MARKET POWER IN FEEDSTOCK PROCUREMENT AND ECONOMIC EFFECTS OF CORN ETHANOL

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Selected Paper prepared for presentation at the 2017 Agricultural & Applied Economics Association and Western Agricultural Economics Association Annual Meeting, Chicago, IL, July 30-Aug 1

1. Introduction

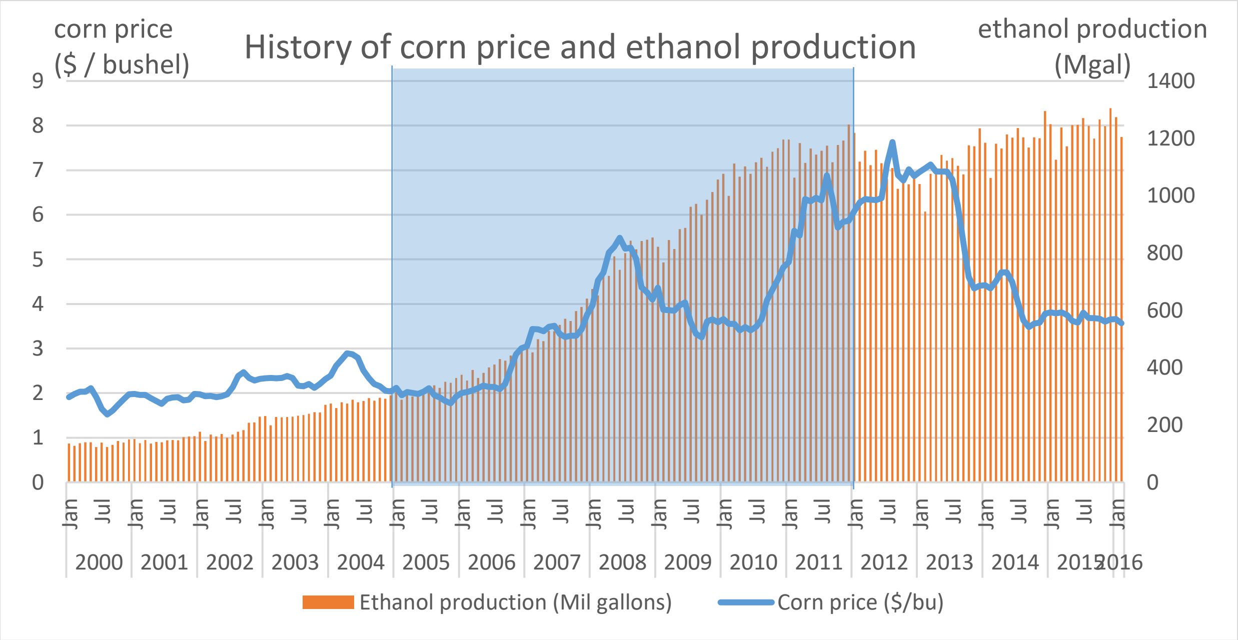
Ethanol as a motor fuel has been supported by the government in its attempt to deploy renewable energy sources, reduce dependence on imported oil, and assist economic development in rural areas. It is the most important source of biofuel in the US, and around the world. According to the Renewable Energy Policy Network for the 21st Century (REN 21, 2016) and the Renewable Fuel Association (RFA, 2016), fuel ethanol accounts for 90 percent of the biofuel productions in the US. Of 16.4 billion gallons of biofuel produced in the US in 2015, 14.8 billion gallons (95 percent) were corn ethanol.

Globally, 25.0 billion gallons of ethanol out of the 33.9 billion gallons of biofuel (74 percent) produced in 2015, consisted of corn ethanol (REN 21, 2016). In addition, the US accounts for 57 percent of the global production of biofuel (RFA, 2016). The production of corn ethanol in the US has increased from 0.2 billion gallons in 1980 to 14.8 billion gallons in 2015 (RFA, 2016). However, most of that growth took place between 2005 and 2011. The fast increase in the latter period was due to a combination of policies (e.g. tax credits, Renewable Fuel Standards (RFS)) and market conditions (i.e. high petroleum prices). Yet, many aspects of the corn ethanol market remain largely unexamined, which diminishes our understanding of the economic and welfare implications of government policies.

1.1. Impact of ethanol industry on corn prices

Since corn is the main feedstock for ethanol production in the US, the evolution of the ethanol industry is closely tied to the corn market and, through market interconnections, with soybean and other agricultural commodities. Data from the National Agricultural Statistics Service (NASS) of the US Department of Agriculture (USDA) seem to suggest that a rise in ethanol production induced an increase in corn price particularly over the period of ethanol boom that began in 2005 and continued until 2011 (shaded area on Figure 1). Many researchers have turned their attention to this apparent link.

Figure 1. History of monthly average price of corn in the US



* Source: NASS of USDA (2016). Available at https://www.nass.usda.gov/index.php

Urbanchuk and Kappell (2002) estimates that location of a plant producing 40 million gallons of ethanol a year increases the price of corn in the surrounding area by an amount between $0.05 and $0.10 per bushel. Ferris and Joshi (2004) had predicted that producing 4.67 billion gallons of ethanol would result in an 18 percent increase in corn price. Based on data around 12 plants built between 2000 and 2003, McNew and Griffith (2005) estimates that ethanol plants increase corn prices by $0.06 per bushel on average; and this increase in price is effective up to 68 miles away from plants. They further found that the change of price ranges from $0.05 to $0.19 per bushel depending on the local corn supply.

Parcel and Fort (2006) find the premium in corn price associated with production of corn ethanol is $0.09 per bushel. Taylor et al. (2006) estimate that corn price will be $2.46 per bushel if 7 billion gallons of ethanol are produced in 2014, and $3.00 per bushel if 14 billion gallons are produced. Based on the elasticity/flexibility of corn price with respect to ethanol production, Fortenbery and Park (2008) find that a 1% increase in ethanol production raises corn price by 0.16% in the short run, at the national level. In contrast, the Food and Agricultural Policy Research Institute (FAPRI, 2005) estimates that a 100-million gallon-ethanol plant will have almost no effect on corn price. Therefore, most studies find that expansion of ethanol production increases corn price. But they differ in the magnitude, as well as the spatial pattern of those price changes.

The objective of this research is to examine the role of the spatial market structure of the corn ethanol industry on the magnitude and spatial pattern of corn price premium. This is in line with previous criticism of the competitive market structure assumption found in previous studies (e.g. Saitone et al., 2008).

1.2. Motivation

1.2.1. Market Structure

Agricultural production is usually characterized by relatively few processors purchasing from a large number of spatially dispersed producers. This, in combination with relatively high cost of transporting agricultural raw material, provides processors with a certain degree of market power (Rogers and Sexton, 1994; Graubner et al., 2011). As a result, many agricultural processing industries, including corn ethanol plants, food processors, or livestock operators, may operate as oligopsonies. In turn, this market structure allows agricultural processors to suppress corn prices below the Marginal Value Product (MVP). In addition to marking down corn prices, firms may also engage in spatial price discrimination (Graubner et al., 2011; Sesmero, 2016).

A pervasive issue in the literature on corn ethanol is that issues of market structure and spatial pricing have received little attention. This might be due to two major reasons. First, Scherer and Ross (1990) argue that, on average, market concentration on the buyer side is not high enough to justify serious concerns. Second, Tirole (1988) argues that analyses of oligopsony situations are natural extrapolations of oligopoly and, as such, do not deserve special attention. However, the US Department of Justice (US DOJ) challenged the merger between Cargill and Continental Grain Company (US DOJ, 1999). The US DOJ's stated concern was that the merger may lower the price received by farmers for crops such as grain, oilseed crops, corn, soybeans, and wheat.

Such concerns have been shared by agricultural economists across the country. Rogers and Sexton (1994) characterize and document certain patterns in the farm-retail price spread (i.e. the difference between the price paid by consumers for a certain food and the price received by farmers for the corresponding food commodity) that are inconsistent with competitive settings. They found that, in many agricultural procurement markets, higher transportation cost and smaller number of processors are typically associated with higher farm-retail price spreads. This price spread has been closely followed by the Economic Research Service (ERS) of US Department of Agriculture (USDA) in an attempt to keep anti-competitive pricing in check.

1.2.2. Literature on oligopsony in agriculture

Agricultural economists have been at the forefront of rigorous analysis of oligopolies, given the pervasiveness of this type of market structure in agricultural processing industries. An extensive literature focuses on the meat industry. Extending Appelbaum's model (Appelbaum, 1979, 1982), Schroeter (1988) finds evidence of market power exertion in the US meat-packing industry. However, the study concludes that this does not result in serious welfare losses. Azzam and Pagoulatos (1990) consider oligopolistic intermediaries in the US meat-packing industry that exert market power both upstream (purchase of livestock) and downstream (sales of meat). They find that market power exertion upstream is ampler than downstream, suggesting that the industry approaches an oligopsonistic structure.

In contrast, Muth and Wohlgenant (1999) measure oligopsony power in the US beef-packing industry over 1967-1993 and conclude that there is no evidence of marked deviations from a competitive market structure over that period. Weldegebriel (2004) focuses on the link between market power (oligopsony and oligopoly power) and the nature of price transmission from the farm to the consumer. They demonstrate that the impact of upstream and downstream market power on the degree of price transmission cannot be unambiguously determined. In fact, the link between market power and price transmission depends on the properties of demand for the retail product, and input supply.

Many other studies have examined oligopsonistic market structurers in different agricultural industries (Rogers and Sexton, 1994; Gallagher et al., 2005; Richards et al., 2013). Some even focused on spatial market power and pricing (Graubner et al., 2011). In the corn ethanol industry, the spatially dispersed and un-concentrated nature of corn production, in combination with higher concentration in the processing stage and high transportation cost, makes considerations of spatial market power warranted. Yet, with the exception of Saitone et al. (2008), market power has been largely overlooked in studies of the corn ethanol industry. Saitone et al. (2008) find that the presence of market power in corn procurement diminishes the effect that ethanol policies have on corn prices. They also find that, while market power does not seem to introduce large deadweight losses, it does influence welfare distribution. However, Saitone et al. (2008) did not explicitly consider spatial market power and, consequently, the spatial pattern of corn price markdown (or, conversely, the increase in corn price triggered by ethanol-induced demand).

In competitive factor market, the firm will set the price of the input equal to its MVP:

$$W_{input} = MP_{input} \times P_{ethanol} \tag{1}$$

where W_{input} is the price of a unit of the input, MP_{input} is a marginal productivity of the input, and $P_{ethanol}$ is the ethanol price (which the firm does not control as it is determined by oil price).

However, when the firm exerts market power it prices the input below its MVP. The difference between the input's MVP and its prices is typically referred to as markdown. When market power is due to spatial location and non-trivial transportation costs, the firm can engage in spatial price discrimination; i.e. the firm can vary markdown by distance. Therefore, the effect of an ethanol plant's entry or production expansion on corn prices will depend upon the degree of market power exertion by the biofuel firms or other processors, and it is unlikely to display a spatially homogeneous pattern. This calls for closer scrutiny of ethanol firms' and processors' conducts, and its effects on corn prices over space.

1.3. Limitation of previous work and contribution of this research

There has been significant theoretical work on spatial market power and pricing behavior (Hotelling, 1929; Salop, 1979; Anderson et al., 1989; Vogel, 2008). Unfortunately, empirical estimations of spatial market power exertion and price discrimination are largely absent from the literature. One major, and perhaps the main, hurdle for empirical work is the unavailability of firm-level data. Miller and Osborne (2010; 2011; 2014) introduce a method that overcomes this limitation. Their approach consists of identifying firm-level parameters that can generate an observed set of market-level equilibrium outcomes. Once firm-level parameters are estimated, unobservable and spatially explicit pricing patterns can be recovered. Implementation of this approach requires information on market-level equilibrium quantity and prices in the corn procurement market in the State of Indiana.

Using this approach, this research makes a following key contribution to the literature on the economics of corn procurement. I examine the magnitude of input price markdown and whether relevant processors conduct spatial price discrimination when they procure corn. I also evaluate the extent to which spatially differentiated markdown affects economic and welfare outcomes in different locations in Indiana. This will be achieved by measuring surplus under the estimated markdown and spatial price discrimination, and compare it to a counterfactual with no market power exertion.

2. Market information

2.1. Status of the industry in Indiana

Corn ethanol is a prominent industry in Indiana. Almost 40% of the total farmland in Indiana, 5.9 million acres out of 14.7 million acres, are cultivated to corn (USDA, 2014); and 431 million bushels of corn (around 40% of total corn produced) were processed to produce ethanol in 2014 (NASS, USDA). Meanwhile, there are 14 corn ethanol plants currently operating in Indiana (Table 2). In addition, Food processors are broken down into two categories of wet- and dry- corn mills. Wet-milling plants produce corn oil, sweeteners, or starch products and dry-milling plants produce cereals, corn meal, or corn flour (Table 3). 21% of the total corn produced is consumed by 5 big wet-milling plants for food processing.

The benchmark price of corn at a given location is determined by the Chicago Board of Trade price minus the cost of transporting corn from that location to a Chicago terminal. However, local market conditions introduce deviations of prices from that benchmark. In locations where competition for corn is more intensive (e.g. due to existence of a large number of elevators, corn ethanol plants, or other processors), the price can raise substantially above the benchmark, and towards corn's MVP (corn's marginal productivity multiplied by the price of the firms' output).

Table 2. Ethanol Production Facility Status in Indiana

Facility	County	Operating Capacity[1]	Corn Demand[2]	Year Built
Abengoa Bioenergy Corp.	Posey	90	33.3	2009
Cardinal Ethanol	Randolph	100	37.0	2008
Central Indiana Ethanol, LLC	Grant	55	20.4	2007
Grain Processing Corp.[3]	Daviess	20	7.4	1999
Green Plains Renewable Energy	Wells	120	44.4	2008
Iroquois Bio–Energy Company, LLC	Jasper	50	18.5	2007
Noble Americas South Bend Ethanol LLC	St. Joseph	102	37.8	1984
POET Bio-refining	Madison	68	25.2	2008
POET Bio-refining	Putnam	92	34.1	2008
POET Bio-refining	Wabash	68	25.2	2008
POET Bio-refining	Jay	68	25.2	2007
The Andersons Clymers Ethanol, LLC	Cass	110	40.7	2007
Valero Renewable Fuels Company, LLC	Montgomery	110	40.7	2007
Valero Renewable Fuels Company, LLC	Posey	110	40.7	2010
Total	Indiana Total	1,163	431.0	-

***** Source: Official Nebraska Government (2015) and The Biofuel Atlas of NREL

1. Unit: Million Gallons of ethanol per Year (MGY) for operating capacities

2. Unit: Million Bushels of corn per Year (MBY) for corn demand

3. Grain Processing Corp. (GPC) operates as both of ethanol plants and wet-milling processor

Table 3. Food Milling Processors Status in Indiana

	Facility	County	Capacity[1] (Corn Demand)	Corn Production[2]
Wet-Milling Plants	Cargill	Lake	67	9.8
	Grain Processing Corp.[3]	Daviess	32	18.5
	Ingredion	Marion	22	1.4
	Tate & Lyle	Tippecanoe	75	21.4
	Tate & Lyle	Tippecanoe	17	
	Total	Indiana Total	213	-
Dry-Milling Plants	Agricor	Grant	4	14.1
	Azteca	Vanderburgh	4	5.6
	Nunn Milling Co.	Vanderburgh	4	
	Cargill	Marion	12	1.4
	Wilson’s Corn Products	Fulton	4	17
	Total	Indiana Total	28	-

1. Unit: MBY

2. Unit: MBY

3. Grain Processing Corp. (GPC) operates as both of ethanol plants and wet-milling processor

Figure 2. Ethanol Plants Locations in Indiana

* Source: Renewable Fuel Association (2016)

Figure 2 shows the locational pattern of ethanol plants in Indiana. In locations where competition among ethanol plants is intense (i.e. locations surrounded by many ethanol plants), the price of corn is expected to approach its MVP for ethanol plants. Where competition is less intense, plants may be able to markdown the price which will then be below MVP, but still above the benchmark. Previous studies tried to quantify the extent to which ethanol production increases corn price above the benchmark, but fail to consider the role of spatial market structure on that premium. As local market conditions for ethanol vary widely, so will the impact of ethanol on corn price. Similarly, plants behavioral responses to policy will be influenced by these local market conditions. Therefore, the effect of policies supporting deployment of ethanol plants in Indiana will likely be spatially heterogeneous. They may also vary over time as market conditions change. It is therefore critical to relax the assumption of perfect competition and deepen our understanding of spatial market structure and conduct in this market. This is the objective of the first essay of this dissertation.

2.1.1. Corn procurement market in Indiana

Dominant firms and competitive fringe market structure

Corn market cannot be assumed to be perfectly competitive because buyers in some certain industries may have market power as is usual in agricultural factor markets. Many studies support the dominant buyers' market power in corn market. Blair and Harrison (1992) derive the dominant buyers' market power index and it increases with

(1) dominant buyers' market share,

(2) less elastic demand of competitive fringe, and

(3) inelastic market supply of a product.

Corn procurement market in Indiana mostly satisfies these three conditions and suggests a high dominant buyers' market power in this context. Based on our estimated corn use from each consumer group in Indiana, we may be able to describe the market structure as dominant firms and competitive fringe. We estimate the corn demand of different industries for different uses in

Indiana based on several sources of data (Hurt, 2012) and author's estimation based on NASS Quick Stats, USDA; ERS, USDA) (Table 4). For some data unavailable for more recent information such as corn demand from wet- and dry- milling, we follow the estimation by Hurt (2012) because changing capacities usually takes long time and the amount of corn demanded by food milling processors based on its capacities have actually stayed constant from 2007 (Hurt, 2012). In 2014, 40% (431 million bushels) of total corn production in Indiana is used for ethanol production, 24% (259 million bushels) for food processors (21% (231 million bushels) for wet-mills and 3% (28 million bushels) for dry-mills), and 17% (186 million bushels) for animals feeding of livestock operators, and around 25% (248 million bushels) for export. Export varies substantially from year to year.

Table 4. Estimated Indiana Corn Use at Processing Capacities

		Estimated Corn Use at Processing Capacities in Indiana (million bushels)							
		2007	2008	2009	2010	2011	2012	2013	2014
Dominant firms	Ethanol	104	237	291	284	366	381	431[1]	431[1]
	Wet Milling	213	213	213	213	213	213	213[2]	213[2]
Competitive fringe	Animals Feeding	169	182	182	183	185	186	197[3]	197[3]
	Dry Milling	28	28	28	28	28	28	28[2]	28[2]
	Corn Export[4]	186	264	182	135	176	87	89	248
	Total Corn Use estimated[5]	515	661	715	709	793	808	869	869
	Total Corn Use estimated[6]	701	925	897	844	969	895	958	1,117
	Indiana Total Corn Supply	1,049	968	1,007	971	898	1,046	1,070	1,162
	Indiana Corn Production[7]	981	874	934	898	840	978[8]	1,032	1,085
	Indiana Corn Stock[9]	68	94	73	73	58	68	38	77

* Data source: Hurt (2012) for the period from 2007 to 2012

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

1. Estimated based on the information of ethanol plants capacities
2. Assume to stay constant from 2012 (Hurt, 2012)
3. Estimated based on the data (NASS, USDA). With the assumption of 11.6 bushels of corn per head of a hog a year, 50 bushels of corn per head of a cattle a year, 0.62 bushels of corn per head of poultry a year.
4. State Export Data (ERS, USDA) and Survey Data for price of corn received in Indiana (NASS, USDA) for 2013 and 2014.
5. Estimated at capacity without export
6. Estimated at capacity with export
7. Survey Data (2015), Quick Stats. NASS, USDA for both Hurt (2012) and author
8. Estimated by Hurt (2012). Actual data is 597 million bushel which is low due to drought
9. This is the corn stock on based on crop year, Sep 1st, which is just before the next harvest. Then, total corn supply in Indiana is the sum of the corn stock from the last crop year and corn production harvested in the next crop year.

However, in order to understand the market power, it is necessary to look at capacity of each consumer in individual industry. If the small number of consumers with big capacities share the large amount of corn supply, they may be considered as dominant firms, have market power, and determine market price. On the other hand, if the large number of consumers with small capacities share the small amount of corn supply, they may become competitive fringe and cannot affect market price. We assume that ethanol plants and wet-milling plants are dominant firms based on their market share (61% of total corn supply), and large capacity of individual plant (Table 2 and 3).

On the other hand, dry-mills, livestock, and export are competitive fringe. Suh and Moss (2017) estimate that livestock operators (competitive fringe in this study) have inelastic demand for corn in response to an increase in corn prices. This makes sense because livestock operators cannot let their animal die. In addition, usually agricultural product supply is inelastic because farming is usually a long producing process longer than 6 months.

Therefore, ethanol plants and wet-milling plants may have dominant buyers' market power and dry-mills, livestock operators, and exports are a competitive fringe.

Dominant firms

In 2014, 14 ethanol plants in Indiana share 431 million bushels of corn and 5 wet-milling companies consume 231 million bushels of corn in Indiana (61%). Information of the ethanol plants and wet-mills are described in Table 2 and Table 3. As we can see, individual plant has huge capacity and corresponding corn demand. GPS's ethanol production is so small (20 million gallons annually) that it may not behave as oligopsony alone. However, considering that they also have wet-milling plant at the same location with the demand of 32 million bushels (Table 3), we can count them as the one dominant firm owning both wet-milling and ethanol plants with the large total capacity and corn demand (39.4 MBY).

For 5 wet-milling plants in Indiana, Tate & Lyle owns 2 plants in Lafayette (Tippecanoe County), Cargill owns 1 in Hammond (Lake County), Ingredion owns 1 in Indianapolis (Marion County), and GPC owns 1 in Washington (Daviess County) (Table 3). As mentioned, GPC also produces 20 million gallons of ethanol from the plant at the same location (Table 2). GPS's wet-milling plant can compete with ethanol plants as a dominant firm jointly with its ethanol plants. In addition, Cargill and Tate & Lyle own grain elevators. Based on the location, Cargill's wet-milling plant is 27 miles away from its own closest grain elevator. Tate & Lyle's plants are 40 miles away from its own grain elevator. This means that Cargill's and Tate & Lyle's plants are provided with corn from their own elevators. Even so, however, each county produces much less corn and they have to compete for unfulfilled corn from other counties (Table 3). Therefore, we also count them as dominant firms.

Therefore, we assume that all the wet-mills are dominant firms competing with ethanol plants for corn procurement. Thus, there are 18 dominant plants in total competing for corn procurement. In other words, in addition to the 14 ethanol plants inclusive of GPS's wet-milling plants capacity, 4 other wet-milling plants may act as dominant firms in oligopsonies.

Competitive fringe

We assume that all the dry-milling food processing plants, livestock operators and exports are competitive fringe. As is described, 5 dry-milling companies share 28 million bushels of corn and capacities of individual plants are small. According to the Quick Stats of USDA, 19,276 livestock operators (2,823 for hog, 14,106 for cattle, 2,347 for poultry) share 197 million bushels of corn in Indiana. Specifically, hog industry in Indiana consumes 113 million bushels, cattle industry consumes 32 million bushels, and poultry industry consumes 52 million bushels. Hog industries in all the counties but Randolph county needs annually less than 6 million bushels of corn. Randolph county demands 9 million bushels but 24 facilities each of which has more than 1,000 heads share the 9 million bushels. Thus, each facility is not expected to be large enough to be oligopsonistic. Exports varies year to year and it share 248 million bushels in 2014 (ERS, USDA) and are marketed at the price exogenously given from supply-demand relationship in the international market. Also, the US dominates the world corn export market, a world corn price normally follows the US domestic corn price.

When it comes to livestock industry in more detail, operators are usually under production contracts. Since, under production contracts, contractors normally provide operators with feed such as corn, it can be argued that contractors with many operators may be big enough to have oligopsonistic market power. According to the QuickStats of USDA, however, 18.5% of operators in number or 55.5% of hog production in head on average in a single county are under production contract. Therefore, in order for a contractor to have market power, we have to assume extremely that a single contractor accounts for a large part of the contract. For example, with the extreme assumption that only one contractor absorbs all the hog production contracts in Indiana, its total corn purchase estimate is 62.7 million bushels. Even under this assumption, its total corn purchase is a little higher than the corn purchase from one large ethanol plant producing over 100 million gallons of ethanol (Indiana has 6 ethanol plants with capacities over 100 million gallons). However, this is an extremely unreal assumption. Thus, despite considering production contracts, we can treat livestock operators as a competitive fringe.

2.2. Transportation cost and spatial pricing

Large transportation cost weakens competition among firms (as it reduces a nearby farmer's opportunity cost of selling corn to that firm), and enhances firms' ability to markdown input prices and engage in spatial price discrimination. We now take a closer look at the nature and importance of transportation cost in the corn procurement market. According to Denicoff et al. (2014), domestic hauling of corn is primarily handled by trucks, followed by rail and barge. Adam and Marathon (2015) also estimates that about 76 percent of corn was hauled by truck in 2013. The share of corn transported by truck gradually increased over time from 67 percent in 1998 to 82 percent in 2013 (Denicoff et al., 2014). This is mostly due to domestic demand for ethanol production which increased by 294 percent from 1995 to 2013. Since plants are located in local corn producing regions and trucking is less costly than other forms of transportation in relatively short distances (i.e. below 500 miles), ethanol plants typically ship corn in trucks (Denicoff et al., 2014). This percentage raises to almost 100% for distances within 250 miles, as trucks are cheaper than other transportation options in relatively short distances.

Also, as we already have noted, transportation cost of agricultural commodity is usually very high and this limits the ability of producers to ship their agricultural products to processors. The Transportation and Marketing Programs (TMP) of the Agricultural Marketing Service (AMS) at USDA issues quarterly information on transportation costs through its Grain Truck and Ocean Rate (GTOR) report. According to that report, the transportation rate in Indiana on the 1st quarter of 2016 was \$3.36, \$2.11, and \$2.08 per truckload loaded-mile for 25, 100, and 200 miles, respectively. A total of 25 metric tons or 984 bushels of corn are transported per truckload. Therefore, the truck transportation rate converts to 0.34 cents, 0.21 cents, and 0.21 cents per bushel-mile for 25, 100, and 200 miles, respectively. This means that transportation cost can amount to about 5 to 10% of procurement cost within these distances. This underscores the potential local market power of ethanol plants.

3. Methods

3.1. Empirical measurement of spatial pricing: Methodological challenges

A big hurdle for empirical analyses of spatial pricing by agricultural processing firms is the lack of firm-level data. In the absence of such data, firm-level technological parameters cannot be directly estimated econometrically; which may hinder predictions of pricing behavior (Davis, 2006; McManus, 2007; Houde, 2012). This is in fact typical of industries where a large percentage of transactions are conducted through private contracts (Miller and Osborne, 2010; 2011; 2014). In the US agricultural market, in particular, contracts govern at least 39% of the value of the US agricultural production in 2008 and this has been increasing from 28% in 1991 and from 11% in 1969 (MacDonald and Korb, 2011). In an empirical analysis of the cement industry, Miller and Osborne (2014) overcome this limitation by implementing a minimum-distance estimator that matches predicted with observed market-level outcomes. We follow this approach, and proceed to describe in the following sections.

3.2. Economic model

3.2.1. Strategy

The overall strategy consists of solving the structural model (price paid for corn by each competing plant in each county) based on a set of *candidate* (arbitrarily imposed) structural parameters (corn supply parameters and plant's cost parameters). The solution is a Bertrand-Nash equilibrium of the spatial pricing game among competitors. The equilibrium is composed of a vector of plant-price-location values (i.e. prices offered by each firm in each location). The geographical area of our analysis is a county. Plant-county prices are then aggregated to a single county-level price (weighting plant-specific prices by the plant's share on total corn purchases) and compared to *observed* county-level prices. The process is iteratively repeated until a set of structural parameters is found under which the predicted aggregate outcome matches the observed (Miller and Osbourne refer to this procedure as the Minimum Distance Estimation, MDE, approach, 2014). This procedure results in a firm-county level equilibrium that reveals the degree of spatial price discrimination prevalent in the industry (in the study area, all the counties in Indiana) and a set of estimated structural parameters that can be used to calculate surplus for each plant, for farmers in each county, and for the industry as a whole.

3.2.2. The structural model

Corn demand – computing predicted equilibrium prices for corn

There are 14 ethanol plants inclusive of a GPC's wet-milling plant currently under operation in Indiana and they are owned by single- and multi-plant firms. In addition, there are 4 wet-milling plants in Indiana. The 18 plants are dominant plants competing for corn procurement. We use the ownership and location information contained in Table 2 and Figure 1 for ethanol plants (Official Nebraska Government, 2015; NREL; RFA, 2015) and Table 3 for wet-milling plants. Dominant plants are assumed to choose corn prices in different counties so as to minimize cost of production subject to capacity constraints and other firms' behavior. There are two reasons behind this cost minimization assumption. First, plants operate under (typically binding) capacity constraints. Second, the prices of processed products such as ethanol and food products are mostly determined by competitive output markets such as oil/gasoline and, thus, exogenous to plants.

We follow previous literature on spatial differentiation and model competition among plants as a Bertrand game, where firms set corn prices in each location. Assuming free on board pricing, therefore, a firm sets a county-specific vector of corn prices at each plant gate, $\boldsymbol{p}_F^c = (p_{ij}^c;\ i \in IN^C, j \in F)$. Consequently, the program to be solved by the firm can be written as:

$$\min_{p_{ij}^c} C_F = \sum_{i\in IN^C}\sum_{j\in F} p_{ij}^c q_{ij}^c(\boldsymbol{p}_i^c; \boldsymbol{x}_i, \boldsymbol{\beta}) + \sum_{j\in F}\left\{\int_0^{q_j^{prod}} MC_j(q^{prod})dq^{prod}\right\} + \sum_{j\in F}(FC_j * CAP_j)\ ) \tag{2}$$

subject to

$$\sum_{i\in IN^C} q_{ij}^c(\boldsymbol{p}_i^c) = \frac{CAP_j}{\alpha_j} \quad \forall\, j \in F \tag{3}$$

$$\sum_{j\in IN^P} q_{ij}^c(\boldsymbol{p}_i^c) \le RSUP_i \quad \forall\, i \in IN^C \tag{4}$$

$$q_{ij}^c(\boldsymbol{p}_i^c) \ge 0 \quad \forall\, i \in IN^C,\ j \in F \tag{5}$$

The first term on the right hand side of the equation (2) illustrates the firm F's cost of purchasing corn which is the sum of purchasing cost for each plant j owned by firm F, from each county i located in Indiana ($i \in IN^C$, where IN^C represents the set of all the counties in Indiana). The second term represents the variable cost of operating plants owned by firm F. The third term is the fixed cost of plants owned by firm F. Equations (3) through (5) specify constraints that the firm is subject to. Equation (3) guarantees a balance between capacity-binding production and total corn purchased by a dominant plant j. Equation (4) guarantees that total corn purchases from dominant plants in some county $i \in IN^C$ do not exceed residual corn accounting for the fringe demand available in that county. Equation (5) are non-negativity constraints.

In Indiana there are currently 14 ethanol plants (some owned by the same firm) and 4 wet-mills that could compete for corn from 92 different counties. With this information, a more detailed description of notations, variables, and parameters is as follows:

- $C_F(\boldsymbol{p}_F^c, \boldsymbol{p}_{-F}^c)$: a cost function of a firm F
- $i \in IN^C$: all of the 92 counties in Indiana
- $j \in IN^P$: all of the 18 dominant plants in Indiana inclusive of ethanol plants wet-mills
- F: a firm that owns single- or multi- plants in Indiana, and a subset of IN^P
  - $j \in F$: plants owned by the firm F
  - a firm F determines corn prices $\boldsymbol{p}_F^c = p_{ij}^c\ \forall\, i \in IN^C, j \in F$ in dollar per bushel given corn prices determined by other firms, $\boldsymbol{p}_{-F}^c\ \forall\, i \in IN^C,\ j \in plants\ NOT\ owned\ by\ F$
- $q_{ij}^c(\boldsymbol{p}_i^c; \boldsymbol{x}_i, \boldsymbol{\beta})$: the quantity of corn supplied by corn suppliers in county i to plant j
  - $\boldsymbol{p}_i^c = [p_{i,1} \cdots p_{i,18}]$: corn prices paid by all the dominant plants procuring corn from county i in dollar per bushel
  - $\boldsymbol{x}_i$: a vector of corn supply shifters
  - $\boldsymbol{\beta}$: a vector of parameters of the corn supply function

- $q_j^{prod} = \alpha_j^{prod} \sum_{i \in IN^C} \{ q_{ij}^c(\boldsymbol{p}_i^c;\ \boldsymbol{x}_i, \boldsymbol{\beta}) \} = CAP_j$: the amount of processed output produced by a plant j in gallons for ethanol or in another unit for processed food products. A super script $prod$ includes ethanol and processed food processed products.
  - α_j^{prod}: a conversion rate of the plant j in the unit of each processed good produced from one bushel of corn assumed to be homogeneous over ethanol plants and over wet-milling plants respectively since there are a few plant builders and technology is similar over the builders
- $MC_j(q^{prod})$: marginal cost of producing processed goods in plant j in dollars
  - This is assumed to be constant at mc_j^{prod}.
- FC_j: fixed cost of plant j in $ per unit of plants installed
- CAP_j: a capacity of plant j
- $RSUP_i$: a residual corn supply in county i

Consistent with a fixed proportions production technology (Gardner, 2007; Lambert et al., 2008; Stewart and Lambert, 2011), the marginal cost of ethanol and food production, $MC_j(q^{prod})$, is assumed to be constant at mc_j^{prod}($ per unit of processed output). Therefore, variable cost is $MC_j(q^{prod}) = mc_j^{prod} * q_j^{prod}$.

I modify the Lagrangian to maximize the negative of the cost:

$$\mathcal{L}_F(\boldsymbol{p}_F^c, \boldsymbol{\lambda}_F, \boldsymbol{\tau}_j, \boldsymbol{\mu}_{Fj}; \cdot) = -\Big[\sum_{i \in IN^C} \sum_{j \in F} p_{ij}^c q_{ij}^c(\boldsymbol{p}_i^c; \boldsymbol{\beta}) \sum_{j \in F} \Big\{ \int_0^{q_j^{prod}} MC_j(q^{prod}) dq^{prod} \Big\} + \sum_{j \in F}(FC_j * CAP_j)\Big] - \sum_{j \in F}\Big[\lambda_j \Big\{\sum_{i \in IN^C} q_{ij}^c(\boldsymbol{p}_i^c; \boldsymbol{\beta}) - \frac{CAP_j}{\alpha_j}\Big\}\Big] - \sum_{i \in IN^C}\big[\tau_i\{\sum_{j \in IN^P} q_{ij}^c(\boldsymbol{p}_i^c; \boldsymbol{\beta}) - RSUP_i\}\big] - \sum_{i \in IN^C} \sum_{j \in F}\big[\mu_{ij}\{-q_{ij}^c(\boldsymbol{p}_i^c; \boldsymbol{\beta})\}\big] \tag{6}$$

The Karush-Kuhn-Tucker (KKT) conditions are as follows:

$$\frac{\partial \mathcal{L}_F(\cdot)}{\partial p_{ij}^c} = -q_{ij}^c(\boldsymbol{p}_i^c) - \sum_{m \in IN^C} \sum_{n \in F}\Big[(p_{mn}^c + \lambda_n - \mu_{mn})\Big\{\frac{\partial q_{mn}^c(\boldsymbol{q}_m^c)}{\partial p_{ij}^c}\Big\}\Big] - \sum_{a \in IN^C} \sum_{b \in IN^P}\Big[\tau_a \times \Big\{\frac{\partial q_{ab}^c(\boldsymbol{q}_a^c)}{\partial p_{ij}^c}\Big\}\Big] \quad \forall\, i \in IN^C, j \in F \tag{7}$$

$$\frac{\partial \mathcal{L}_F(\cdot)}{\partial \lambda_j} = -\sum_{i \in IN^C} q_{ij}^c(\boldsymbol{p}_i^c; \boldsymbol{\beta}) + \frac{CAP_j}{\alpha_j} = 0 \quad \forall\, j \in F \tag{8}$$

$$\frac{\partial \mathcal{L}_F(\cdot)}{\partial \tau_i} = -\sum_{j \in IN^P} q_{ij}^c(\boldsymbol{p}_i^c; \boldsymbol{\beta}) + RSUP_i \geq 0 \perp \tau_i \geq 0 \quad \forall\, i \in IN^C \tag{9}$$

$$\frac{\partial \mathcal{L}_F(\cdot)}{\partial \mu_{ij}} = q_{ij}^c(\boldsymbol{p}_i^c; \boldsymbol{\beta}) \geq 0 \perp \mu_{ij} \geq 0 \quad \forall\, i \in IN^C, j \in F \tag{10}$$

In addition, in order to introduce a matrix including information on each firm's ownership, we represent equation (7) in a matrix form by putting equation (7) together for the combination of each i and j into matrix form, equation (7)' could be obtained.

$$\frac{\partial \mathcal{L}_F(\cdot)}{\partial \boldsymbol{p}_F^c} = -\boldsymbol{q}^c(\boldsymbol{p}^c;\boldsymbol{\beta}) - \boldsymbol{\Omega}(\boldsymbol{p}^c)\{\boldsymbol{p}_F^c + \boldsymbol{\Lambda} - \mathbf{M}\} - \boldsymbol{\Phi}(\boldsymbol{p}^c)\mathbf{T} = \mathbf{0} \;\; \forall\, i \in IN^C, j \in F \qquad (7)'$$

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 number of the plants owned by the firm F,

$$\Omega_{jk}^i(\boldsymbol{p}_i^c;\boldsymbol{\beta}) = \begin{cases} \frac{\partial q_{ij}^c(\boldsymbol{p}_i^c;\boldsymbol{\beta})}{\partial p_{ik}} & if\ plants\ j\ and\ k\ have\ the\ same\ owner \\ 0 & otherwise \end{cases} \qquad (11)$$

$\boldsymbol{\Lambda}$ is a vector of λ_js which are the multipliers of capacity constraints. Each entity of the vector is expressed as follows:

$$\Lambda_j = \lambda_j \qquad \forall\, j \in F \qquad (12)$$

M is a vector of Lagrangian multipliers for non-negativity constraints (μ_{ij}) in equation (5).

$$M_{ij} = \mu_{ij} \qquad \forall\, i \in IN^C, j \in F \qquad (13)$$

$\boldsymbol{\Phi}(\boldsymbol{p}^c)$ is another block diagonal matrix that combines $i = 1,\cdots,92$ submatrices accounting for all the counties in Indiana, each of dimension 18×18 since there are 18 dominant plants for total in Indiana,

$$\Phi_{jk}^i(\boldsymbol{p}_i^c;\boldsymbol{\beta}) = \begin{cases} \frac{\partial q_{ij}^c(\boldsymbol{p}_i^c;\boldsymbol{\beta})}{\partial p_{ik}} & if\ plants\ j\ and\ k\ have\ the\ same\ owner \\ 0 & otherwise \end{cases} \qquad (14)$$

The difference between equations (11) and (14) is that equation (11) addresses the plants owned by a firm and equation (14) addresses all the plants in Indiana.
T is a vector of Lagrangian multipliers for supply requirement constraints (τ_i) illustrated in equation (4)

$$T_i = \tau_i \qquad \forall\, i \in IN^C \qquad (15)$$

The system (7)-(10) is a system of constrained best responses that yield a Bertrand-Nash equilibrium of the competition game. For a firm with J plants and 92 counties in Indiana, there are J*92 equations (7). In addition, in the Lagrangian, we have J plants and the corresponding J λ_js. Therefore, there are J equations (8). Also, since we have 92 counties with their corresponding τ_is, 92 equations (9). For non-negativity constraints, we have J*92 $q_{ij}^c(\boldsymbol{p}_i^c;\boldsymbol{\beta})$s and the corresponding J*92 μ_{ij}s. Thus, there are J*92 equations (10). In total, accounting for all the 13 firms owning 18 plants in total in Indiana, our model results in a system of 1,656+18+92+1,656=3,422 equations to be solved simultaneously. Then, the predicted equilibrium price vector is of length 1,656, the λ_js vector is of length 18, τ_is vector is of length 92, and the μ_{ij}s vector is of length 1,656. Once the predicted equilibrium price vector is obtained, it is aggregated to the county level and the predicted aggregated outcome is compared to the observed aggregated outcome. Miller and Osborne (2014) suggest an aggregation strategy that calculates supply weighted average prices charged by plants in specific regions. Applying this to our study, the predicted county-level price in county j is:

$$\tilde{p}_i^c(\boldsymbol{\beta}, \boldsymbol{X}) = \sum_{j\in IN^C} \frac{q_{ij}^{c,*}(\boldsymbol{p}_i^{c,*}; \boldsymbol{x}_i, \boldsymbol{\beta})}{\sum_{j\in IN^C} q_{ij}^{c,*}(\boldsymbol{p}_i^{c,*}; \boldsymbol{x}_i, \boldsymbol{\beta})} p_{ij}^{c,*} \tag{16}$$

Corn supply in one county i is aggregated as follows:

$$RSUP_i = \tilde{q}_i^c(\boldsymbol{p}_i^c; \boldsymbol{x}_i,\ \boldsymbol{\beta}) = \sum_{\boldsymbol{j}\in IN^P} q_{ij}^{c,*}\left(\boldsymbol{p}_i^{c,*}\right) \tag{17}$$

Corn supply

Indirect utility

As is specified later in this chapter, we use the multinomial logit supply system to model the behavior of a supplier within each county. We specify the indirect utility that a supplier n in county i receives from selling their corn to plant j to capture the market share of corn by each plant in each county as

$$u_{nj}^i = \beta^0 + \beta^p p_{ij}^c + \beta^d d_{ij} + \beta^e e_i + \beta^l l_i + \varepsilon_{nj}^i \tag{18}$$

where p_{ij}^c is the price of corn paid by a plant j for the corn in county i, d_{ij} is a measured distance between the centroid of a county i and the centroid of the county where a plant j is located, e_i is a measured distance between the centroid county of a county i and a closest exporting port as a supply shifter accounting for export of competitive fringe. l_i is the weighted average of the livestock heads in neighboring counties of the county i based on distances between the county i and each of the neighboring counties. We define the weighted average as follow.

$$l_i = \sum_{nc\in NC_i} \omega_{nc}^i * livestock_{nc}^i \tag{19}$$

where $\omega_{nc}^i = \frac{distance_{i,nc}}{\sum_{h\in NC_i} distance_{i,h}}$ as a weight, NC_i is a set of neighboring counties of the county i, nc and h are neighboring counties included in the set NC_i. This serves as the other shifter accounting for the demand for livestock feed of competitive fringe. In addition, ε_{nj}^i captures unobservables such as a farmer n's preference in county i depending on their relationship with a plant j. As we can see later in Figure 5. b, the residual corn supply curve that dominant firms face is a negative parallel shift of the total market corn supply because we assume that the demand of the competitive fringe is fixed at its total capacities. Thus, by setting up e_i and l_i as shifters for competitive fringe, we are able to capture the shift of supply curve and to estimate the residual corn supply function. We denote the two fringes as "plants" $J+1$ for export and $J+2$ for livestock feed.

The market shares can be estimated from the multinomial logit model and are specific to the combination of each county-plant.

$$S_{ij}(\boldsymbol{p}_i^c;\boldsymbol{\beta}) = Prob(Y_n = j) = \frac{\exp(\boldsymbol{z}'_{ij}\boldsymbol{\beta})}{\sum_{j=1}^{J+2}\exp(\boldsymbol{z}'_{ij}\boldsymbol{\beta})} \tag{20}$$

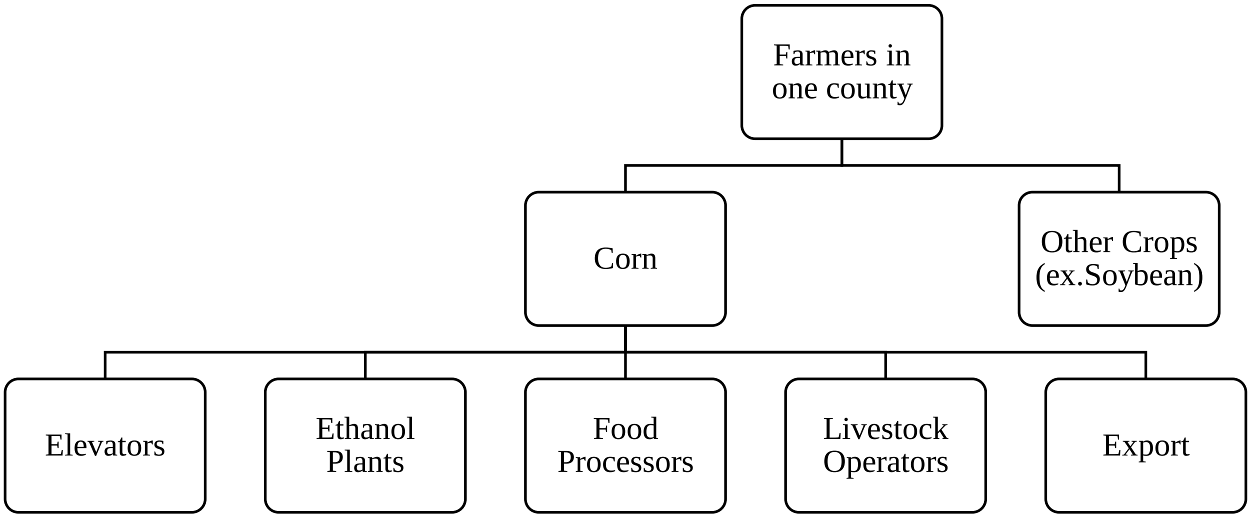
where $\boldsymbol{z}'_{ij} = [p_{ij}^c, d_{ij}, e_i, l_i]$ and Y_n represents the choice of a farmer n among ethanol plants, wet-milling plants, livestock operators, or export. Since we have a data for the total corn supply in each county (SUP_i), a sum of the annual production and the storage carried over from the last year in each county, the quantity that is sold from a county i to a plant j is $q_{ij}^c(\boldsymbol{p}_i^c;\boldsymbol{\beta}) = S_{ij}(\boldsymbol{p}_i^c;\boldsymbol{\beta}) * SUP_i$. Then, this is the analytical functional form for $q_{ij}^c(\boldsymbol{p}_i^c;\boldsymbol{\beta})$ that can be plugged into cost minimization model, equation (2) through (5), to compute predicted equilibrium corn prices.

$$q_{ij}^c(\boldsymbol{p}_i^c;\boldsymbol{\beta}) = S_{ij}(\boldsymbol{p}_i^c;\boldsymbol{\beta}) * SUP_i \tag{21}$$

Suppliers' behavior – Multinomial logit structure

We model supply behavior of suppliers based on a conventional discrete-choice system. We begin with assumption that farmers in each county show a nested structure of their decision behavior (Figure 3). Each farmer in Indiana plants either corn or other crops such as soybean. Then, if they choose corn, they decide whom to sell their corn among consumers for different uses of corn such as ethanol plants, food processors, livestock feeders, or export. In this structure, we set corn and other crops as different outside options and place ethanol plants and other non-ethanol corn consumers under the nest of corn sales.

Figure 3. Nested structure of farmers' decision behavior

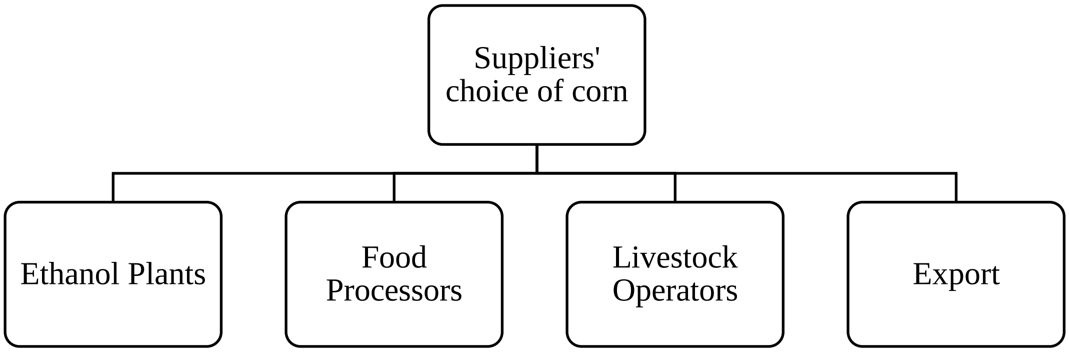


The outside nest options, whether to choose corn or other crops such as soybean, depends on farmer's expected profit from crops and the expected profit is dependent on many factors. For example, it relies not only on prices received from consumers but also on whether farmers are under long-term contract with consumers such as ethanol plants, how they decide to rotate corn and soybean (soil quality), and how they market their crops.

Normally, farmers supply large portion of their corn production to elevator first or store them in its own storage rather than shipping directly to ethanol plants. Then, various processors purchase it from elevators or farmers. According to MacDonald Korb (2008), 66 percent of corn sales is shipping directly to grain elevators and only 13 percent directly to ethanol plants. This means that ethanol plants do not affect much farmers' decision on which crop to plant.

Therefore, we assume that the outside choices are not closely affiliated with processors and remove the nest of the outside options. Thus, we locate farmers, elevators, or other forms of corn suppliers at the same level of corn supply chain as suppliers because we are interested in how much corn is supplied at county level to each plant regardless of its source. As a result, the nested structure collapses to a multinomial logit structure only of the inside options under corn planting (Figure 4).

Figure 4. Multinomial structure of farmers' decision behavior.



Adopting a logit structure conveys two critical advantages in our estimation. First, it yields an analytical expression for the market shares of corn and corresponding sales of corn in one county captured by each plant (i.e., $q_{ij}^{c}(\boldsymbol{p}_{i}^{c};\boldsymbol{x}_{i},\boldsymbol{\beta})$) and makes estimation computation less burdensome. Second, this makes the objective function smooth by making the supply continuous on prices. In other words, if we treat all the farmers in one county as homogeneous, small changes in parameters may cause the entire supply in the county to swing from one plant to another plant. This could lead to a discontinuity in the objective function.

Residual supply faced by dominant ethanol plants and wet-milling plants

With the assumption of dominant firms and a competitive fringe structure, the supply curve that dominant ethanol plants and wet-milling plants face is a residual supply curve rather than the total market supply curve of corn from each county. We assume a vertical demand of the competitive fringe (D_f on Figure 5. b.). Livestock operators have a perfectly inelastic demand for corn in the shout-run such as a year because they cannot let their animals die. Food processing companies cannot modify their capacities in the short-run. Exports are demanded given an exogenous corn price. In addition, since ethanol price is exogenous and marginal product of corn is fixed at 2.7 gallon per bushel, ethanol plants' MVP (=$MP_{corn}\times P_{ethanol}$) is constant. This means ethanol plants' corn demand curve is horizontal because MVP represents input demand. With the assumption of the perfectly inelastic demand for corn from the competitive fringe and horizontal demand for corn of dominant firms, graphical analysis shows this slightly different from usual oligopsonies. Figure 5 illustrates the difference between usual oligopsony market (Figure 5. a) and the oligopsonistic corn market in Indiana (Figure 5. b). S_{market} is the total corn market supply, S_r is the residual corn supply accounting for the corn demand from competitive fringe (D_f), D_{df} is the corn demand of dominant firms, MFC is the marginal factor cost (a derivative of residual supply curve, P^* is the price of corn determined by dominant firms, Q^*_{df} is the corn demanded by dominant firms, Q^*_f is the corn demanded by competitive fringe, and Q^* is the total corn demanded by dominant firms and competitive fringe.

Unlike the usual market where a residual supply curve has a kink, in the corn market where residual demand is fixed at capacities, residual supply curve is just a negative parallel shift and there is no kink on the curve.

Figure 5. Graphical analysis of oligopsony market

Figure 5. a. Description of usual oligopsony market

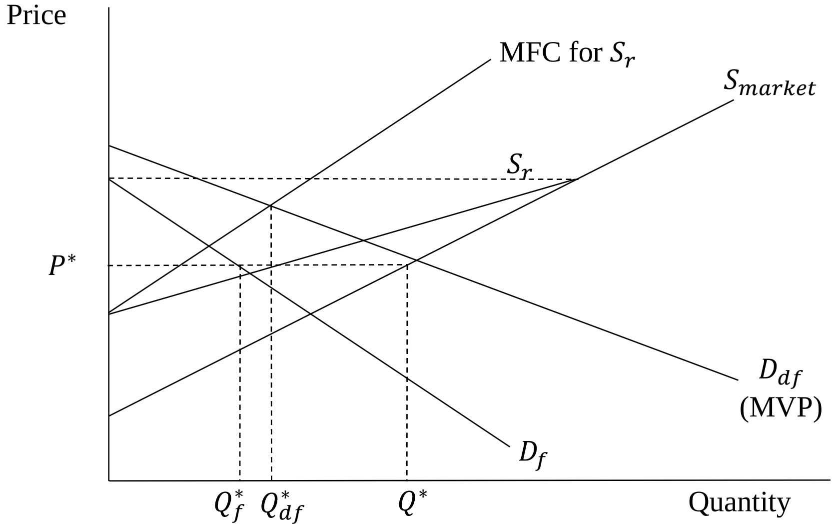
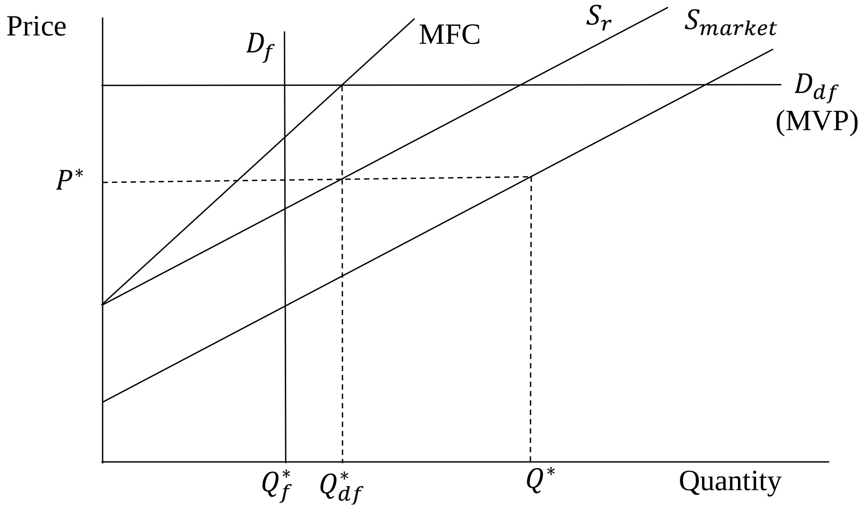


Figure 5. b. Description of oligopsony in Indiana corn market with the assumptions



3.3. Estimation strategy

3.3.1. Estimation of structural parameters

Following Miller and Osborne (2014) we use the MDE that minimizes the distance between observed and predicted market equilibrium. We denote the vector of observed data by $\boldsymbol{y}_t$ in period t, which contains the average price of corn and corn production at the county level. We denote the predictions from the model by $\widetilde{\boldsymbol{y}}_t(\widetilde{\boldsymbol{\beta}}; \boldsymbol{X_t})$, where $\widetilde{\boldsymbol{\beta}}$ are initial guesses of parameters, and $\boldsymbol{X_t}$ is a vector of exogenous variables such as distances between a plant and a county centroids or demand and cost shifters. Thus, $\widetilde{\boldsymbol{y}}_t(\widetilde{\boldsymbol{\beta}}; \boldsymbol{X_t})$ is a function of the candidate parameters and exogenous data. The estimated parameter is the one minimizing the weighted sum of squared deviations between the observed data and the aggregated predictions:

$$\widehat{\boldsymbol{\beta}} = arg \min_{\boldsymbol{\beta} \in \Theta} \frac{1}{T} \sum_{t=1}^{T} \left[\boldsymbol{y}_t - \widetilde{\boldsymbol{y}}_t(\widetilde{\boldsymbol{\beta}}; \boldsymbol{X_t})\right]' \boldsymbol{C}_t^{-1} \left[\boldsymbol{y}_t - \widetilde{\boldsymbol{y}}_t(\widetilde{\boldsymbol{\beta}}; \boldsymbol{X_t})\right] \tag{22}$$

where Θ is a compact parameter space, $\boldsymbol{C}_t^{-1}$ is a positive definite matrix that weights equations defined in the vector $\boldsymbol{y}_t - \widetilde{\boldsymbol{y}}_t(\widetilde{\boldsymbol{\beta}}; \boldsymbol{X_t})$. For instance, Miller and Osborne (2014) used sample variances rather than identity matrices as they argue they result in a better fit to observed data. Our weighting method will be determined based on overall goodness of fit.

The iterative procedure by which $\widehat{\boldsymbol{\beta}}$ is estimated can be summarized as follows:

1. Select a candidate parameter vector $\widetilde{\boldsymbol{\beta}}$.
2. Solve the firm cost minimization model to compute the equilibrium prices and estimated corn supply purchased by each plant from each county.
3. Aggregate the equilibrium prices and quantity supplied to the observed data level, which is county-level.
4. Evaluate the "distance" between the aggregate predictions against the observed data.
5. Update $\widetilde{\boldsymbol{\beta}}$ with an increase by 0.01 (or some other arbitrary number) and repeat this procedure until convergence.

This estimation process includes an inner loop and an outer loop. The inner loop solves for the Bertrand-Nash equilibrium given the candidate parameters, and the outer loop minimizes the distance between the observed and predicted equilibria. A detailed algorithm of the iterative estimation procedure can be found in *Appendix A*. The General Algebraic Modeling System (GAMS) is used to solve the system of equations of the inner loop. GAMS is a high-level modeling system for mathematical programming and optimization and it can build and maintain complex and large scale models.

3.3.2. Aggregation issues and multiple equilibria

In the inside loop of computing equilibrium prices, point estimates can fail in two cases. First, a single candidate parameter produces multiple equilibria (uniqueness). The other is that multiple candidate parameters generate equilibrium predictions that are identical when aggregated.

Miller and Osborne (2014) also specified how to check these two failure and conclude that neither arise in their model. Therefore, I can follow their way to check these failures.

To check the existence of the first problem, we conduct a Monte Carlo simulation experiment to search for the multiple equilibria. We introduce 300 different vectors of candidate parameters and, for each of the different vector of candidate parameter, 11 different initial vectors of corn prices. 300 vectors of candidate parameters are generated from the normal distribution $N(\hat{\beta}^g, \hat{\sigma}_g^2)$ where $\hat{\beta}^g$ and $\hat{\sigma}_g^2$ are from the estimation result and g includes 0 for intercept, p for the price variable, and d for the distance variable, and e and l for the indicator variable for the competitive fringe. 11 different vectors of corn prices come from observed data available as $p_{ij}^{c,initial} = \phi\overline{p^c}$ where $\overline{p^c}$ is the average observed corn prices and $\phi = 0.5, 0.6, \cdots, 1.4, 1.5$. Then, for each vector of candidate parameters, we compute the 11 vectors of equilibrium prices for the different initial vectors and finally calculate the mean and standard deviation over 11 different initial vectors. Since a vector of equilibrium prices has 1,288 elements for the all plant-county units, there are 1,288 means and standard deviation for each plant-county combination. The experiment provides a uniqueness condition if these standard deviations are small.

The other problem occurs occasionally when the data are coarse so that a substantial loss of information happens when aggregated. We conduct an artificial data experiment to check the existence of the aggregation problem in our empirical estimation. We draw 40 random exogenous datasets and pair them with a vector of true parameters. Parameters and datasets are chosen to mimic our estimation. The exogenous dataset includes the plant capacities, the total corn productions in each county, and export prices. They are randomly drawn from the data with replacement and others are generated from the normal distribution for each data element based observed data. Then, for each set of the exogenous dataset, we compute equilibrium predictions, aggregate it up to the county-level, and estimate the parameters. If the parameters computed from this experiment are close to the true parameters, the parameters can be reasonably identified.

4. Data

4.1. Source

I have collected the county-level equilibrium information. Specifically, I have collected historical data on corn production and corn stock from NASS, USDA. NASS provides annual census and survey data for corn production at county, state, and national level. County-level corn price data is from GeoGrain. Parameters for marginal cost, fixed cost, corn-to-ethanol conversion factor are from literatures. For current preliminary modeling, I assume that marginal operating cost is \$0.54 per gallon of ethanol produced, fixed cost is \$0.34 per gallon of capacity installed, and ethanol corn-to-ethanol conversion factor is 2.7 gallon per bushel of corn. This will also be changed later for more detailed analysis. The information on ethanol plants' location, ownership, capacity, and starting year comes from the Official Nebraska Government Website, RFA, US Environmental Information Administration (EIA), and the Biofuel Atlas published by the National Renewable Energy Laboratory (NREL). The information on food-milling plants' capacities and locations is based on Hurt (2012). NASS also provides with livestock information for hog, cattle, and poultry separately in various units such as the number of heads, weights, or weights per head, and values. For example, annual sales, production, or slaughtered of livestock information for the level of county, state, agricultural district, and US is available in different units.

4.2. Crop year

We modify all the data based on the *crop year of corn*, which starts on Sep 1st and ends on Aug 31st next year. We do this in order to account for the total supply of corn in Indiana, which is the sum of the corn stock from the last crop year right before harvesting and the corn production in the current crop year. For consistency, other data should also be modified based on the same crop year. The average corn price can easily be updates based on the *crop year of corn*.

The number of livestock do not vary much in the same month from year to year based on the monthly state level data. Since monthly county level data is not available, however, we proportionally estimate based on the state level. We take the proportion of livestock head from Sep to Dec in the previous year and from Jan to Aug in the next year and apply these proportions for annual county level data on the previous and next year. Then, add them to estimate the livestock heads in the crop year.

However, other information such as capacities of plants do not need to be corrected to the crop year. Plants work at the capacity and there is no idle period in each year and work constantly 24/7. In other words, we can expect that plants produce the same amount on the same month in the different year and it is just a shift from the usual calendar year to the crop year. Therefore, plant capacity in calendar year can be used as in *crop year of corn*.

5. Result

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6. Future research

Based on this approach and results, several further contributions can be made. I have two of them, policy analysis and the effect of industry consolidation.

6.1. Policy Analysis

Ethanol production has mostly been induced by policy supports such as subsidies and mandates. In this context, it is worth investigating how much policies achieve its objectives. One of the objectives of the policies which is our interest here is to boost corn farm incomes. Although market power scheme may affect the outcome of the objective, most of the previous studies ignore oligopsonies and possible spatial price discrimination.

Therefore, I examine the impact of different policy instruments (a re-examination of mandates vs subsidies in the presence of spatial price discrimination) on market outcomes, incorporating predicted behavioral responses to those policies. Furthermore, policy simulations under predicted behavioral responses will be contrasted with simulations under no market power exertion to evaluate how innocuous the competitive market assumption (widely held in previous studies) is to the analysis of ethanol policies.

6.2. The Effects of Industry Consolidation

In general, consolidation in the ethanol industry has been a cause of great concern for regulators. This is because market power exertion that may result from such consolidation could potentially reduce the benefits of ethanol policy to the farm sector; an important objective of such policies. We characterize the wave of consolidation by changing the ownership structure under which firms engage in a spatial pricing game.

Consolidation among ethanol plants has taken place in Indiana over the last 8 years. Noble America purchased an ethanol plant in 2013 from New Energy Corp., and Green Plains bought one from Indiana Bio-Energy in 2008. Valero Renewable Fuels Company LLC, a subsidiary of Valero Energy Corp. purchased an ethanol plant from VeraSun Energy Corp. in 2010, and another from Aventine Renewable Energy in 2014.

Therefore, I investigate and quantify the effect of recent waves of consolidation in the corn ethanol industry on equilibrium prices, industry's surplus, and surplus distribution. This will be achieved by simulating equilibria under counterfactual ownership structures.

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