The Expanding Ethanol Market and Farmland Values: Identifying the Changing Influence of Proximity to Agricultural Market Channels

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Abstract

We investigate the spatial capitalization of the expanding biofuels market in farmland values using parcel-level farmland sales data from 2001 to 2010 for a 50-county area within Ohio's Corn Belt region. We construct two instruments by exploiting the spatial competition among agricultural markets to address the non-random ethanol plant site selection process. Our results reveal a positive capitalization of $19 per acre for each mile closer a farmland parcel is to the nearest ethanol plant post-construction. This translates into a $380 ($570) per acre premium—roughly 7 (10) percent of the average sales price—for parcels 20 (30) miles closer to ethanol plants than comparable, but more distant, parcels. The effect of proximity to grain elevators became a positive and significant determinant after the ethanol market expansion, conveying an added value of $57 per acre with every mile closer to a grain elevator. In contrast, the effect of proximity to agricultural terminals diminished over 30 percent, from an average of $48 to $30 per acre per mile, providing evidence of changing spatial competition among local agricultural market channels.

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Ethanol production in the United States increased dramatically in the 2000s. Helped by strong federal support from the Energy Policy Act of 2005 and the Energy Independence and Security Act of 2007, total production increased by more than five times in the first decade of the 2000s, the number of ethanol plants increased four-fold, and the United States became the largest ethanol producer in the world. This rapid growth in bioenergy production is speculated to have elevated agricultural commodity prices, farmers' expectations about future profits, and farmland values (Low and Isserman 2009; Wallander et al. 2011). Given the likelihood of expanding markets for second generation biofuels, wind farms, and other land-based forms of renewable energy production, understanding the impacts of new energy production on farmland values is important for quantifying the costs of energy and food production, potential future changes in agricultural land use patterns, and the implications for farmer welfare.

Recent research on the impacts of the ethanol industry on agricultural markets considers the responses of crop prices and local basis to ethanol expansion in the U.S. Midwest and Canada (Gallagher 2006; McNew and Griffith 2005; Wu et al. 2016) and resulting land use changes (Arora et al. 2016; Stevens 2015). In addition, several studies examine the capitalization effect of proximity to ethanol plants on farmland values (Blomendahl et al. 2011; Henderson and Gloy 2009; Nehring et al. 2006). However, these papers employ a standard hedonic price model, which, despite its popularity, suffers from identification challenges (Bajari et al. 2012). The location of an ethanol plant is a non-random process affected by surrounding locational features such as the availability of nearby feedstock and access to road networks (Lambert et al. 2008), and thus estimates from a hedonic model will be biased if unobserved characteristics that affect land values also influence the location choice of an ethanol plant. Towe and Tra (2012) address this issue using a difference-in-difference propensity score matching (PSM) estimator to quantify the average effect of the 2005 ethanol mandate on proximate farmland values. Using farmer-reported survey data on land values from 2002–2006, they find that new ethanol facilities had no effect on farmland values prior to the mandate (2002–2004) but had significant effects after the policy (2004–2006). They conclude that this finding confirms their main hypothesis—that the 2005 federal ethanol mandate led to exuberant confidence in the expected farmland returns beyond market fundamentals.

The objective of this article is to identify the spatially explicit capitalization of new ethanol plants and other agricultural market channels into surrounding farmland and to test for structural change in these effects before and after the ethanol market expansion that occurred in the United States in the mid-2000's. We hypothesize that changes in agricultural output markets, including increased demand for biofuels and grain exports, were capitalized into agricultural land values, and that, due to transportation costs, these effects vary systematically with proximity to ethanol plants and grain elevators. We also hypothesize a potential decrease in the influence of traditional agricultural output terminals due to additional competition pressure from newly constructed ethanol plants, and that the growth in the ethanol sector offset the downward pressure of the Great Recession on land values (Zhang and Nickerson 2015). To examine these hypotheses we use parcel-level data on agricultural land sales from a 50-county area of the Ohio Corn

Belt (figure 1), which represents a majority of the state's grain production during a period (2001–2010) that encompasses the rapid expansion of ethanol facilities in the state.

We address the endogeneity of farmland parcels' proximity to ethanol plants using an instrumental variables (IV) approach. We construct two instruments that are based on the idea of spatial competition among agricultural market channels to address the non-random nature of the site selection process of ethanol plants. Specifically, given the significance of transportation costs in the value of agricultural commodities (Fackler and Goodwin 2001), a new ethanol plant should find it optimal to locate a certain distance from other agricultural markets in order to minimize competitive pressure and maximize their market area within a region. With this in mind, we construct two instruments: capacity weighted average distances to other, non-nearest ethanol plants and capacity-weighted distances to other agricultural output terminals. These instruments, which capture the regional competitive pressure faced by the ethanol plant that is nearest to a given farmland parcel, affect the site selection of this plant and thus the distance from it to the farmland parcel. However, because the spatial extent of the capitalization effect is localized, non-nearest ethanol plants and other terminals are sufficiently far away that they do not directly impact the value of the farmland parcel itself. We also investigate the influence of the expanding biofuels market on proximity to traditional agricultural market channels to test whether increased competition from newly constructed ethanol plants changed the capitalization effects of proximity to grain elevators and agricultural output terminals. We use separately constructed matched samples based on proximity to these other market channels to control for unobserved spatial correlations.

The main result provides evidence of a positive and significant capitalization effect of proximity to an ethanol plant in farmland values. Based on our preferred IV model, we find that, following the construction of an ethanol plant, the marginal value of a farmland parcel increases its sale price by $19 per acre, on average, for each mile closer to the nearest ethanol plant. This translates into a $380 ($570) per acre premium for parcels 20 (30) miles closer to ethanol plants than comparable, but more distant parcels, roughly 7 (10)% of the average sale price, which is similar to findings by Towe and Tra (2012). Results also reveal an increase in the influence of proximity to grain elevators, from an insignificant effect to $57 per acre per mile, as well as a reduction in the magnitude and significance of the effect of proximity to agricultural terminals after early 2007, from an average of $48 to $30 per acre per mile, which is consistent with our hypothesis that competition from the newly constructed ethanol plants reduced the value of proximity to traditional outlets. By comparison, the effect of proximity to nearest city center and second-nearest city is $46 and $32 per mile per acre, respectively. The results are robust to alternative specification, instruments, IV regressions on a sample matched on observable parcel characteristics, a difference-in-difference model on the matched sample, and falsification tests.

This article makes several important contributions to the literature on farmland valuation. First, we provide the first evidence of the spatial gradient generated by ethanol market expansion on market values of farmland and its magnitude relative to other fundamental spatial features of agricultural land markets, including proximity to other agricultural channels and urban centers. Second, we develop a novel IV approach that allows us to address the potential endogeneity of the proximity of farmland parcels to ethanol plants. In so doing, we improve upon previous hedonic estimates, which typically yields a much lower capitalization effect (Blomendahl et al. 2011; Henderson and Gloy 2009). Our results are similar with the findings of Towe and Tra (2012), which reported a 9%–12% increase in reported land value for parcels within 30 miles of ethanol plants right after the 2005 Renewable Fuel Standard biofuel mandate. Second, our results support the common wisdom that the rise of the ethanol industry helped the farm sector withstand the strong economic downturn during the Great Recession (Nickerson et al. 2012). Third, given the strong role that U.S. energy policies played in establishing the ethanol market, and are likely to play in future bioenergy production, our results underscore the importance of accounting for the role of land markets as a fundamental force that mediates the influence of policies on the food-energy nexus.

Conceptual Framework

Given limited supply and future expectations, the value of farmland is the capitalized value of the expected net present value of economic returns to land:

$$V_{it} = E_t \sum_s \frac{R_{is}}{(1+\delta_t)^{s-t}}, \qquad where\ s = t, t+1, \ldots \qquad (1)$$

where V_{it} is the value of agricultural land parcel i at time t, and is defined as the expected future annual returns to farmland R_{it} discounted at rate t, and δ_t is the discount rate in period t. Heterogeneous factors influencing R_{it} that are capitalized into V_{it} include productive differences in land quality or location that influence agricultural productivity or the expected returns from converting land to an urban or other alternative use. We assume that R_{it} can be approximated by a linear combination of parcel attributes and location characteristics $\boldsymbol{X_{it}}$ using Taylor expansion, a common linear specification, defined as

$$R_{it} = \beta' \boldsymbol{X_{it}} + \tau_t + \eta_{it} \qquad (2)$$

where τ_t is time fixed effects and η_{it} is the remaining normally distributed error term.

The vector of parcel attributes and location characteristics $\boldsymbol{X_{it}}$ can be further specified as: (*a*) parcel-specific agronomic variables $\boldsymbol{A_{it}}$, such as soil quality and slope of the parcel; (*b*) natural amenities variables $\boldsymbol{N_{it}}$, such as varied topography and proximity to surface water; (*c*) urban influence variables $\boldsymbol{U_{it}}$, such as surrounding urban population and access to highways; and, (*d*) newly emerging set of agricultural market influence variables $\boldsymbol{M_{it}}$, such as proximity to ethanol plants, grain elevators, and agricultural product terminal ports. This results in the following model specification:

$$V_{it} = E_t \sum_s f(\boldsymbol{A_{is}}, \boldsymbol{N_{is}}, \boldsymbol{U_{is}}, \boldsymbol{M_{is}};\ \delta_t)\ , where\ s = t, t+1, \ldots \qquad (3)$$

We focus on the influence of agricultural market influence variables $\boldsymbol{M_{it}}$ and for context compare these capitalization effects to urban influence variables $\boldsymbol{U_{it}}$. Supported by federal energy policies, increased production of biofuels has increased demand for corn, leading to elevated corn and other agricultural commodity prices (Nickerson et al. 2012), and stronger crop basis (McNew and Griffith 2005). Our main hypothesis is that this increased demand for corn is capitalized in farmland values and that, due to transportation costs, these effects vary systematically over space with proximity to ethanol plants and grain elevators. In addition, by attracting corn supplies from surrounding land parcels or nearby grain elevators, the new ethanol plants may constitute a competing source of demand for grains for traditional agricultural export terminals (Nickerson et al. 2012).

Econometric Challenges and Empirical Strategy

Identifying the Localized Effect of Proximity to an Ethanol Plant

Following a broad literature on land valuation that employs the hedonic price method (Rosen 1974; Palmquist 1989), a common specification of (4) is the linear form:

$$V_{it} = \beta_0 + \beta_A{}'\boldsymbol{A_{it}} + \beta_U{}'\boldsymbol{U_{it}} + \beta_R{}'\boldsymbol{R_{it}} + \beta_M{}'\boldsymbol{M_{it}} + \tau_t + \varepsilon_{it}, \quad (5)$$

where the agricultural land values V_{it} are approximated by the nominal sale prices of the agricultural land without structures P_{it}. In this setting, agricultural land is regarded as a differentiated product with a bundle of agricultural quality and location characteristics, and each characteristic is valued by its implicit price (Nehring et al. 2006; Rosen 1974).

Despite its popularity, the hedonic price method suffers from a number of well-known econometric problems (Bajari et al. 2012; De Vor and De Groot 2011). In our case, the selection of a location for an ethanol plant is a non-random process affected by factors that influence its relative profitability. Personal communications with managers of the new ethanol plants in our study region reveal that abundant corn supply, land costs, competition with other markets, and access to highways, railways, sewer service, and natural gas pipelines are all important site characteristics. Depending on the relative magnitudes of these factors, a negative or positive bias may result. If plant managers seek to minimize land costs (Towe and Tra 2012) or if spatial competition with other agricultural markets is sufficiently strong, then areas with low corn basis levels or areas that are farther from existing market channels are more likely to be chosen as sites for ethanol plants. This would lead to a downward bias in the hedonic estimates. On the other hand, it could be that agricultural parcels closer to the ethanol plants are more productive or have easier access to the transportation network than parcels further away, in which case, the resulting endogeneity would bias the estimates in an upward direction.

We investigate the potential direction of this bias for our study region using descriptive spatial data analysis. Figure 2 presents a map of the six ethanol plants as well as towns that can be considered *potential* sites based on abundant corn supply and access to highways, railways, sewer service, and natural gas pipelines .[1] We note that, relative to the number of actual ethanol plants, there is an abundance of sites with these desirable features, suggesting that these characteristics have not played a strong differentiating role in determining the actual location of the ethanol plants. We further investigate whether plant locations are systematically spatially correlated with more localized variations in corn supply. Figure 3 plots the cumulative number of both actual and potential sites with respect to the percentage of nearby corn acreage over all land within 50 miles of the town center. The plot indicates that the actual locations of ethanol plants are no more clustered in areas with greater corn access than potential locations. Together, figures 2 and 3 indicate that the six ethanol plant locations are not systematically spatially correlated with the distribution of potential ethanol plant sites, suggesting that key site characteristics that could have caused a more clustered pattern of ethanol plants to emerge have not been a strong differentiator. Instead, we hypothesize that other factors, such as land costs and spatial competition, are more likely to have played a determining role in the location of these new ethanol plants.

This motivates our IV approach, which is based on the idea of spatial competition among agricultural market channels. Previous studies have shown that transportation costs account for a significant fraction of the value of agricultural commodities (Fackler and Goodwin 2001). Due to transportation costs, a standard result from models of spatial competition is the principle of maximum differentiation—each firm has an incentive to locate farther away from its rivals to avoid price competition (d'Aspremont et al. 1979). Specifically, transportation costs imply a new ethanol plant should find it optimal to locate a certain distance away from other agricultural market channels in order to maximize their market area. With this in mind, we construct two instruments: capacity weighted average distance to other, non-nearest ethanol plants; and, capacity-weighted average distance to other agricultural output terminals.[2] These instruments, which capture market competition at a regional scale, are hypothesized to affect the site selection of a new plant; however, the value of farmland parcels that are closer to the new plant will not be affected by the location of these other (non-nearest) ethanol plants and other terminals, provided these other channels are sufficiently far away. This relies on the assumption that the market extent is regional, but that the capitalized effect of proximity to any given ethanol plant, grain elevator, or output terminal is limited to a more localized spatial extent. This is consistent with previous studies that reveal the effects of proximity to ethanol plants are relatively local (Gallagher 2006).

To investigate this assumption for our study region, we use the double residual semiparametric regression developed by Robinson (1988) to examine the spatial correlation of land values and proximity to ethanol plants (figure 4). In this regression, the distance to nearest ethanol plant enters the model non-parametrically, while other parcel characteristics such as soil characteristics and proximity to urban centers are used as controls. The results show that land values decline monotonically with distance up until about 15 miles, are level or slightly increasing after this up to about 35 miles, and then decline rapidly at greater distances. The plot clearly demonstrates the localized correlation and negative gradient of land values and proximity to an ethanol plant. That other spatial heterogeneities affect land values is also evident, given the variation between about 15–35 miles. Importantly, the average distances of competing agricultural markets are substantially farther than 15 miles (e.g., the average distance to the second (third)-nearest ethanol plant is 41 (61) miles away and the average distance of non-nearest other agricultural terminals is 90 miles), as shown in table 1. The limited spatial extent of the localized declining gradient and the much greater average distances to non-nearest agricultural markets support our assumption that distance to non-nearest facilities is not capitalized into land values. Empirically, we expect that the closer a parcel is to the nearest ethanol plant or grain elevator, the farther it is from the next-nearest facility. Thus, a negative correlation between these instruments and the distance to the nearest ethanol plant variable is consistent with spatial competition.

We implement this strategy using a two-stage least squares approach and estimate the following equations:

$$\boldsymbol{M_{it}} = \beta_0 + \beta_A{}'\boldsymbol{A_{it}} + \beta_U{}'\boldsymbol{U_{it}} + \beta_R{}'\boldsymbol{R_{it}} + \pi_Z{}'\boldsymbol{Z_{it}} + \tau_t + e_{it}, \quad (7a)$$

$$\boldsymbol{M_{it}} * D\_POST = \beta_0 + \beta_A{}'\boldsymbol{A_{it}} + \beta_U{}'\boldsymbol{U_{it}} + \beta_R{}'\boldsymbol{R_{it}} + \pi_Z{}'\boldsymbol{Z_{it}} + \tau_t + \epsilon_{it}, \quad (7b)$$

$$P_{it} = \beta_0 + \beta_A{}'\boldsymbol{A_{it}} + \beta_U{}'\boldsymbol{U_{it}} + \beta_R{}'\boldsymbol{R_{it}} + \beta_M{}'\widehat{\boldsymbol{M_{it}}} + \beta_{M\_POST}{}'\widehat{\boldsymbol{M_{it}} * D\_POST} + \tau_t + \varepsilon_{it},$$

(7c)

where D_POST is a binary time dummy indicating that the parcel is sold after the month of construction of the nearest ethanol plant, $\boldsymbol{Z_{it}}$ are the two instruments, and $\widehat{\boldsymbol{M_{it}}}$, $\widehat{\boldsymbol{M_{it}} * D\_POST}$ are the predicted values from the first-stage regressions.

Ethanol plants in or near western Ohio all started construction in late 2006 to early 2007. As a result, β_{M_POST} captures the significance and magnitude of the spatial effects of proximity to ethanol plants following construction of these plants, and can be interpreted as the local average treatment effects of ethanol plant proximity on nearby farmland values.

Identifying the Effect of Proximity to Other Market Channels

We are interested not only in the effect of proximity to newly constructed ethanol plants, but also in the effects of proximity to grain elevators and agricultural output terminals after the new ethanol plant construction. We use a standard hedonic regression to test this using the following specification:

$$P_{it} = \beta_0 + \beta_A{}'\boldsymbol{A_{it}} + \beta_U{}'\boldsymbol{U_{it}} + \beta_R{}'\boldsymbol{R_{it}} + \beta_M{}'\boldsymbol{M_{it}} + \beta_{M\_POST}{}'\boldsymbol{M_{it}} * D\_POST + \tau_t + \varepsilon_{it},$$

(6)

The coefficient, β_M, on variables like distances to nearest grain elevators or agricultural terminals captures the capitalization effects of proximity to these destinations before late 2006–2007, while β_{M_POST}, the coefficient on the interaction term between these proximity variables and the time dummy, represents the significance and magnitude of the structural change in their effect.

While the locations of grain elevators and agricultural terminals are exogenous, endogeneity problems may still arise due to systematic differences in observable characteristics for parcels closer to grain elevators and agricultural terminals versus those farther away, including distance to urban centers and structures. To address this, we construct two separate matched samples based on proximity to grain elevators and agricultural output terminals, respectively, using PSM (Rosenbaum and Rubin 1983). Specifically, we use distance cutoffs of 5 and 15 miles, respectively, to construct the matched samples for grain elevators and agricultural output terminals. This reflects the differences in the market extent for the local grain elevators and agricultural output terminals that serve larger regional markets.[3]

Data

Western Ohio hosts a vast majority of the state's agricultural land and provides an excellent laboratory to study the structural change in the proximity to agricultural market channels on farmland values in the context of ethanol market expansion. We assembled a detailed database of 21,342 arm’s-length agricultural land sale records for 51 counties in or near western Ohio from 2001 to 2010, obtained from a combination of purchased data from Corelogic (29 counties), data from USDA ERS (14 counties), and data collected from eight other county auditor offices.[4] Only those agricultural parcels sold between 2001 and 2010 and with a valid arm’s-length indicator are kept.[5] Those valid agricultural sale records are merged with GIS parcel boundaries or are geocoded based on property addresses using Google Maps API. Sales prices are adjusted for the value of the structures on the farmland, using the percentage of assessed values of land only over assessed values of land and buildings altogether. Parcels with sales prices above $20,000/acre or below $1,000/acre are dropped, as are parcels sold in the year 2007, farmland parcels inside a census-defined urban area boundary, and those within 15 miles of a city of at least 10,000 people. Figure 1 shows a plot of the filtered sample consisting of 11,991 valid transactions. As is evident from the figure, these data are widely distributed over virtually the entire region. The locations of three sets of agricultural market channels—ethanol plants, grain elevators and agricultural terminal ports—are also shown.

Data on parcel attributes and location characteristics were obtained largely from the USDA Natural Resources Conservation Services GeoSpatial Data Gateway, including the Census TIGER/Line Streets, National Elevation Dataset, National Land Cover Dataset, and Soil Survey Spatial Data. Additional data on locations of cities and towns in Ohio was obtained from Ohio Department of Transportation (2012). We also used Census Block Shapefiles with 2010 Census Population and Housing Unit Counts (U.S. Census TIGER/Line 2012) to calculate the surrounding urban population. Data on ethanol plants, grain elevators, and agricultural terminal ports were obtained from the Ohio Ethanol Council (2012), Farm Net Services (2012) and Ohio Department of Agriculture (2012). Using these data and ArcGIS software, we were able to create the parcel attributes and location characteristics vector $\boldsymbol{X_{it}}$. See table 1 for summary statistics.

Most variables in table 1 are self-explanatory; however, three variables warrant further explanation. First, the variable National Commodity Crops Productivity Index (NCCPI) is an interpretation in the National Soil Information System. Specifically, the interpretation uses natural relationships of soil, landscape, and climate factors to model the response of commodity crops (see Dobos et al. 2008 for details). Second, soil class 1 is defined as "All areas prime farmland," class 2 as "Prime farmland if drained," class 3 as "Farmland of local importance," and class 4 as "not prime farmland." Third, a proximity variable for each of the three agricultural market channels is calculated as driving distance from farmland parcels to the nearest market.

Figures 5 and 6 plot the number of agricultural land sales and the average farmland values in western Ohio since 2001, respectively. Although the number of farmland sales dropped precipitously after the housing market bust, there was no corresponding dip in the average sales price of agricultural land. Instead, figure 5 suggests that the average farmland sale prices stayed fairly constant at around $5000/acre over the 2000s decade.

Results and Discussion

We start with the hedonic model as a benchmark model and the IV regression as our main specification (table 2). Considering the hedonic model first in panel i, we see that proximity to ethanol plants is positive and significant after construction of these plants (*Dist_Ethanol * Post construction dummy)*: on average the farmland value per acre would be $19 higher for every additional mile closer an ethanol plant. Most of the other estimates are intuitive: poor soil quality or presence of steep slope decreased farmland values, while proximity to urban areas or highway ramps led to an increase. The negative coefficient on acres seems to confirm the "small parcel size premium" in farmland sales due to stronger demand (Brorsen et al. 2015), while the significant coefficient on acres squared implied a nonlinear relationship between per acre farmland values and total acreage.

Turning to the IV regressions (table 2 panel ii), we find a similar result for the estimated coefficient associated with the interaction term *Dist_Ethanol * Post construction dummy*: the marginal value of farmland increases by $19 per mile per acre within proximity to the nearest ethanol plant following plant construction. By comparison, the effect of proximity to nearest city center and second-nearest city is about $45 and $32 per mile per acre, respectively.

Table 3 panel i reports the change in the effects of proximity to other types of agricultural markets in a hedonic regression using the unmatched sample and interactions with the *Post construction dummy* variable. The negative coefficient on the interaction terms for grain elevators and the positive coefficient on the interaction term for agricultural terminals suggest after the constructions of ethanol plants, there seems a growing effect of proximity to grain elevators and a reduction in the effects of the marginal value of proximity to agricultural output terminals. However, these two coefficients are statistically insignificant. Table 3 panels ii and iii present the estimation results using the matched samples that control for the potential endogeneity that could result from systematic differences across distance that may bias these coefficients. These two models reveal an increased influence of proximity to grain elevators and a reduction in the magnitude and significance of the effect of proximity to agricultural terminals after early 2007. Specifically, proximity to grain elevators did not exert significant influence in surrounding farmland values before 2006, but became a positive and significant determinant after the ethanol market expansion in Ohio, conveying an added value of $57 per acre with every mile closer to a grain elevator. This result is intuitive because local grain elevators meet part of the increased demand for corn due to construction of ethanol plants. In addition, we find that the marginal value of being close to an agricultural terminal reduces from $48 to $30 per mile per acre after early 2007, which suggests that the newly constructed ethanol plants constitute a significant competing source of demand for grains for traditional agricultural output terminals (Nickerson et al. 2012). This also provides support for our IV approach, which relies on the spatial competition among ethanol plants and agricultural terminals.

We test the robustness of our results by focusing on a sample with close proximity to ethanol plants. In particular, we drop observations that are 40, 30, and 20 miles away from the nearest ethanol plant in table 4 panel i, ii, and iii, respectively. These three models reveal that as we narrow the sample to focus on farmland parcels closer to ethanol plants, the marginal value of being within close proximity to an ethanol plant increases from $19 per mile in the main model to $38 per mile for parcels within 40 miles, $54 per mile for parcels within 30 miles, and finally to $129 per mile if we only look at parcels less than 20 miles away from an ethanol plant. The increase in the marginal value is intuitive because when we focus on a smaller sample closer to ethanol plants, arguably they enjoy most savings in grain hauling costs and thus experience a greater impact on average. This also confirms the declining slope in figure 4. In addition, by dropping observations beyond 40 miles from ethanol plants, panel i also serves as a test of the monotonicity assumption in the instruments that greater distance from other agricultural markets, which signals a lower competitive pressure, would imply a closer proximity to ethanol plants.

To assess the stableness of our main IV regressions, table 5 present a series of robustness checks on the validity of instruments and the assumption of the hedonic market. The instruments relying on the distances to other plants would not be valid if any of the non-nearest agricultural markets affected the value of farmland parcels nearest to the instrumented ethanol plant location. We test this by excluding two or three nearest ethanol plants and agricultural output terminals in the construction of instruments, so that only the farther away agricultural markets are used in constructing the instruments. Table 5 panels ii, iii, and iv reveal similar results as the main specification, suggesting that our instruments are valid and unlikely to be endogenous. In particular, panel iv just uses agricultural terminals when constructing the instruments, and the similarity with the main specification suggests that overall the IV regressions yield robust and reliable estimates.

Table 5 panel v shows the results of a falsification test based on location. In particular, we randomly picked seven other towns with abundant corn supply and adequate transportation network, yet currently with no ethanol plants, as if these were the ethanol plant sites. The results show no evidence of capitalization effects of proximity to these random towns, suggesting that our results are robust to this location falsification test. In addition, we note that among all seven ethanol plants, three are owned by the same company, POET. We run another robustness check by focusing on parcels which are close to non-POET ethanol plants only, assuming that these three plants owned by POET might coordinate in locations and thus consider more factors than spatial competition. Table 5 panel vi shows that this model focusing on parcels near non-POET plants yields qualitatively similar results as our main specification.

To test the validity and relevance of our instruments, we run a series of specifications and other statistical tests for the IV regressions. Tables A1, A2, and A3 in the appendix present results of the first stage regressions of the potentially endogenous variables, a regression of instruments on other exogenous covariates, and some regression diagnostics tests. The significant and negative coefficient of the proposed instrument on ethanol plant proximity confirms our conjecture of spatial competition among ethanol plants. In addition, the instrument is not correlated with most covariates, the Kleibergen-Paap Wald F statistic reveals that these instruments are relevant and not weak (Kleibergen and Paap 2006; Stock and Yogo 2005), and we cannot reject the over-identification test based on the Hansen J statistic (Hansen 1982), acknowledging the strong assumption of at least one valid instrument.

Table 6 reports the results of a different set of robustness tests with alternative sample sizes based on differing time windows used to define the post-construction period for the ethanol plants, as well as a timing falsification test in which we assume the ethanol plants were constructed two years earlier than actual timing. Table 6 panels i, ii, and iii reveal that there is evidence of expectations before the construction of ethanol plants; however, the expectations argument is only relevant six months before the plant construction. The timing falsification in panel iv shows that there is no structural change in the spatial effects of proximity to ethanol plants before and after 2004, suggesting that our main finding is not just a result of shifts in preferences over time.

To further assess the robustness of our results, we run several alternative specifications and models. These results are presented in table 7. In particular, panel i uses a log-linear specification when estimating the IV regression, and panel ii combines PSM with the current IV approach. The log-linear IV model shown in panel i yields qualitatively similar results as table 2. In panel ii, we first match parcels closer to ethanol plants and those farther away on observable characteristics using PSM, and then run the IV regression on the matched samples with credible treatment and control groups whose characteristics are arguably similar in every other way except for the proximity to ethanol plants. Since PSM essentially trims the sample by dropping the distant farmland parcels that are dissimilar with those nearby ethanol plants, we expect a strengthening of the capitalization effects due to proximity to ethanol plants compared to our main specification shown in table 2. The cutoff distances used in the four-nearest-neighbor PSM to define proximity to ethanol plants is 10 miles following figure 4, and the results shown in panel ii confirms our conjecture and shows that the marginal value of farmland increases by $46 per mile per acre within proximity to the nearest ethanol plant following plant construction. This result is robust to various alternative matching algorithms, including covariate matching (Rubin 1980) and kernel-based matching (Heckman et al.

1998), as well as alternative distance cutoffs that define proximity to the agricultural markets.[6]

Table 7 panels iii, iv, and v present results using difference-in-difference framework as opposed to an IV approach. The key distinction is that rather than using the continuous proximity measure as in the IV approach, the DID approach specifies a binary proximity dummy based on the aforementioned distance cutoff from parcel to corresponding agricultural markets. The coefficient on the interaction term between the proximity dummy and post-construction dummy serves the DID estimator, which captures the average structural change of the impact of the proximity to an agricultural market channel on nearby farmland values after the establishment of ethanol plants. Table 7 panels iii and iv presents the results of these DID regressions for ethanol plants for the raw sample as well as matched sample. For sake of brevity, we focus the discussions to the regressions on the raw sample. In general, the DID results are consistent with our main specification. It reveals that, on average, being close to an ethanol plant was valued more after their construction in 2007, and the average capitalization effect is a $335 per acre rise in farmland prices for parcels within 15 miles of ethanol plants compared to those farther away. Table 7 panel v also presents DID-style regressions in which, rather than using the user-defined binary proximity variable, we directly use the distance to nearest ethanol plant and its interaction with the post-construction timing dummy.[7] This model essentially yields similar insights as in our main specification—that the marginal value of being in close proximity to ethanol plants increases value at an average of $13 per mile per acre.

Conclusion

The first decade of the 2000s saw dramatic changes in the forces that influence farmland values. On the one hand, rapid expansion of biofuels markets supported by federal energy policies has dramatically increased demand for corn, which elevated agricultural commodity prices and farmland values (Wallander et al. 2011). On the other hand, the residential housing market bust in 2006 that precipitated the Great Recession had a substantial negative effect on the value of exurban farmland proximate to urban areas (Zhang and Nickerson 2015). Using a dataset of parcel-level farmland sales in western Ohio from 2001 to 2010, we examine the changes in farmland values resulting from an expanding biofuels market and regional competition among agricultural market channels. To address the non-random ethanol plant site selection process, we construct two instruments using a novel identification strategy that relies on spatial competition among agricultural markets. We use separately matched samples based on proximity to grain elevators and agricultural output terminals respectively to identify the changing effect of proximity to these other agricultural markets.

The main results from the IV estimation show that the marginal value of farmland increases by $19 per mile per acre with close proximity to the nearest ethanol plant following plant construction. This translates into a $380 ($570) per acre premium—roughly 7 (10) percent of the average sales price—for parcels 20 (30) miles closer to ethanol plants than comparable, but more distant parcels. The effect of proximity to other agricultural markets changed as ethanol markets expanded. We find an increase in the influence of proximity to grain elevators, from an insignificant effect to $57 per acre per mile, as well as a reduction in the magnitude and significance of the effect of proximity to agricultural terminals after early 2007, from an average of $48 to $30 per acre per mile. These results reveal the changing spatial competition among local agricultural market outlets and are consistent with our hypothesis that competition from the newly constructed ethanol plants reduced the value of proximity to traditional outlets. In comparison, we find that the effects of proximity to nearest urban area raises farmland values by an average of $45 per mile per acre. Taken together, these results provide evidence of the competition between new and traditional agricultural market channels, the importance of access to biofuel production facilities, and offsetting effect that the growing biofuels market had on agricultural land values in the face of the Great Recession.

Ethanol is now a critical part in the corn industry supply chain, and 2010 marks the first year that corn usage for ethanol production exceeds usage for feed stock (Wallander et al. 2011). However, until recently, ethanol development and utilization have been largely dependent upon government subsidies and other policy support. There is ongoing debate regarding the welfare impacts of ethanol policy and resulting ethanol market expansion, including its impacts on farmer income, commodity prices, farmland values, greenhouse gases, and energy portfolio (Cappiello and Apuzzo 2013; Rajagopal et al. 2011; Tiffany 2009). Our results inform this debate by providing evidence of a spatial capitalization effect of proximity to ethanol plants in farmland values. Given the strong role that U.S. energy policies, such as the Renewable Fuel Standard, are likely to play in future bioenergy production, our results underscore the importance of accounting for the role of land markets as a fundamental force that mediates the influence of policies on the food-energy nexus. With many of the ethanol subsidies already terminated, it remains to be seen whether potential downward pressures on ethanol development will affect the welfare effects of the ethanol market expansion, and in particular its capitalization in commodity prices and farmland values.

References

Arora, G., P.T. Wolter, H. Feng, and D.A. Hennessy. 2016. “Role of Ethanol Plants in Dakotas Land Use Change: Incorporating Flexible Trends in the Difference-in-Difference Framework with Remotely-Sensed Data.” *CARD Working Paper* WP-583. http://lib.dr.iastate.edu/card_workingpapers/583.

Bajari, P., J.C. Fruehwirth, K. Kim, and C. Timmins. 2012. "A Rational Expectations Approach to Hedonic Price Regressions with Time-Varying Unobserved Product Attributes: The Price of Pollution." *American Economic Review* 102:1898–1926.

Bayer, P., and C. Timmins. 2007. "Estimating Equilibrium Models of Sorting across Locations*." *The Economic Journal* 117:353–374.

Blomendahl, B.H., R.K. Perrin, and B.B. Johnson. 2011. "The Impact of Ethanol Plants on Surrounding Farmland Values: A Case Study." *Land Economics* 87:223–232.

Brorsen, B.W., D. Doye, and K.B. Neal. 2015. "Agricultural Land and the Small Parcel Size Premium Puzzle." *Land Economics* 91(3): 572-585.

d'Aspremont, C., J. Jaskold Gabszewicz, and J.-F. Thisse. 1979. "On Hotelling's" Stability in Competition". *Econometrica* 47:1145–1150.

De Vor, F., and H. L.F. De Groot. 2011. "The Impact of Industrial Sites on Residential Property Values: A Hedonic Pricing Analysis from the Netherlands." *Regional Studies* 45:609–623.

Dobos, R., H. Sinclair, and K. Hipple. 2008. *User Guide National Commodity Crop Productivity Index (Nccpi) Version 1.0.* Washington DC: U.S. Department of Agriculture, Natural Resources Conservation Service.

Fackler, P.L., and B.K. Goodwin. 2001. "Spatial Price Analysis." *Handbook of Agricultural Economics* 1:971–1024.

Farm Net Services 2012 "Ohio Grain Elevators." In *Farm Equipment and Agriculture Business Directory*, *http://www.farmnetservices.com/farm/Grain%20Elevators/OHIO%20GRAIN%20ELEVATORS/66-0.html*.

Gallagher, P.W. 2006. "Energy Production with Biomass: What Are the Prospects?" *Choices: The Magazine of Food, Farm, and Resource Issues* 21:21–25.

Guiling, P.B., W. Brorsen, and D. Doye. 2009. "Effect of Urban Proximity on Agricultural Land Values." *Land Economics* 85:252–264.

Hansen, L.P. 1982. "Large Sample Properties of Generalized Method of Moments Estimators." *Econometrica: Journal of the Econometric Society* 1029–1054.

Heckman, J.J., H. Ichimura, and P. Todd. 1998. "Matching as an Econometric Evaluation Estimator." *The Review of Economic Studies* 65:261–294.

Henderson, J., and B.A. Gloy. 2009. "The Impact of Ethanol Plants on Cropland Values in the Great Plains." *Agricultural Finance Review* 69:36–48.

Hite, D., W. Chern, F. Hitzhusen, and A. Randall. 2001. "Property-Value Impacts of an Environmental Disamenity: The Case of Landfills." *The Journal of Real Estate Finance and Economics* 22:185–202.

Kleibergen, F., and R. Paap. 2006. "Generalized Reduced Rank Tests Using the Singular Value Decomposition." *Journal of Econometrics* 133:97–126.

Lambert, D.M., M. Wilcox, A. English, and L. Stewart. 2008. "Ethanol Plant Location Determinants and County Comparative Advantage." *Journal of Agricultural and Applied Economics* 40:117–135.

Low, S.A., and A.M. Isserman. 2009. "Ethanol and the Local Economy Industry Trends, Location Factors, Economic Impacts, and Risks." *Economic Development Quarterly* 23:71–88.

McNew, K., and D. Griffith. 2005. "Measuring the Impact of Ethanol Plants on Local Grain Prices." *Applied Economic Perspectives and Policy* 27:164–180.

Nehring, R., C. Barnard, D. Banker, and V. Breneman. 2006. "Urban Influence on Costs of Production in the Corn Belt." *American Journal of Agricultural Economics* 88:930–946.

Nickerson, C.J., M. Morehart, T. Kuethe, J. Beckman, J. Ifft, and R. Williams. 2012. *Trends in US Farmland Values and Ownership*. Wasington DC: US Department of Agriculture, Economic Research Service.

Ohio Department of Agriculture. 2012. "Ohio Licensed Commodity Handlers." In *Grain Warehouse Program.*

Ohio Department of Transportation. 2012. "Active Rails, Airports, Cities and Townships." In *ESRI/Statewide Digital Data.*

Ohio Ethanol Council. 2012. "Ohio Ethanol Industry Quick Facts." In *http://ohethanol.com/ohio_ethanol*.

Palmquist, R.B. 1989. "Land as a Differentiated Factor of Production: A Hedonic Model and Its Implications for Welfare Measurement." *Land Economics* 65:23–28.

Rajagopal, D., G. Hochman, and D. Zilberman. 2011. "Indirect Fuel Use Change (Ifuc) and the Lifecycle Environmental Impact of Biofuel Policies." *Energy Policy* 39:228–233.

Robinson P.M. 1988. "Root-N-consistent semiparametric regression." *Econometrica* 56: 931-954.

Rosen, S. 1974. "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition." *The Journal of Political Economy* 82:34–55.

Rosenbaum, P.R., and D.B. Rubin. 1983. "The Central Role of the Propensity Score in Observational Studies for Causal Effects." *Biometrika* 70:41–55.

Rubin, D.B. 1980. "Bias Reduction Using Mahalanobis-Metric Matching." *Biometrika* 36:293–298.

Stevens, A. 2015. "Fueling Local Water Pollution: Ethanol Refineries, Land Use and Nitrate Runoff." Manuscript.

Stock, J.H., and M. Yogo. 2005. "Testing for Weak Instruments in Linear Iv Regression." *Identification and inference for econometric models: Essays in honor of Thomas Rothenberg*.

Tiffany, D.G. 2009. "Economic and Environmental Impacts of Us Corn Ethanol Production and Use." *Regional Economic Development* 5:42–58.

Towe, C., and C.I. Tra. 2012. "Vegetable Spirits and Energy Policy." *American Journal of Agricultural Economics* 95:1–16.

U.S. Census TIGER/Line. 2012. "Census Block Shapefiles with 2010 Census Population and Housing Unit Counts." In ftp://ftp2.census.gov/geo/tiger/TIGER2010BLKPOPHU/.

Wallander, S., R. Claassen, and C. Nickerson. 2011. *The Ethanol Decade: An Expansion of US Corn Production, 2000-09*. Washington DC: U.S. Department of Agriculture, ERS. Economic Information Bulletin 79.

Wu, Z., A. Weersink, A. Maynard, G. Hailu, and R. Vyn. 2016. "The Impact of Local Ethanol Production on the Corn Basis in Ontario" *Canadian Journal of Agricultural Economics* 1-22

Zhang, W., and C.J. Nickerson. 2015. "The Housing Market Bust and Farmland Values: Identifying the Changing Influence of Proximity to Urban Centers." *Land Economics* 91(4): 605–626.

Zhang, W. 2015. *Three Essays on Land Use, Land Management, and Land Values in the Agro-Ecosystem*, Ph.D. Dissertation, the Ohio State University.

Tables

Table 1. Summary Statistics of Agricultural Land Sales 2001–2010 in the Corn Belt region of Ohio

	Unit	Mean	Std. Dev.	Min.	Max.
General Parcel Attributes					
Sale price	Dollars	206711	288181	311	12800000
Sale price per acre	Dollars	5537	4417	500	20000
Assessed land value	Dollars	73583	135582	0	3221930
Assessed improvement value	Dollars	29513	58874	0	1368000
Assessed land value % of total assessed	%	73.6%	30.5%	0	1
Total acres	Acres	51.28	56.80	5.17	2381
Sale year	Year	2004.84	2.76	2001	2010
Agricultural Productivity Variables					
NCCPI	Number	5837.16	1560.6	0	8761
Cropland % of parcel	%	55.0%	37.2%	0	100%
Soil class 1 area % of parcel	%	30.8%	35.4%	0	100%
Soil class 2 area % of parcel	%	25.5%	32.5%	0	100%
Soil class 3 area % of parcel	%	5.4%	15.6%	0	100%
Steep slope (>15 degrees)	Binary	0.26	0.59	0	1
Urban Influence Variables					
Building area % of parcel	%	3.5%	12.7%	0	100%

Distance to urban area of over 25k people	Miles	11.9	8.0	0.1	35.5
Total urban population within 25 miles	Thousand	263.7	190.0	84.0	926.5
Distance to highway ramp	Miles	3.4	2.2	0	11.7
Distance to nearest city	Miles	27.0	12.2	0.1	66.0
Distance to 2^{nd} nearest city	Miles	14.2	13.3	0	62.5
Distance to nearest railway access point	Miles	3.2	1.8	0.01	11.3
Gravity index using three nearest cities	Number	1122.1	39906.1	57.8	4255332
Agricultural Market Influence Variables					
Distance to nearest ethanol plant	Miles	24.5	12.9	0.4	68.0
Distance to nearest ethanol plant * post_dummy	Miles	9.1	13.8	0	66.4
Production capacity of nearest ethanol plant	Mgal	85.9	24.6	54	120
Number of ethanol plants within 25 miles	Number	1.4	0.9	0	4
Total production capacity of ethanol plants within 25 miles	Mgal	96.1	76.5	0	304
Distance to nearest grain elevator	Miles	6.2	3.7	0.0	23.9

Distance to nearest agricultural terminal	Miles	31.9	13.3	0.2	72.8
Distance to 2nd nearest ethanol plant	Miles	41.0	16.1	6.7	82.3
Distance to 2nd nearest agricultural terminal	Miles	61.1	21.6	12.9	109.7
Average distance to other ethanol plants	Miles	76.4	16.6	42.2	117.2
Average distance to other agricultural terminals	Miles	89.5	20.7	58.7	147.3
Capacity-weighted distance to other ethanol plants	Miles	67.0	15.2	38.8	109.2
Capacity-weighted distance to other AG terminals	Miles	89.5	40.9	7.2	164.2
Environmental Amenities Influence Variables					
Forest area % of parcel	%	10.1%	21.0%	0	100%
Wetland area % of parcel	%	0.4%	0.3%	0	100%
Pasture area % of parcel	%	12.1%	24.1%	0	100%
Open water % of parcel	%	0.3%	2.4%	0	74.6%
Observations			11, 991		

Table 2. OLS and IV Regressions with Structural Changes of Proximity to Ethanol Plants

Nominal farmland values ($/acre)	(i) OLS		(ii) IV	
	Coef.	Robust SE	Coef.	Robust SE
Distance to nearest ethanol plant	5.21	6.79	24.11	16.53
Dist_Ethanol * Post construction dummy	-12.07**	5.42	-19.10**	8.44
Assessed land value % of total assessed	-3751.15***	181.05	-3742.86***	180.68
Total acres	-28.70***	1.50	-28.74***	1.50
Total acres squared	0.015***	0.0038	0.016***	0.004
NCCPI	0.0057	0.029	0.0015	0.030
Prime farmland	-222.80	143.98	-229.13	143.57
Steep slope (>15 degrees)	-84.98	78.66	-98.87	79.15
Building area % of parcel	-113.13	310.71	-120.52	309.89
Forest area % of parcel	-177.39	220.13	-210.79	221.10
Wetland area % of parcel	-305.49	886.73	-356.22	886.57
Distance to highway ramp	-39.23**	17.23	-40.92**	17.29
Distance to nearest city	-47.14***	9.18	-45.53***	9.21
Incremental distance to 2nd nearest city	-30.35**	6.82	-31.89**	6.92
Surrounding population within 25 miles	1.14***	0.36	1.00***	0.38
Gravity index of three nearest cities	0.0003*	0.0002	0.0003*	0.0002
Distance to railways	-5.21	19.99	-3.07	19.92
Distance to nearest grain elevator	8.80	13.61	2.80	14.85
Distance to nearest agricultural terminal	-30.25***	6.74	-35.33***	8.17

Intercept	12757.03***	2141.29	12911.66***	2106.37
County FE	Yes		Yes	
Year FE	Yes		Yes	
Adjusted R^2	0.2547		0.2542	
Number of observations	11991		11991	

Table 3. Results of Hedonic Regressions on Matched Samples for Proximity to Grain Elevators and Agricultural Output Terminals

		Coef.	Std. Err.
Panel i: OLS on raw sample	Dist_Ethanol plant	4.78	6.85
	Dist_Ethanol * Post_Dummy	-10.66*	6.01
	Dist_Grain	18.72	16.66
	Dist_Grain * Post_Dummy	-22.81	20.62
	Dist_Ag Terminal	-31.48***	7.00
	Dist_Ag Term * Post_Dummy	4.05	5.26
	Number of observations	11,991	
	Adjusted R^2	0.255	
Panel ii: OLS on matched sample with treated parcels 5 miles or less to grain elevators	Dist_Grain	5.36	20.93
	Dist_Grain * Post_Dummy	-57.50**	29.47
	Number of observations	8123	
	Adjusted R^2	0.262	
Panel iii: OLS on matched sample with treated parcels 15 miles or less to agricultural output terminals	Dist_Ag Terminal	-48.48***	20.09
	Dist_Ag Term * Post_Dummy	18.12**	7.86
	Number of observations	4864	
	Adjusted R^2	0.289	

Table 4. Robustness Checks on the Spatial Gradient in the Effects of Proximity to Nearest Ethanol Plants

		Coef.	Std. Err.
Panel i: Only use parcels within 40 miles from an ethanol plant	Dist_Ag Market	32.30	22.34
	Dist_Ag Mkt * Post_Dummy	-37.98***	14.15
	Number of observations	10524	
	Adjusted R^2	0.254	
Panel ii: Only use parcels within 30 miles from an ethanol plant	Dist_Ag Market	9.86	32.21
	Dist_Ag Mkt * Post_Dummy	-54.38**	24.14
	Number of observations	8264	
	Adjusted R^2	0.242	
Panel iii: Only use parcels within 20 miles from an ethanol plant	Dist_Ag Market	-41.69	62.84
	Dist_Ag Mkt * Post_Dummy	-129.36***	46.46
	Number of observations	4844	
	Adjusted R^2	0.252	

Table 5. Robust Checks on IV Regressions using Alternative Definitions of Instruments

		Coef.	Std. Err.
Panel i: IV Regression without covariates	Dist_Ag Market	10.22	14.86
	Dist_Ag Mkt * Post_Dummy	-23.02**	9.42
	Number of observations	11991	
	Adjusted R^2	0.098	
Panel ii: Exclude 2 nearest ethanol plants and agricultural terminals	Dist_Ag Market	17.96	13.55
	Dist_Ag Mkt * Post_Dummy	-15.57*	8.15
	Number of observations	11991	
	Adjusted R^2	0.252	
Panel iii: Exclude 3 nearest ethanol plants and agricultural terminals	Dist_Ag Market	15.15	13.62
	Dist_Ag Mkt * Post_Dummy	-15.53*	8.40
	Number of observations	11991	
	Adjusted R^2	0.252	
Panel iv: Just include agricultural terminals	Dist_Ag Market	23.87	18.13
	Dist_Ag Mkt * Post_Dummy	-36.50**	15.01
	Number of observations	11991	
	Adjusted R^2	0.253	
	Dist_Ag Market	7.19	16.56

Panel v: location falsification test: use seven other random candidate towns	Dist_Ag Mkt * Post_Dummy	-0.38	19.76
	Number of observations	12084	
	Adjusted R^2	0.252	
Panel vi: parcels near non-POET ethanol plants only	Dist_Ag Market	-12.02	41.59
	Dist_Ag Mkt * Post_Dummy	-30.61**	15.18
	Number of observations	11991	
	Adjusted R^2	0.247	

Table 6. Robustness Checks on IV Regressions using Different Timing and Time-falsification Test

		Coef.	Std. Err.
Panel i: Change timing 6 months earlier	Dist_Ag Market	22.86	16.57
	Dist_Ag Mkt * Post_Dummy	-12.08*	6.49
	Number of observations	11991	
	Adjusted R^2	0.254	
Panel ii: Change timing 1 year earlier	Dist_Ag Market	16.92	16.62
	Dist_Ag Mkt * Post_Dummy	0.48	6.73
	Number of observations	11991	
	Adjusted R^2	0.254	
Panel iii: Change timing from plant construction to plant opening	Dist_Ag Market	4.80	6.76
	Dist_Ag Mkt * Post_Dummy	-15.34**	6.58
	Number of observations	11991	
	Adjusted R^2	0.255	
Panel iv: timing falsification test: assume construction timing is fall 2004	Dist_Ag Market	-1.75	7.23
	Dist_Ag Mkt * Post_Dummy	4.69	5.76
	Number of observations	11991	
	Adjusted R^2	0.254	

Table 7. Robustness Checks using Alternative Specifications and Models

		Coef.	Std. Err.
Panel i: IV regression with log-linear specification	Dist_Ag Market	0.0005	0.0013
	Dist_Ag Mkt * Post_Dummy	-0.0039***	0.0010
	Number of observations	11991	
	Adjusted R^2	0.323	
Panel ii: IV regression on a propensity score matched sample	Dist_Ag Market	16.53	49.59
	Dist_Ag Mkt * Post_Dummy	-46.39**	19.57
	Number of observations	3443	
	Adjusted R^2	0.2473	
Panel iii: DID regressions treating parcels within 15 miles from ethanol plants as treatment group	Dummy_Ag Mkt Proximity	-211.68*	127.73
	Post_Dummy	-341.08	247.72
	Dummy_Ag Mkt Proximity * Post_Dummy	335.40**	159.40
	Number of observations	11991	
	Adjusted R^2	0.255	
Panel iv: DID regressions treating parcels within 15 miles from ethanol plants as	Dist_Ag Market	-250.06	193.26
	Post_Dummy	-1092.7**	550.41
	Dist_Ag Mkt * Post_Dummy	505.52**	256.16
	Number of observations	3343	

treatment group on matched sample	Adjusted R^2	0.242	
Panel v: DID-style regressions using miles to ethanol plant	Dist_Ag Market	5.45	6.87
	Post_Dummy	68.47	332.01
	Dist_Ag Mkt * Post_Dummy	-12.68**	5.98
	Number of observations	11991	
	Adjusted R^2	0.255	

Figures

Figure 1. Agricultural land sales 2001–2010 and agricultural market channels in the Corn Belt region of Ohio

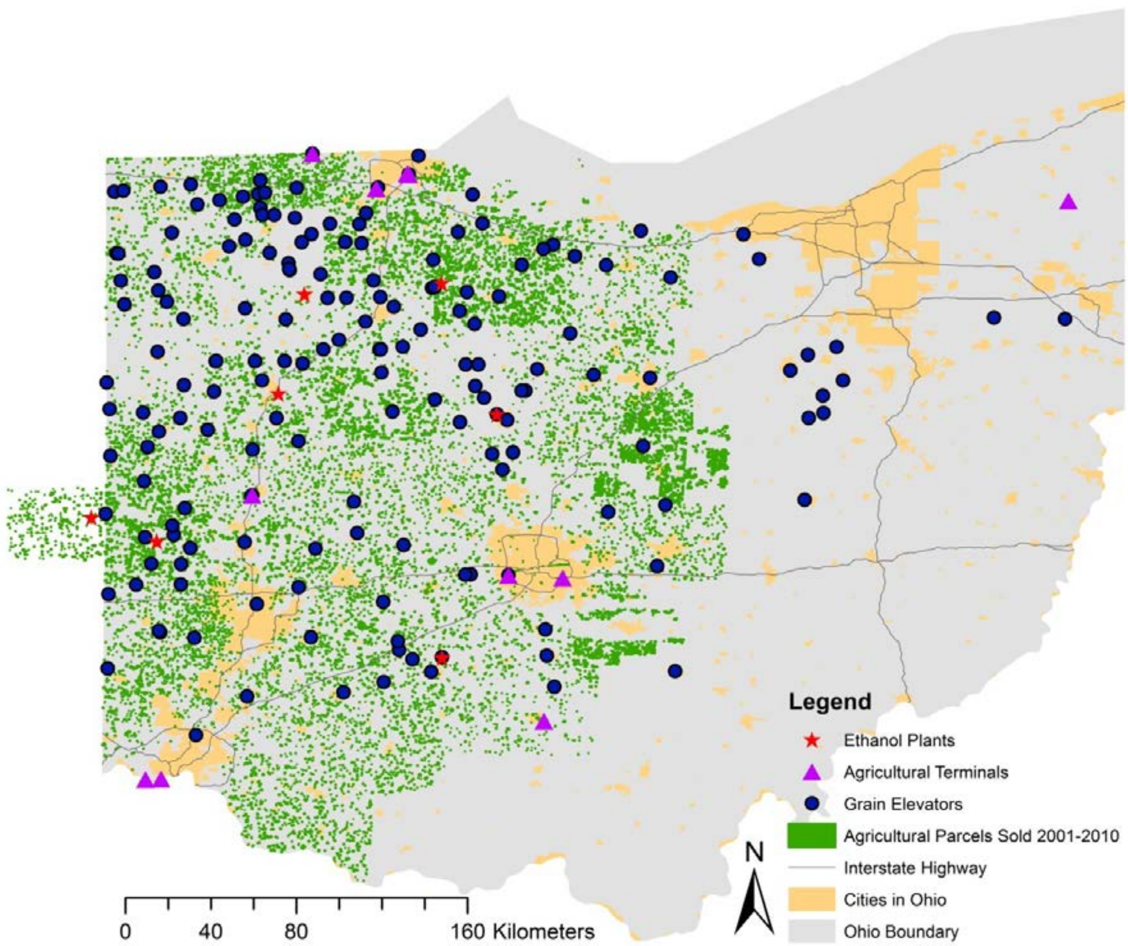


Figure 2. Actual and potential location of ethanol plants in towns with access to state highways, railways, and natural gas pipelines in areas that have at least 15% of the land within 50 miles of the town center in corn production

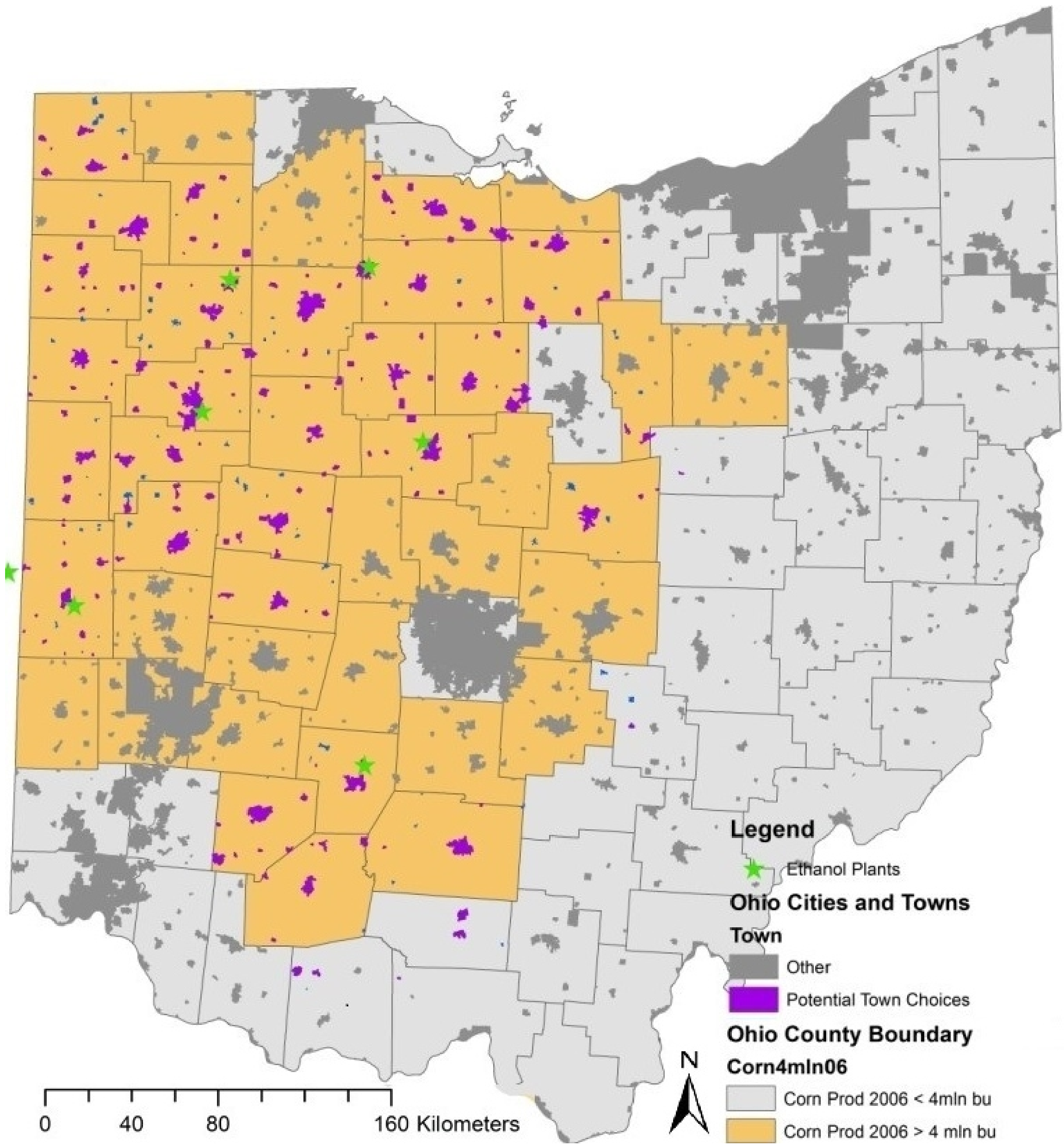
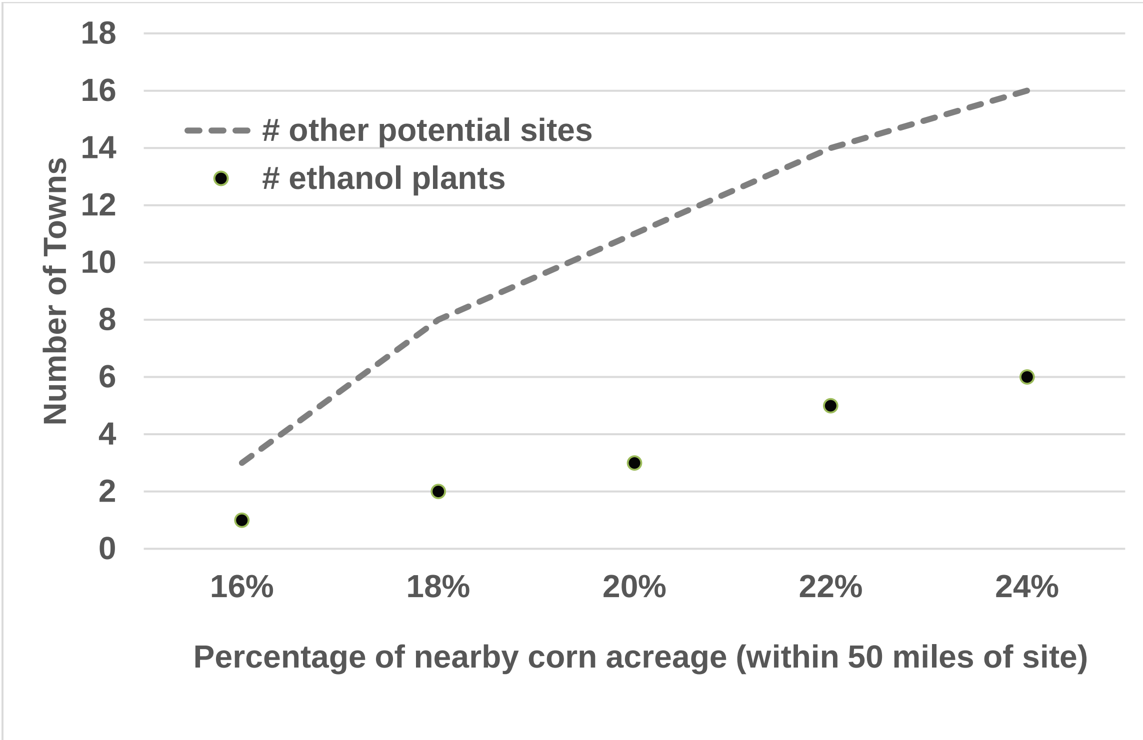


Figure 3. Total number of ethanol plants and other potential ethanol plant sites in western Ohio by the amount of nearby corn acreage (within 50 miles of site)



Note: A site is considered a potential ethanol plant site if it has access to railways, highways, and natural gas pipelines and is located in a major corn county with 4 million annual bushels of corn and at least 15% of nearby land (within 50 miles) in corn production.[8]

Figure 4. Semiparametric estimation of farmland values with respect to proximity to nearest ethanol plant

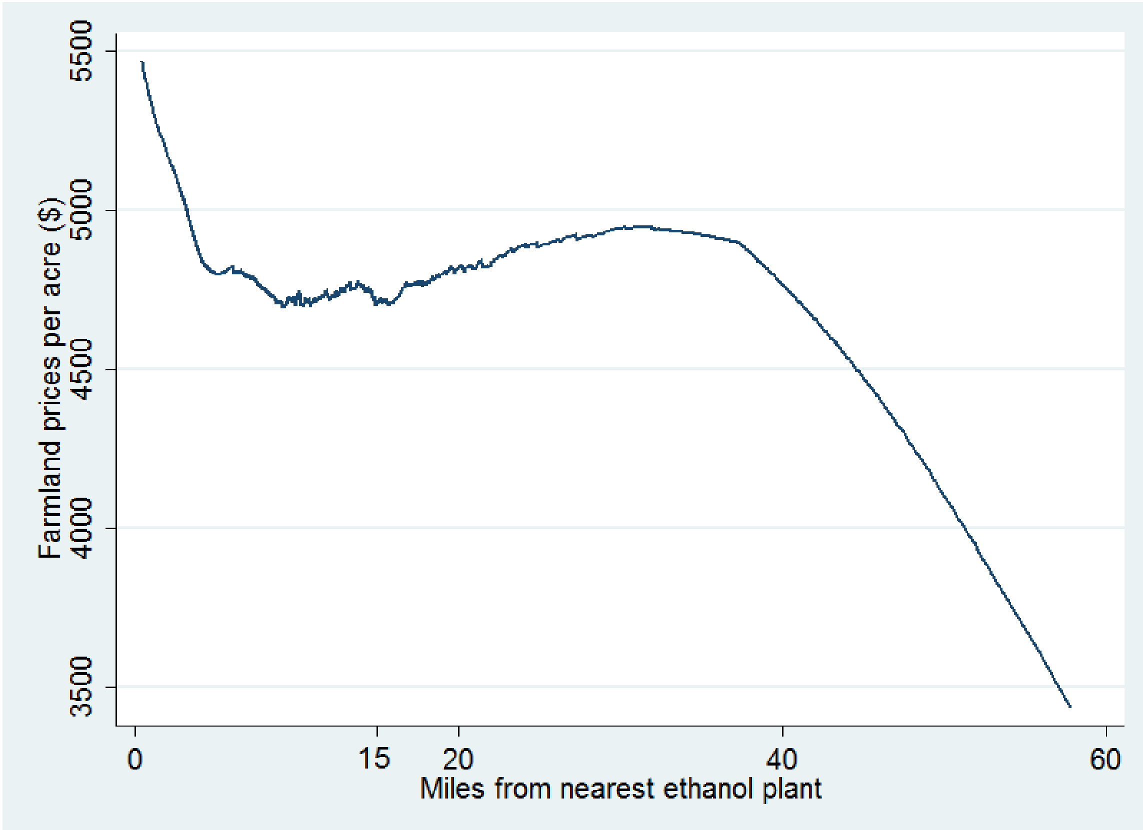


Figure 5. Number of arm's-length agricultural land sales 2001–2010 in western Ohio

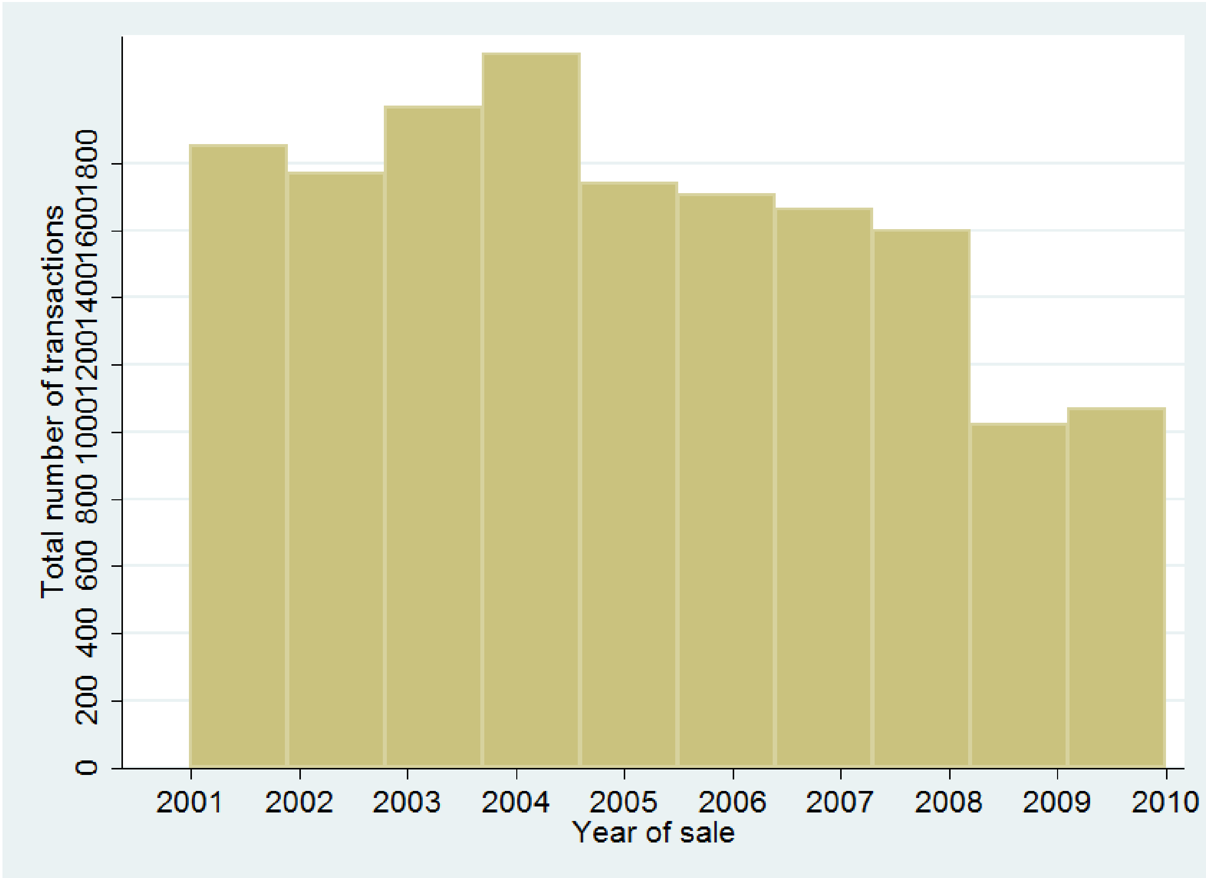
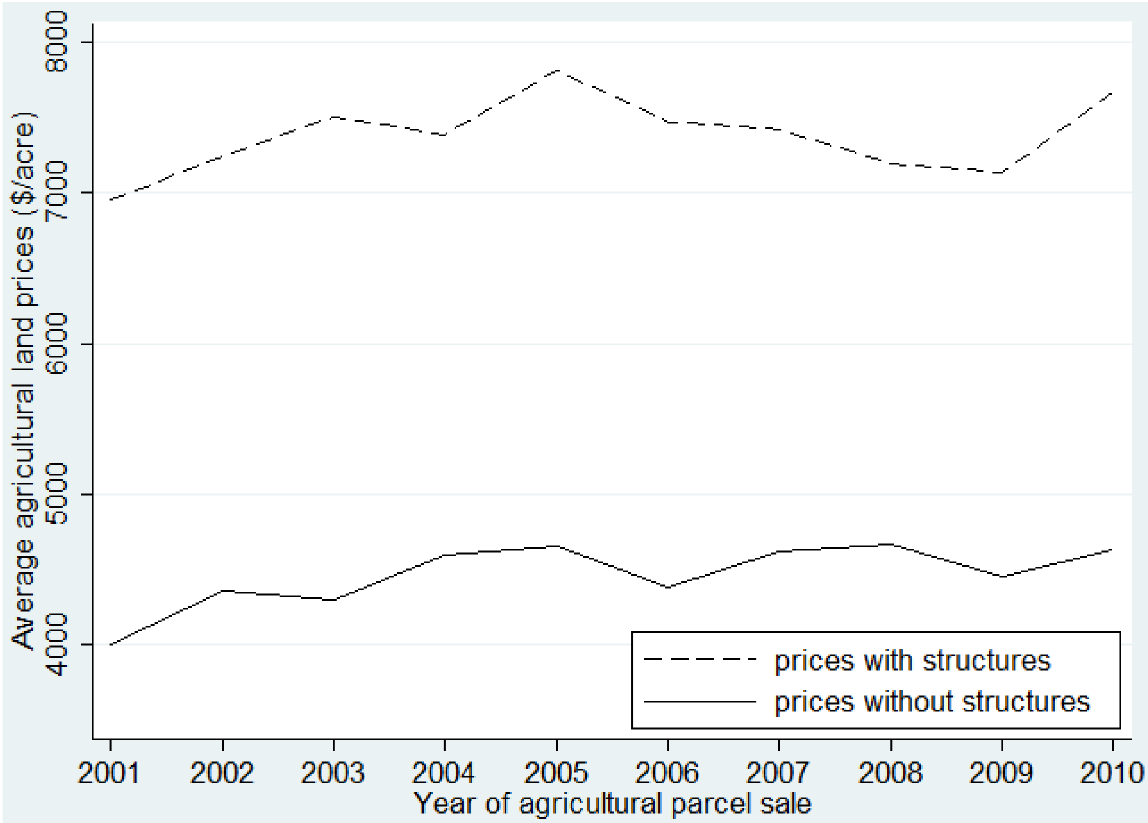


Figure 6. Distribution of arm's-length farmland prices 2001–2010 in western Ohio



Tables

Table A1. First Stage Regressions of the Instrumental Variables Estimation

	(i) Dist_Ethanol		(ii) Dist_Ethanol* Post construction dummy	
	Coef.	Std. Err.	Coef.	Std. Err.
Assessed land value % of total assessed	-0.1549	0.1992	-0.3078	0.5078
Total acres	0.0011	0.0012	0.002	0.0034
Total acres squared	8.46E-07	9.80E-07	-3.17E-06	0
NCCPI	0.0001**	0.0001	0.0002**	0.0001
Prime farmland	0.1892	0.1736	0.9595**	0.4387
Steep slope (>15 degrees)	0.1915**	0.0973	0.146	0.4698
Building area % of parcel	0.0405	0.3213	0.5067	0.6605
Forest area % of parcel	0.8926***	0.2555	0.0401	0.7424
Distance to highway ramp	0.0569**	0.0229	-0.0077	0.0468
Distance to nearest city	-0.0829***	0.0133	-0.0276	0.0266
Incremental distance to second nearest city	0.0903***	0.0103	0.0397	0.0249
Surrounding population within 25 miles	0.0098***	0.0005	-0.001	0.0017
Gravity index of three nearest cities	2.03E-07	3.93E-07	0.0013	0.0011
Distance to railways	0.0097	0.0271	0.2016***	0.0512
Distance to nearest grain elevator	0.2378***	0.0180	0.2061***	0.0489
Distance to nearest agricultural terminal	0.2174***	0.0091	0.0819***	0.022

Capacity-weighted dist to other ethanol plants	0.2329***	0.0139	-0.0752***	0.026
Capacity-weighted distance to other terminals	0.0003***	8.94E-06	0.0001***	0
Avg_Dist_Ethanol * Post construction	-3.75E-06*	2.13E-06	-2.91E-05***	0
Avg_Dist_Terminal * Post construction	0.0013	0.0043	0.3103***	0.0105
Intercept	-27.9255***	3.6389	-8.1465***	2.8081
Year FE	yes		yes	
County FE	yes		yes	
F-statistic	396.63		1158.53	
Number of observations	11991		11991	

Note: *, **, and *** indicates the coefficient is significant at 10%, 5%, and 1% levels, respectively.

Table A2. Indirect Test for Instrument Validity

Capacity-weighted distances to other agricultural terminals * post_dummy	Coef.	Std. Err.
Assessed land value % of total assessed	-0.2817	0.4633
Total acres	0.0006	0.0025
Total acres squared	9.97E-07	2.39E-06
National Commodity Crops Productivity Index	0.0002*	0.0001
Prime farmland	0.4050	0.4026
Steep slope (>15 degrees)	-0.1139	0.2270
Building area % of parcel	0.6058	0.8550
Forest area % of parcel	-0.0266	0.6090
Wetland area % of parcel	6.8533**	3.7228
Distance to highway ramp	0.0803	0.0523
Distance to nearest city	0.0139	0.0276
Incremental distance to second nearest city	0.0074	0.0206
Surrounding population within 25 miles	-0.0036***	0.0010
Gravity index of three nearest cities	-1.43E-06	2.62E-06
Distance to railways	-0.1038*	0.0608
Distance to nearest grain elevator	0.1677***	0.0393
Distance to nearest agricultural terminal	0.0086	0.0193
Intercept	49.7677***	6.9659
Year FE	yes	

County FE	yes
Adjusted R^2	0.884
Number of observations	11991

Note: *, **, and *** indicates the coefficient is significant at 10%, 5%, and 1% levels, respectively.

Table A3. Tests of Weak Identification, Over-identification of All Instruments, and Endogeneity Test of Endogenous Regressors

(i) Weak identification test	
Kleibergen-Paap rk Wald F statistic	396.69
Cragg-Donald Wald F statistic	584.50
Stock-Yogo weak ID test critical value for 10% maximal IV size	7.56
(ii) Test of overidentifying restrictions	
Hansen J statistic	2.65
p-value	0.27
(iii) Endogeneity test of endogenous regressors	
GMM distance test of endogeneity statistic	2.70
p-value	0.26

Grouped Endnotes

[1] We define abundant local corn supply as being locating in counties with at least 4 million bushels of corn produced annually and 15% of surrounding acres devoted to corn production annually.
[2] This is similar in spirit to spatial instruments that are used in urban economics literature. For example, in a spatial equilibrium model of a residential location, Bayer and Timmins (2007) use the attributes of other locations as instruments for the share of individuals who choose a given location, based on the idea that the attributes of these other locations do not directly influence the demand for that location, but that they are related via the spatial price equilibrium.
[3] Alternative distance cutoffs were used as robustness checks and yielded qualitatively similar results.
[4] These counties include Seneca, Hardin, Allen, Lucas, Auglaize, Henry, and Hamilton Counties in Ohio, as well as Randolph County in Indiana, which is also included in the analysis since Randolph County shares a border with Darke County, Ohio.
[5] In practice, some counties do not have an arm's-length sale indicator. In that case, we delete those transactions with identical seller last name and buyer last name.
[6] Please see Zhang (2015) for more details.
[7] It is very similar to the OLS specification except with the addition of the post-construction timing dummy on the right hand side.
[8] The maximum percentage of corn acres as of all land 50 miles from town center for actual and potential sites for ethanol plants is less than 25 percent, while the maximum percentage for corn and soybean acreage combined (considering crop rotation) and all crops is 58 percent and 77 percent, respectively.