each plant *j* sources corn from multiple counties. If firm *F* owns multiple plants, then it will internalize pricing externalities

across its plants. In other words, if plant 1 increases its corn bid to county i (an increase in p_{i1}), it will reduce the residual supply of corn from that county faced by plant 2 (all else constant, it will reduce q_{i2}^c)—which is the business stealing effect. If the same firm owns both plants, it will fully internalize this negative externality, $\frac{\partial q_{i2}^c(\boldsymbol{p}_i^c;\boldsymbol{x}_i,\boldsymbol{\beta})}{\partial p_{i1}}$. Otherwise, the plant would not internalize the externality, and $\frac{\partial q_{i2}^c(\boldsymbol{p}_i^c;\boldsymbol{x}_i,\boldsymbol{\beta})}{\partial p_{i1}}$ would take a value of zero.

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

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:

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

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

b. 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:

(A5) $$\min_{\boldsymbol{\theta}\in\Theta} \frac{1}{T}\sum_{t=1}^{T}[\boldsymbol{p}_t^c - \widetilde{\boldsymbol{p}}_t^c(\boldsymbol{\theta};\boldsymbol{X}_t)]'\boldsymbol{C}_t^{-1}[\boldsymbol{p}_t^c - \widetilde{\boldsymbol{p}}_t^c(\boldsymbol{\theta};\boldsymbol{X}_t)]$$

subject to

(A1)

(A2)

(A6) $$RSUP_i - \sum_j q_{ij}^c(\boldsymbol{p}_i^c;\boldsymbol{x}_i,\boldsymbol{\beta}) \geq 0 \qquad \forall\, i.$$

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[18] by using the algorithm solver developed by Dirkse and Ferris (1998). We apply a bootstrap method to compute standard errors of each parameter.

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

Appendix B. Algorithm of the Iterative Parameter Estimation