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

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Job Market Paper

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Abstract

Farmland values in the Corn Belt states have been on the rise throughout the 2000s, which is in part fueled by the expansion of the biofuels market. Using parcel-level data on agricultural land sales from 2001 to 2010 for a 50-county region of western Ohio and a quasi-experimental design, this paper tests for structural change in the relative effects of proximity to agricultural market channels before and after the construction of seven ethanol plants in or near western Ohio in late 2006 and early 2007. I address the endogeneity problem associated with proximity to the nearest ethanol plants using propensity score matching and instruments relying on the spatial competition among ethanol plants and other agricultural markets. Instrumental variables regression on the matched sample demonstrates the positive effects of proximity to newly constructed ethanol plants. In contrast, the effect of proximity to agricultural terminals is significantly less after 2007 due to competition from newly constructed ethanol plants.

Keywords: propensity score matching (PSM); instrumental variables; ethanol plants

1. Introduction

Farmland values represent over 80 percent of the value of the farm sector assets, and farmland represents the largest asset in the typical farm household investment portfolio (Nickerson et al. 2012). As a result, U.S. farmland values and the factors influencing these values have long been of the subject of a great deal of economic research (Nickerson et al. 2012). With the strong federal support represented by the Energy Policy Act of 2005 and the Energy Independence and Security Act of 2007, the number of ethanol plants saw a four-fold increase along with a dramatic increase in U.S. ethanol production, making U.S. the largest ethanol producer in the world. These macroeconomic trends in the ethanol market are speculated to have elevated agricultural commodity prices, farmers' expectations about future profits, and farmland values (Low and Isserman 2009; Wallander et al. 2011). The growing biofuels market, along with other factors such as historically low interest rates (Schnitkey and Sherrick 2010) and rising demand for U.S. grain exports (Gloy et al. 2011), helped fuel the recent remarkable rise in farmland values in Corn Belt states. The steady increase in rural farmland values in the Corn Belt states indicates that these macroeconomic shifts in agricultural markets seem significant enough to offset the downward pressure resulting from the recent residential housing market bust (Zhang and Nickerson 2014). Understanding how farmland values respond to these agricultural market changes, and in particular to expanding ethanol production, is of critical policy interest given the importance of farmland values for the farm sector and farm household wellbeing.

Numerous studies have analyzed the farm and non-farm determinants of farmland values, including soil quality measures (e.g., Huang et al. 2006; Palmquist and Danielson 1989), urban proximity (e.g., Livanis et al. 2006; Shi et al. 1997; Guiling et al. 2009), environmental amenities (e.g., Bastian et al. 2002; Henderson and Moore 2006), wildlife recreational opportunities (e.g., Henderson and Moore 2006), zoning (e.g., Chicoine 1981), and farmland protection easements (e.g., Nickerson and Lynch 2001). In contrast, evidence of the potential impact of access to agricultural market channels, such as proximity to ethanol plants or grain elevators, is limited. Despite some recent research on the impacts of the ethanol industry on crop prices (McNew and Griffth 2005; Gallagher 2006), most previous studies of farmland markets have not considered the influence of agricultural market variables such as proximity to ethanol plants. Of the several studies (Henderson and Gloy 2009; Blomendahl et al. 2011; Nehring et al. 2006) that have considered the capitalization effect of proximity to ethanol plants on farmland values, all employ the standard hedonic price model, which, despite its popularity, suffers from a number of limitations in terms of identification (Bajari et al. 2012). In particular, the location of an ethanol plant is a non-random process affected by surrounding locational features such as the availability of feedstock nearby and the access to road networks (Lambert et al. 2008). As a result, the estimates from a simple hedonic model may suffer from sample selection bias due to observables since there is no control for systematic differences between those parcels that are located nearer versus farther away from an ethanol plant (Imbens and Wooldridge 2009), and the proximity to nearest ethanol plant may be endogenous as well.

The study closest in spirit to this paper is Towe and Tra (2013), who used a difference-in-difference propensity score matching estimator to quantify the effect of the 2005 ethanol mandate into farmland values. They find that new ethanol facilities had no effect on nearby farmland values prior to the mandate (2002-2004) but had significant effects after the policy

(2004-2006). However, there are a number of important differences that distinguishes my work. First, Towe and Tra (2013) aims to examine average effect of the 2005 federal ethanol mandate with a focus on its creation of exuberant confidence in the expected farmland returns beyond market fundamentals, while this paper seeks to quantity the spatial-explicit capitalization of new ethanol plants in surrounding farmland values due to reduced . Second, Towe and Tra (2013) used farmer-reported survey data on land values while I use actual arms-length sales records of farmland parcels. Finally, the longer span from 2001 to 2010 in my dataset, as opposed to 2002-2006 in Towe and Tra (2013), allows me to empirically investigate the role of ethanol sector during the recessionary time due to the recent housing market bust.

The objective of this paper is to identify the marginal value of proximity to ethanol plants and other agricultural market channels and to test for structural change in these effects before and after the ethanol market expansion in Ohio in late 2006-early 2007. I hypothesize that changes in agricultural output markets, including increased demand for biofuels and grain exports, were capitalized into agricultural land values and thus a greater influence of proximity to ethanol plants after their operations is expected. This paper uses parcel-level data on agricultural land sales from 2001 to 2010, a period which encompasses the expansion of ethanol facilities in Ohio, for a 50-county region of Ohio that encompasses the great majority of grain production in Ohio.

I address the aforementioned sample selection bias and potential endogeneity of proximity to ethanol plants using matching and instrumental variables (IV). Specifically, for each of the three types of agricultural market channels, I use propensity score matching (PSM) to construct a matched sample that controls for systematic differences in observable parcel characteristics between parcels that are within close proximity to these destinations and those located farther away. To control for the potential endogeneity of the location of ethanol plants, I construct two instruments that are based on the idea of spatial competition among agricultural market channels. 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, I construct two instruments: capacity weighted average distances to other ethanol plants and capacity-weighted distances to agricultural output terminals. These instruments, which capture the competitive pressure faced by a particular ethanol plant, would affect the site selection of this plant and thus the distances from it to farmland parcels, but would not directly impact the value of farmland parcels closer to this plant since effects of proximity to ethanol plants are relatively local (Gallagher 2006). The instrumental variables regression on the matched sample for ethanol plants is used to test for the effects of proximity to newly constructed ethanol plants, which is subject to less bias than the standard hedonic estimates by controlling for sample selection bias and endogeneity (Imbens and Wooldridge 2009). For grain elevators and agricultural output terminals, standard hedonic regressions on the matched sample are used to test for the relative effect of proximity to these destinations has changed due to the constructions of ethanol plants.

The main result provides evidence for positive and significant marginal value of being within close proximity to an ethanol plant following construction of seven ethanol plants in or near western Ohio in late 2006-early 2007. Specifically, results from the instrumental variables estimation with the matched sample suggest that the marginal value of farmland increases by $46 per mile per acre within proximity to the nearest ethanol plant following construction of these plants. By comparison, the effect of proximity to nearest city center and second nearest city is $30-66 and $30-40 per mile per acre, respectively. Results also reveal a stronger influence of proximity to grain elevators as well as a reduction in the magnitude and significance of the effect of proximity to agricultural terminals after early 2007 due to competition from the newly constructed ethanol plants. Specifically, I find that the marginal value of being close to an agricultural terminal reduces from $48 to $30 per mile per acre after early 2007. These results demonstrate the growing importance of the biofuels market for farmland values. A comparison between the standard hedonic estimates and the instrumental variables estimates confirms the endogeneity of proximity to ethanol plants, which, if left uncontrolled for, would result in a downward bias in the standard hedonic estimates due to unobserved characteristics.

This study makes an important contribution to the literature on farmland valuation and the policy debate about the welfare effects of ethanol market expansion. While the ethanol market expansion results in elevated commodity prices, farmer income, and farmland values as shown in this paper, it has been criticized for its high dependency on government subsidies and potential negative impacts on environmental quality through its incentives for corn expansion (e.g., Tiffany 2009; Cappiello and Apuzzo 2013). To the best of my knowledge, this study is the first to provide formal evidence of the effects of ethanol market expansion on farmland values during a strong recessionary time that exerted substantial downward pressure – the common wisdom that the rise of ethanol industry has helped the farm sector withstand the downturn (Nickerson et al., 2012). Second, by combining matching and instrumental variables approaches, this paper directly addresses the potential endogeneity of the proximity of farmland to ethanol plants and is thus subject to less bias than the commonly used hedonic estimates, which typically yields a much lower capitalization effect (e.g., Henderson and Gloy 2009; Blomendahl et al. 2011).

This paper is organized as follows. After a brief description of a theoretical model of agricultural land values, this paper assesses the sample selection bias inherent in standard hedonic price model and presents the quasi-experimental method as one tentative solution. Section 4 introduces the data, section 5 contains a discussion of the results and section 6 concludes.

2. Theoretical framework

Among the most influential theories that help explain the value of land is Ricardo's economic theory of rent (Ricardo 1817). Ricardo's key insight was that land which differs in quality and which is limited in supply generates rents that arise from the productive differences in land quality or in differences in location. Farmland value is comprised of the net present value of economic returns to land. The capitalization formula is written as

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

In this formulation, the value of agricultural land parcel i at time t V_{it} is defined as the expected future annual returns to farmland R discounted at rate t. Any factor affecting the farmland returns R, either in terms of agricultural productivity, recreational opportunities or potential profitability of development for urban uses, would impact the farmland values. Formally, the farmland returns R_{it}

can be approximated by a linear combination of parcel attributes and location characteristics $\boldsymbol{X_{it}}$ using Taylor expansion (Guiling et al., 2009); a common linear specification is defined as

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

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 decomposed into four categories: (1) the parcel-specific agronomic variables $\boldsymbol{A_{it}}$ such as soil quality and slope of the parcel; (2) the natural amenities variables $\boldsymbol{N_{it}}$ such as varied topography and proximity to surface water; (3) urban influence variables $\boldsymbol{U_{it}}$ such as surrounding urban population and access to highway; and (4) newly emerging set of agricultural market influence variables $\boldsymbol{M_{it}}$ such as proximity to ethanol plants, grain elevators, and agricultural product terminal ports, so that

$$\boldsymbol{X_{it}} = \boldsymbol{A_{it}} + \boldsymbol{N_{it}} + \boldsymbol{U_{it}} + \boldsymbol{M_{it}} \quad (3)$$

Therefore I get the following model specification:

$$V_{it} = E_t \sum_s f(\boldsymbol{A_{is}}, \boldsymbol{N_{is}}, \boldsymbol{U_{is}}, \boldsymbol{M_{is}};\ \delta_t)\ , where\ s = t, t+1, \ldots \quad (4)$$

The study region - Western Ohio - is fairly homogenous in soil type, slope of the land, climatic conditions and surrounding land uses. As a result little variation in generating recreational income is expected among all the parcels. Hence the urban influence variables $\boldsymbol{U_{it}}$ and the agricultural market influence variables $\boldsymbol{M_{it}}$ are of particular interest. Agricultural land closer to urban fringe could sell for a premium, an option value that equals to the expected returns from the conversion into urban development at a future date (Capozza and Helsley 1989). The recent Great Recession may greatly diminish the urban option conversion value of the agricultural land, and as a result, a declining relative significance of the urban influence variables $\boldsymbol{U_{it}}$ in determining the farmland values is expected.

At the same time, much has changed in terms of agricultural market influence variables. Most notably, ethanol has been embraced enthusiastically as a promising alternative renewable energy (Low and Isserman 2009). Federal energy policies supporting the production of biofuels have increased demand for corn, which elevated corn and other agricultural commodity prices (Nickerson et al. 2012). Previous studies have identified increased corn basis prices in the vicinity of an ethanol plant (McNew and Griffth 2005), which could translate into higher farmland values through capitalization. This increased demand, in part met by the supplies from local grain elevators, could also enhance the positive impact of the proximity to the grain elevators on farmland values. By attracting corn supplies from surrounding land parcels or nearby grain elevators, the new ethanol plants constitute a competing source of demand for grains for traditional terminal markets (Nickerson et al., 2012). However, whether the competition from ethanol plants is strong enough to o set the benefits of increased grain exports to China for the agricultural terminal markets, is an empirical question.

3. Econometric challenges and empirical strategy

3.1 The identification problem in the hedonic price estimation

With Rosen's (1974) seminal work as a backdrop, the hedonic price method has become the workhorse model for valuing local public goods and environmental amenities (Bishop and Timmins, 2011). Specifically, hedonic regression is the most commonly used approach for estimating the impact of environmental amenities and disamenities on real estate or land values (see Hite et al. (2001); Kohlhase (1991); Palmquist (1989) for applications and Palmquist (2005) for a comprehensive review). Almost all of aforementioned literature on agricultural land values has employed the land value hedonics model. A common specification is the linear form defined as

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

where the agricultural land values V_{it} are approximated by the nominal sale prices of the agri-cultural 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 (Rosen, 1974; Nehring et al., 2006).

Despite its popularity, the hedonic pricing method suffers from a number of well-known econometric problems (De Vor and de Groot, 2009; Bajari et al., 2012). In particular, the location of an ethanol plant is a non-random process affected by the availability of feedstock nearby, the access to navigable rivers, highways, or railroads, the access to sewer service and natural gas pipeline, and the extent of the product markets (Lambert et al., 2008), which could lead to a upward bias for the hedonic estimates. Arguably, agricultural parcels closer to the ethanol plants could have better soil quality and easier access to the transportation network than that of those parcels further away. On the other hand, areas with low corn basis levels or low competitive pressure may also be chosen as sites for ethanol plants to minimize the land purchase costs (Towe and Tra 2013) or to minimize spatial competition with other agricultural markets, which would lead to a downward bias in the hedonic estimates. As a result, the estimates from a simple hedonic model have two interrelated econometric problems: first, with no control for systematic differences between those parcels that are located nearer versus farther away from an ethanol plant may be biased due to the unequal distribution of the covariates across the treatment and control subsamples (Imbens and Wooldridge 2009). Second, due to the non-random site-selection process of ethanol plants, the distance from farmland parcels to nearest ethanol plant may also be endogeneous.

3.2 Quasi-experimental design

I address the potential sample selection bias and endogeneity of distance to ethanol plant by employing a two-tiered quasi-experimental design which combines matching and instrumental variables (IV) approaches. Specifically. I use matching to address the sample selection on observables, and then use two instruments based on the idea of spatial competition to address the residual endogeneity of the proximity to ethanol plants, recognizing the potential limitations of matching in dealing with bias resulting from unobservables.

Matching is an increasingly popular procedure to control for sample selection bias due to observables (Zhao 2004; Imbens and Wooldridge 2009), which selects treated observations and control observations with similar characteristics, by covariates Rubin (1980), or by propensity score (Rosenbaum and Rubin 1983). Zhao (2004) finds that propensity score matching (PSM) has smallest bias and performs well for a relatively large sample given his specific design. With a sample size of over 10,000, this study, as a result, uses PSM as the main matching technique. For each of the three types of agricultural market channels, I use PSM to construct treatment and control subsamples based on their proximity to these agricultural markets and then use regressions on the matched sample to test for the hypothesis that the relative effect of proximity to these destinations has changed since the construction of all seven ethanol plants in late 2006-early 2007. For grain elevators and agricultural output terminals, standard hedonic regressions on the matched sample are used, which, however, would yield biased estimates for ethanol plants due to their non-random site-selection problem. To address the residual endogeneity of proximity to ethanol plants, I construct two instruments that are based on the idea of spatial competition among agricultural market channels and estimate instrumental variables regressions on the matched sample instead.

3.3 Propensity score matching

The propensity score matching (PSM) estimator, as a way to identify average treatment effect, has gained popularity in land use and agricultural economics literature in recent years (e.g., Bento et al. 2007; Lynch et al. 2007). This study's application involves a two-step matching strategy. First, it trims the pre-construction sample to remove extremely dissimilar parcels with those sold after the month of construction of the nearest ethanol plant using one to four (oversampling) nearest neighbor matching technique suggested by Caliendo and Kopeinig (2005). Specifically, the propensity score (the probability of being sold after the month of construction of the nearest ethanol plant given observed parcel attributes $\mathbf{X_{it}}$) is calculated using a logit model in which treatment is modeled as a function of parcel attributes and other location characteristics, including parcel size, soil suitability, proximity to nearest employment center, proximity to nearest highway, surrounding land uses, and neighborhood population density. I dropped parcels with propensity scores not on common support and those with propensity scores greater than 0.9 or lower than 0.05, as recommended by Crump et al. (2009). Similar sample trimming technique has been used by Busso et al. (2010).

With the trimmed sample, I then construct the treatment and control subsamples based on the proximity to a given type of market channels. Specifically, with *a priori* defined cutoff value for distance which defines proximity, parcels that are located within this cutoff distance to agricultural markets are assumed to be in the treatment group. These parcels are then matched with those parcels located farther away than the cutoff distance following the one to four nearest neighbor PSM technique illustrated above. The cutoff distances used to define proximity to ethanol plants, grain elevators, and agricultural output terminals are 10 miles, 5 miles, and 15 miles, respectively. These cutoff values are determined using semiparametric regressions and the covariate imbalance tests.[1]

The validity of the PSM approach hinges on the assumption that the model specification is correct and all relevant conditioning variables have been included in the PSM model (Diamond and Sekhon 2013). As a result, to ensure the main results do not depend crucially the particular matching methodology, I conduct multiple robustness checks by changing the matching algorithms (e.g., using covariate matching using Mahalanobis metric (Rubin, 1980)), altering the parameters of PSM (use one or two nearest neighbors instead of four), or employing longer or shorter cutoff distances used to define proximity to agricultural market channels.

3.4 Instrumental variables regressions on the matched sample

Following Imbens and Wooldridge (2009) and for each of the three matched samples, regressions on the matched samples are used to test for a structural change over time in the influence of proximity to a given type of market channel before and after construction of the ethanol plant.

[1] A series of robustness checks on the cutoff distances are presented in the results section.

Through matching, this study constructed the counterfactual control subsample for each type of agricultural market channel, which differs from the treatment subsamples only in the proximity to this type of market channel. For grain elevators and agricultural output terminals, standard hedonic regressions on the matched samples are used to test for the relative effect of proximity to these destinations has changed due to constructions of ethanol plants. In particular, I use the following specification:

$$P_{it} = \beta_0 + \beta_A{}'\boldsymbol{A_{it}} + \beta_U{}'\boldsymbol{U_{it}} + \beta_R{}'\boldsymbol{R_{it}} + \beta_M{}'\boldsymbol{M_{it}} + \beta_{M\_POST}{}'\boldsymbol{M_{it}} * D\_POST + \tau_t + \varepsilon_{it}, \quad (6)$$

where D_POST is a binary time dummy indicating that the parcel is sold after the month of construction of nearest ethanol plants. The coefficient on variables like distances to nearest grain elevator 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.

For the matched sample constructed based on proximity to ethanol plants, standard hedonic estimates could be biased due to the potential endogeneity of the location of ethanol plants. The endogeneity mainly results from the fact that the location of ethanol plants are more likely to be in areas with abundant corn supply or better soil quality, which would also affect the value of these neighboring farmland parcels. However, personal communications with managers of all seven ethanol plants in or near western Ohio reveal that abundant corn supply is only one factor in the site-selection process; other equally important factors include the access to highway and railway, and access to sewer service and natural gas pipeline. An ideal location of an ethanol plant would require that all these factors are satisfied, which rules out remotely rural area without sewer system and leaves use towns and villages as candidate sites. Figure A1 in the appendix plots the percentage of corn acreage within 50 miles for all towns with access to both railways and natural gas pipelines. It reveals that after controlling for these factors and beyond a threshold on county-level corn production, there is no systematic correlation between corn supply and the location of ethanol plants, which suggests that the endogeneity problem of the proximity to ethanol plants may not be serious.

Nonetheless, this anecdote evidence does not clear the endogeneity concern. To control for the potential endogeneity of the proximity to the nearest ethanol plant, I construct two instruments based on the idea of spatial competition among agricultural market channels. Due to existence of transportation costs, a standard result from the 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 (e.g., 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, I construct two instruments: capacity weighted average distances to other ethanol plants and capacity-weighted distances to agricultural output terminals. A negative correlation between these two instruments and the endogenous distance variable is expected due to the spatial competition. Similar instruments are used in the urban economics literature: for example, in a location sorting model, Bayer and Timmins (2007) used the fixed attributes of other locations as instruments for the share of individuals who choose a particular location as the exogenous attributes of other locations influence the demand for the specific location via the sorting equilibrium. These instruments, which capture the competitive pressure faced by a particular ethanol plant, would affect the site selection of this plant and thus the distances from it to farmland parcels, but would not directly impact the value of farmland parcels closer to this plant since effects of proximity to ethanol plants are relatively local (Gallagher 2006). In other words, an instrumental variables regression on the matched sample rather than a standard hedonic regression is estimated to test for the effects of proximity to newly constructed ethanol plants. Specifically, we employ a two stage least squares approach and estimate the following equations:

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

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

$$P_{it} = \beta_0 + \beta_A{}'\boldsymbol{A_{it}} + \beta_U{}'\boldsymbol{U_{it}} + \beta_R{}'\boldsymbol{R_{it}} + \beta_M{}'\widehat{\boldsymbol{M_{it}}} + \beta_{M\_POST}{}'\widehat{\boldsymbol{M_{it}} * D\_POST} + \tau_t + \varepsilon_{it}, \qquad \text{(7c)}$$

where $\boldsymbol{Z_{it}}$ are these two instruments and the excluded exogenous variables, and $\widehat{\boldsymbol{M_{it}}}$, $\widehat{\boldsymbol{M_{it}} * D\_POST}$ are the predicted values from the first-stage regressions.

Unlike the grain elevators and agricultural terminals which existed throughout the 2000s decade, the ethanol plants in or near western Ohio all started construction in late 2006 – early 2007. As a result, the coefficient on the distance to ethanol plants variable β_M has no intuitive interpretation, while β_{M_POST} captures the significance and magnitude of the spatial effects of proximity to ethanol plants following construction of these plants. To address the potential capitalization effects of proximity to an ethanol facility before its construction due to expectations, I run multiple robustness checks which include parcels sold six months or one year before the construction of their nearest ethanol plant in the post period. By controlling for sample selection bias and potential endogeneity of ethanol plant locations, our estimator is subject to less bias than the standard hedonic estimates (Imbens and Wooldridge 2009).

4. 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. The biofuels industry in Ohio is gaining momentum over the last decade, with seven ethanol plants started construction in or near western Ohio in late 2006 – early 2007. I assembled a detailed database of 21,342 arms-length agricultural land sale records for 50 western Ohioan counties 4 from 2001 to 2010 obtained from the U.S. Dept. of Agricultural Economic Research Service (USDA ERS) data and merged with purchased sales data from a private firm, CoreLogic. I now briefly describe the key elements of the data in additional detail.

To form the dataset of agricultural land transactions, this study combines the dataset (29 counties) purchased from CoreLogic, with the data from USDA ERS data (14 counties) and the data collected from county auditor office for counties like Seneca, Hardin, Allen, Lucas, Auglaize, Henry and Hamilton in Ohio and Randolph County in Indiana[2]. Only those agricultural parcels sold between 2001 and 2010 and with a valid arms-length indicator[3] are kept. Those valid agricultural

2 The ethanol plant located at Randolph County, Indiana is also included in the analysis since Randolph County shares border with Darke County, Ohio.

3 In practice, some county does not have a arms-length sale indicator. In that case, we delete those transactions with identical seller last name and buyer last name.

sale records are merged with GIS parcel boundaries or are geocoded based on property addresses using Google Maps API. The sales prices are adjusted for the value of the structures on the farmland. Specifically, the new sales prices are calculated as a fraction of the original prices, with the ratio being 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 along with parcels sold in the year 2007. Figure 1 shows a plot of the filtered sample consisting of 13,865 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 in Figure 1.

Data on parcel attributes and location characteristics were obtained largely from the U.S. Dept. of Agriculture Natural Resources Conservation Services GeoSpatial Data Gateway (GeoSpatial Data Gateway 2012), including the Census TIGER/Line Streets, National Elevation Dataset, National Land Cover Dataset, Soil Survey Spatial Data (SSURGO). Additional data on locations of cities and towns in Ohio was obtained from the Ohio Dept. of Transportation (2012). I 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), the Farm Net Services (2012) and the Ohio Licensed Grain Handlers List (2012). Using these data and ArcGIS software, I was able to create the parcel attributes and location characteristics vector $\boldsymbol{X}_{it}$. See Table 1 for summary statistics.

Most of variables in Table 1 are self-explanatory; however, three remarks need to be made. First, the variable National Commodity Crops Productivity Index is an interpretation in the National Soil Information System (NASIS). 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). Secondly, 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". Finally, this study highlights the set of the urban influence variables $\boldsymbol{U_{it}}$ and the agricultural market influence variables $\boldsymbol{M_{it}}$ in particular. Three aspects of urban influences are considered: distance to nearest city captures the importance of urbanized areas as commuting hub or sources of non-farm income, proximity to urbanized areas and road network and surrounding urban population represent the option value of future land conversion to urban uses. Surrounding urban population also captures the consumer demand for agricultural products, which will drive up the agricultural returns. Proximity variable is generated for each of the three agricultural market channels.

5. Results and discussion

The recent Great Recession have led to a dramatic decline in urban land and housing values across the U.S. The same is not true, however, of agricultural land values. Figure 2 plots the number of agricultural land sales and the average farmland values in western Ohio since 2001. 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 2 suggests that the average farmland sale prices stayed fairly constant at around $5000/acre over the 2000s decade, which was in part due to the growing significance of agricultural markets, exemplified by the surging biofuels market (Wallander et al. 2011) and rising demand for U.S. grain exports (Gloy et al., 2011). I hypothesize that changes in agricultural output markets, including increased demand for biofuels and grain exports were capitalized into agricultural land values and that these effects offset the decline in the urban value of agricultural land parcels. Therefore on average, agricultural land prices remained stable. To further explore these issues especially the change in the effect of proximity to ethanol plants, I first estimate two hedonic models as the benchmark model shown in Table 2. Specifically, model (I) uses all observations without matching while model (II) uses the matched sample based on proximity to ethanol plants but does not control for the potential endogeneity of plant location using instrumental variables. Despite the correct sign on the variable *Dist_Ethanol * Post construction dummy*, both models did not find evidence for significant capitalization effects of proximity to ethanol plants after their construction. In other words, the hedonic estimates show that proximity to ethanol plants became a positive influence after construction of these plants; however, this positive capitalization effect is not statistically significant. Most of the estimates of other variables were intuitive: bad soil quality of presence of steep slope decreased farmland values, while proximity to urban areas or highway ramps led to an increase. The significant coefficient on acres squared implied a nonlinear relationship between the per-acre farmland values and total acreage. Model (II) uses the matched sample which controls for the differences in observable characteristics between parcels closer to ethanol plants and those farther away, and this leads to the insignificance of some variables such as proximity to cities and agricultural terminals. These results are preliminary since they did not control for the potential endogeneity of the location of ethanol plants. Nonetheless, the results are suggestive and provide ample motivation to further investigate potential structural change in these effects using instrumental variables estimation with matched samples.

Table 3 shows the comparison of the difference-in-means of the covariates between treatment and control groups for the raw sample before matching and the matched sample after PSM. The naive control group for the raw sample was constructed as if they were matched using the same cutoff values in timing or distance. To make the second step matching work, the 50 county fixed effects were replaced by six crop reporting district dummies because of too few observations within each county. The distance cutoffs used to construct matched samples based on proximity to agricultural market channels in panel I are 10 miles, 5 miles, and 15 miles for ethanol plants, grain elevators, and agricultural terminals, respectively. Table 3 clearly revealed that without matching, there were systematic distributional differences between the naive control group and the treatment group, which, as a result, led to biased estimates in the standard hedonic approach. In contrast, at the cost of reduced sample size, these differences were successfully removed through PSM, which assures that conditioning on estimated propensity score, there is no remaining distributional differences left for the covariates between the treatment and control groups (Lynch et al. 2007). In a word, tables 3 neatly illustrated the necessity and advantages of propensity score matching in addressing the sample selection bias inherent in the standard hedonic method. Figure A2 shows that the estimated propensity score for the treatment and control groups overlap with each other.

Table 4 presents the main results of regressions on matched samples for each of the three types of agricultural market channels. In particular, instrumental variables regression is used to estimate the effects of proximity to ethanol plants. The main result provides evidence for positive and significant marginal value of being within close proximity to an ethanol plant following construction of seven ethanol plants in or near western Ohio in late 2006-early 2007. Specifically, results from the instrumental variables estimation with the matched sample suggest that the marginal value of farmland increases by $46 per mile per acre within proximity to the nearest ethanol plant following construction of these plants. By comparison, the effect of proximity to nearest city center and second nearest city is $30-66 and $30-40 per mile per acre, respectively. In contrast, there is no declining farmland price gradient over distance to ethanol plants. Since there are no ethanol plants before late 2006, this coefficient on the interaction term can be interpreted as the positive effects of proximity to newly constructed ethanol plants.

Table A1 presents results of the first stage regressions of the potentially endogenous variables. The significant coefficients on the proposed instruments based on the spatial competition idea support the relevance of the instruments, which is also confirmed by the rejection of weak identification test. The negative coefficient of the variable *capacity-weighted distance to other ethanol plants* in Table A1 column (II) confirms my conjecture of spatial competiton among ethanol plants. The test of overidentifying restrictions on other hand confirms the exogeneity of these instruments. A comparison between Table 2 and Table 4 column (a) reveals that, regardless of the significance, the standard hedonic estimates yield similar signs with the instrumental variables approach. This is because the suspected endogenous variable *distance to nearest ethanol plant* is only slightly endogenous (with a p-value of 0.096). However, this comparison between the standard hedonic estimates and the instrumental variables estimates confirms the endogeneity of proximity to ethanol plants, which, if left uncontrolled for, would result in a downward bias in the standard hedonic estimates due to unobserved characteristics.. This underestimation might result from unobserved characteristics that capture rural remoteness or other undesirable traits.

Columns (b) and (c) in Table 4 also reveal a stronger influence of proximity to grain elevators as well as a reduction in the magnitude and significance of the effect of proximity to agricultural terminals after early 2007 due to competition from the newly constructed ethanol plants. 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. This result is intuitive because local grain elevators meet part of the increased demand for corn due to construction of ethanol plants. In addition, I 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 lends support for our instrumental variables approach which relies on the spatial competition among ethanol plants and agricultural terminals.

We test the stableness of the results by employing alternative ways to construct the matched sample and alternative model specifications. Table 5 presents results using alternative matching algorithms, including propensity score matching using one or two nearest neighbors instead of four, as well as completely different matching estimators which includes covariate matching (Rubin 1980) and kernel-based matching (Heckman et al. 1998). Despite greater magnitude, the robustness checks show a similar conclusion as the main specification – a significant and positive effect of proximity to newly constructed ethanol plants after their construction. Results also confirm that finding regarding the reduced impact of proximity to agricultural output terminal due to strong competition of newly constructed ethanol plants. Table 6, on the other hand, tests the robustness of the results by altering the cutoff distances used to define the spatial proximity and the timing used to define when the effect of ethanol plants start to kick in. Results reveal that there is evidence of expectations before the construction of ethanol plants; however, the expectations argument is only relevant 6 months before the plant construction. The log-linear model specification also reveals a similar conclusion. These robustness checks indicate that our results are stable across different model specifications and matching algorithms.

Table 7 tests for 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 more than one agricultural market could affect surrounding farmland values. I test that by excluding two or three nearest ethanol plants and agricultural output terminals in the construction of instruments, which suggests that only other agricultural markets used in the instruments are farther away to affect the farmland values for parcels closer to a particular ethanol plant. Table 7 panels I and II reveal a similar results as in Table 3, suggesting that my instruments are valid and unlikely to be endogenous. Using estimates from semiparametric regressions, Figure A3 shows that the effect of proximity to ethanol plants is likely localized within 15-20 miles, further validating the validity of the instruments. Table 7 Panel III uses only parcels from counties with at least 5 million bushels of corn production in 2010 or within the Corn Belt boundary to ensure the farmland sales data used in this study could be considered as part of one single farmland market.

6. Conclusion

The first decade of the 2000's saw dramatic changes in the forces that influence farmland values. On 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. Using a dataset of parcel-level farmland sales in western Ohio from 2001 to 2010 and a quasi-experimental design, this study tests the common wisdom that the rise of ethanol industry helped the farm sector withstand this downturn (Nickerson et al. 2012). The identification strategy relies on the observed opening of seven ethanol plants in or near western Ohio and the competitive pressures they face in the spatial competition with other ethanol plants and agricultural output terminals. Two instruments are constructed based on this idea of spatial competition to control for the potentially endogeneous proximity of farmland parcels to nearest ethanol plants. Propensity score matching is also used to control for potential sample selection bias resulting from systematic differences in observable parcel characteristics between parcels closer to agricultural market channels versus those farther away.

The main results from the instrumental variables estimation with the matched sample suggest that the marginal value of farmland increases by $46 per mile per acre with close proximity to the nearest ethanol plant following construction of these plants. Despite a short-term effect with data only for the 2000s, these results demonstrate the growing importance of the biofuels market for farmland values and show that proximity to ethanol plants is becoming a more significant determinant of agricultural land values. This study suggests the need to explicitly incorporate agricultural market influence variables such as proximity to ethanol plants and other agricultural market channels in modeling the determinants of U.S. farmland values. This study confirms the endogeneity concerns of the proximity to ethanol plants and reveals systematic differences in observable characteristics between parcels closer to an agricultural market channel and those farther away, which could lead to biased estimates if left uncontrolled for as in the standard hedonic price method. The quasi-experimental design that combines matching and instrumental variables approach employed here presents a superior alternative.

Ethanol is now a critical part in the corn industry supply chain and the year of 2010 marks the first time 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 (e.g., Tiffany 2009; Cappiello and Apuzzo 2013; Rajagopal et al. 2011). In addition to many criticisms of various subsidies offered to ethanol producers, rising concerns are raised regarding the environmental quality impacts of ethanol policy through its incentives for corn expansion (Cappiello and Apuzzo 2013). This paper engages in this debate by providing a piece of evidence on the capitalization effect of proximity to ethanol plants. With many subsidies already or slated to be terminated, it poses an intriguing policy question that how these downward pressure on ethanol development would affect the welfare effects of the ethanol market expansion, and in particular its capitalization in commodity prices and farmland values.

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Tables:

	Unit	Mean	Std. Dev.	Min.	Max.
General Parcel Attributes					
Sale price	Dollars	143175	244364.8	303.7112	1.17E+07
Sale price per acre	Dollars	4362.70	3644.27	1000.161	19988.09
Assessed land value	Dollars	74190.62	162980.20	0	5878840
Assessed improvement value	Dollars	32269.28	68910.37	0	3937580
Assessed land value % of total assessed	%	0.7224	0.312	0.0035	1
Total acres	Acres	44.204	61.289	0.14	2380.66
Sale year	Year	2004.838	2.761	2001	2010
Agricultural Productivity Variables					
National Commodity Crops Productivity Index	Number	5778.153	1518.336	0	8800.8
Cropland % of parcel	%	0.5502	0.3715	0	1
Soil class 1 area % of parcel	%	0.2810	0.3235	0	1
Soil class 2 area % of parcel	%	0.0778	0.1824	0	1
Soil class 3 area % of parcel	%	0.4406	0.4175	0	1
Soil class 4 area % of parcel	%	0.2005	0.2974	0	1
Steep slope (>15 degrees)	Binary	0.1888	0.3913	0	1
Urban Influence Variables					
Building area % of parcel	%	0.0364	0.1314	0	1
Distance to urbanized area of over 25,000 people	Kilometers	19.12	12.7587	0	56.82
Total urban population within 25 miles	Thousands	290.04	231.9361	64.7721	1187.38
Distance to highway ramp	Kilometers	5.2218	3.2932	0	19.10
Distance to nearest city	Kilometers	40.9684	20.3363	0.1983	105.66
Distance to nearest railway access point	Miles	3.1390	1.8080	0.005	11.254
Gravity index using three nearest cities	Number	1072.77	34101.57	52.76	4255332
Agricultural Market Influence Variables					
Distance to nearest ethanol plant	Kilometers	45.99	22.57	0.68	111.75
Production capacity of nearest ethanol plant	Mgal	88.56	25.02	54.00	120.00
Number of ethanol plants within 25 miles	Number	1.13	0.91	0.00	4.00
Total production capacity of ethanol plants within 25 miles	Mgal	96.14	76.48	0.00	304.00
Distance to nearest grain elevator	Kilometers	13.45	11.35	0.04	88.43
Distance to nearest agricultural terminal	Kilometers	52.50	22.74	0.20	119.40
Capacity-weighted distance to other ethanol plants	Kilometers	71.64	15.92	38.76	111.23
Capacity-weighted distance to other agricultural terminals	Kilometers	101.49	45.70	7.21	204.54
Environmental Amenities Influence Variables					
Forest area % of parcel	%	0.153	0.259	0	1
Wetland area % of parcel	%	0.003	0.029	0	1
Pasture area % of parcel	%	0.120	0.241	0	1
Open water % of parcel	%	0.003	0.024	0	0.746
Observations			16434		

Table 1: Summary statistics of agricultural land sales

Nominal farmland values ($/acre)	(I) Coef.	(I) Robust SE	(II) Coef.	(II) Robust SE
Distance to nearest ethanol plant	-0.87	5.77	4.07	13.08
Dist_Ethanol * Post construction dummy	-5.86	3.93	-13.35	9.79
Assessed land value % of total assessed	-3771.54***	145.03	-3354.51***	374.90
Total acres	-26.07***	1.04	-40.15***	3.07
Total acres squared	0.013***	0.0017	0.08***	0.01
National Commodity Crops Productivity Index	0.0028	0.026	0.037	0.05
Prime farmland	-71.25	116.24	-258.21	266.94
Steep slope (>15 degrees)	-100.49*	58.51	309.05	255.31
Building area % of parcel	52.97	268.36	-550.92	394.57
Forest area % of parcel	14.17	159.23	-403.03	521.55
Wetland area % of parcel	-112.28	876.67	845.14	3332.38
Distance to highway ramp	-37.23**	15.18	-30.05	27.94
Distance to nearest city	-62.54***	8.01	-25.52	15.68
Incremental distance to second nearest city	-36.40***	5.99	-31.04**	13.68
Surrounding population within 25 miles	0.62**	0.31	-0.36	0.80
Gravity index of three nearest cities	2.87E-04*	0.0002	0.77	0.56
Distance to railways	-3.69	17.35	-0.28	32.24
Distance to nearest grain elevator	2.63	9.89	-35.76	26.54
Distance to nearest agricultural terminal	-33.15***	5.41	-4.50	11.77
Year 2001	-1145.15***	136.19		
Year 2002	-988.59***	133.54	236.87	303.92
Year 2003	-689.12***	130.90	143.22	278.30
Year 2004	-482.74***	130.22	531.23*	298.65
Year 2005			786.71***	287.15
Year 2006	-14.75	137.92	794.09***	278.99
Year 2007	330.78**	166.07	1434.18***	323.44
Year 2008	409.48***	172.46	1571.89***	314.86
Year 2009	298.46	181.54	1545.48***	322.52
Year 2010	435.43**	188.28	1926.12***	338.35
Intercept	14456.89***	848.59	15742.13***	3340.06
County FE	Yes		Yes	
Adjusted R^2	0.2616		0.2409	
Number of observations	16434		3443	

Table 2: Hedonic regressions with structural changes of proximity to ethanol plants

Note: *, **, and *** indicates the coefficient is significant at 10%, 5% and 1% level, respectively. 50 county fixed effects are included in the model.

Covariates	Matching on timing: month of ethanol plant construction		Matching on distance					
			Ethanol plant		Grain elevator		Agricultural terminal	
	Unmatched	Matched	Unmatched	Matched	Unmatched	Matched	Unmatched	Matched
Sale year			-0.7***	-0.1	2005.4	0	2005.4	0
Assessed land value % of total assessed	-0.0426***	-0.0042	-0.156***	-0.0100	0.7631	0.0066	0.7243	-0.0115
Total acres	-5.8770***	0.9380	-4.953***	-1.7080	46.8740	1.0190	50.0400	1.0580
Total acres squared	662.30***	490.9000	534.30	-406.70	4745.40	120.10	6790.00	1484.60
Agricultural Productivity Variables								
National Commodity Crops Productivity Index	-121.60***	-5.6000	369.40***	-52.50	5870.70	-47.60	5717.80	-3.70
Soil class 2 area % of parcel	0.0110*	-0.0039						
Soil class 4 area % of parcel	-0.0058	0.0043	0.0422***	-0.0417***	0.1283	0.0059	0.1702	0.0056
Steep slope (>15 degrees)	0.0483***	0.0025	0.1688***	0.0005	0.0824	-0.0019	0.1361	0.0313**
Urban Influence Variables								
Total urban population within 25 miles	20.9200***	-3.1600	97.7900***	-2.6	246.47	8.9700**	242.27	-6.69
Distance to highway ramp	-0.2573***	0.0063	0.0630	0.0440	4.9915	0.0535	6.2736	-0.1780
Distance to nearest city	-4.495***	0.0900	-13.885***	-0.3900	44.6890	-0.5520	48.2500	-0.2860
Agricultural Market Influence Variables								
Distance to nearest ethanol plant	5.9380***	-0.0160			35.8380	-0.1260	38.5880	1.2040*
Distance to nearest grain elevator	0.2630***	-0.1070	6.0960***	-0.3842*			11.2920	0.6140**
Distance to nearest agricultural terminal	-1.4780***	-0.0380	2.8640***	-1.2120*	51.9860	0.3640		
Environmental Influence Variables								
Forest area % of parcel	0.0434***	-0.0002	0.0890***	-0.0033	0.0770	-0.0009	0.0851	0.0069
Wetland area % of parcel	0.0010*	-0.0001	0.0014***	0.0001	0.0039	-0.0009	0.0023	-0.0003
Location Fixed Effects								
Northern central crop reporting district					0.0415	0.0018		0.0000
Northwest crop reporting district			0.0886***	0.0154	0.3336	0.0023	0.2781	-0.0228
Central crop reporting district			0.0615***	-0.0144	0.2158	-0.0170*	0.3851	0.0160
West central crop reporting district			-0.3096***	-0.0011	0.4017	0.0124	0.3369	0.0068
Observation	12969	9880	9880	2082	9880	8055	6702	4174

Table 3: Difference in means of the covariates between treatment and control groups for the raw sample and matched sample

Note: *, **, and *** indicates the difference in means of the covariates between treatment and control groups is significant at 10%, 5% and 1% level, respectively.

Nominal farmland values ($/acre)	(a) Ethanol Plant		(b) Grain Elevator		(c) Agricultural Terminal	
	Coef.	SE	Coef.	SE	Coef.	SE
Distance to nearest ethanol plant	16.53	49.59	5.34	7.95	-2.49	10.75
Dist_Ethanol * Post construction dummy	-46.39**	19.57				
Assessed land value % of total assessed	-3331.52***	418.53	-3654.18***	221.23	-3142.85***	259.13
Total acres	-36.80***	2.92	-35.17***	1.81	-50.44***	2.40
Total acres squared	0.06***	0.01	0.038***	0.005	0.093***	0.0159
National Commodity Crops Productivity Index	-4.76E-05	0.05	0.011	0.034	-0.0153	0.0488
Prime farmland	-358.02	289.08	-212.71	181.27	-336.86	237.51
Steep slope (>15 degrees)	276.95	333.64	-123.26	92.75	-10.12	116.38
Building area % of parcel	-345.72	408.32	-541.92	400.67	-543.18	461.43
Forest area % of parcel	-35.50	646.12	94.29	275.95	-315.08	348.59
Wetland area % of parcel	-997.00	3621.69	-265.83	879.32	1092.43	1913.35
Distance to highway ramp	-24.40	30.66	-28.75	21.53	-74.25***	26.31
Distance to nearest city	-30.86**	15.66	-28.91***	11.28	-66.17***	16.89
Incremental distance to second nearest city	-39.59***	14.34	-12.02	8.17	-33.83***	11.99
Surrounding population within 25 miles	-0.74	0.77	0.73	0.46	1.307**	0.556
Gravity index of three nearest cities	1.24*	0.67	-0.05	0.06	0.0214	0.076
Distance to railways	20.34	35.29	-15.35	23.6	-13.77	57.56
Distance to nearest grain elevator	-27.70	31.91	5.36	20.93	33.35*	18.95
Dist_Grain * Post construction dummy			-57.50**	29.47		
Distance to nearest agricultural terminal	6.52	16.19	-15.72*	8.22	-48.48***	20.09
Dist_Terminal * Post construction dummy					18.12**	7.86
Year 2001	-2107.35***	489.92	-767.52***	189.29	-82.82	395.28
Year 2002	-1805.17***	511.64	-810.34***	183.20		
Year 2003	-1835.51***	496.26	-534.37***	183.40	413.05	412.58
Year 2004	-1461.94***	500.03	-518.47***	181.60	879.18**	423.54
Year 2005	-1510.02***	482.23			1008.58**	419.48
Year 2006	-1139.51**	449.77	-44.20	192.85	1227.67***	432.29
Year 2007	-273.13	389.86	645.17***	229.03	1098.40**	540.78
Year 2008	119.12	381.20	791.35***	234.21	1388.33**	560.77
Year 2009	142.56	390.87	828.44***	251.63	1081*	621.25
Year 2010	350.86	391.22	886.47***	263.50	1366.01**	622.75
Intercept	10261.9***	1858.68	9721.26***	744.78	23762.56***	1966.72
Adjusted R^2	0.2473		0.2619		0.2885	
Number of observations	3443		8123		4864	

Table 4: Instrumental variables regressions on the matched samples

Note: *, **, and *** indicates the coefficient is significant at 10%, 5% and 1% level, respectively. 50 county fixed effects are included in the model.

		(a) Ethanol Plant		(b) Grain Elevator		(c) Agricultural Terminal	
		Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Panel I: 1 to 2 nearest neighbor matching	Dist_Ag Market	48.77	68.52	32.00	27.26	-52.16***	12.75
	Dist_Ag Mkt * Post_Dummy	-62.15***	20.57	-121.82**	37.66	20.63**	9.22
	Number of observations	2721		5264		3658	
	Adjusted R^2	0.2505		0.2675		0.2955	
Panel II: 1 to 1 nearest neighbor matching	Dist_Ag Market	173.43	120.91	5.36	20.93	-44.56***	16.14
	Dist_Ag Mkt * Post_Dummy	-66.85***	25.12	-57.50*	29.47	21.32**	10.85
	Number of observations	2151		8123		2828	
	Adjusted R^2	0.2023		0.2619		0.3058	
Panel III: Mahalanobis metric covariate matching	Dist_Ag Market	77.25	110.33	32.96	25.55	-20.20*	12.75
	Dist_Ag Mkt * Post_Dummy	-84.34*	45.12	-74.41**	31.90	16.74	14.25
	Number of observations	2175		7338		2597	
	Adjusted R^2	0.2238		0.2762		0.3025	
Panel IV: Kernel matching	Dist_Ag Market	49.13	38.03	3.49	14.35	-43.05***	8.21
	Dist_Ag Mkt * Post_Dummy	-53.84***	15.92	-30.24*	17.10	21.27***	6.08
	Number of observations	11440		15398		7759	
	Adjusted R^2	0.2654		0.2715		0.2943	

Table 5. Robustness checks using alternative matching algorithms

Note: *, **, and *** indicates the coefficient is significant at 10%, 5% and 1% level, respectively. 50 county fixed effects are included in the model. The distance cutoffs used to construct matched samples based on proximity to agricultural market channels are 10 miles, 5 miles, and 15 miles for ethanol plants, grain elevators, and agricultural terminals, respectively.

		(a) Ethanol Plant		(b) Grain Elevator		(c) Agricultural Terminal	
		Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Panel I: Reduced distance cutoff for proximity	Dist_Ag Market	402.67	317.67	4.82	22.53	-68.19***	22.42
	Dist_Ag Mkt * Post_Dummy	-64.85*	36.50	-63.58**	30.83	45.10***	13.73
	Number of observations	1409		6940		1917	
	Adjusted R^2	0.2551		0.2659		0.2886	
Panel II: Alternative reduced distance cutoff for proximity	Dist_Ag Market	57.81	51.02	22.39	17.91	-53.04***	15.52
	Dist_Ag Mkt * Post_Dummy	-60.08***	20.59	-60.99**	24.30	24.82**	10.26
	Number of observations	2505		9455		3104	
	Adjusted R^2	0.2169		0.2694		0.2867	
Panel III: Increased distance cutoff for proximity	Dist_Ag Market	47.20	39.92	4.13	14.96	-40.14***	8.83
	Dist_Ag Mkt * Post_Dummy	-59.89***	16.74	-37.87**	19.24	14.10**	6.62
	Number of observations	4390		11698		6492	
	Adjusted R^2	0.2303		0.2714		0.2843	
Panel IV: Change timing 6 months earlier	Dist_Ag Market	22.68	44.07	21.21	18.69	-42.84***	8.87
	Dist_Ag Mkt * Post_Dummy	-39.92**	16.20	-49.43**	23.19	18.07***	6.27
	Number of observations	3443		9455		6492	
	Adjusted R^2	0.2395		0.2693		0.2847	
Panel V: Change timing 1 year earlier	Dist_Ag Market	-4.69	44.17	9.89	18.90	-43.51***	8.93
	Dist_Ag Mkt * Post_Dummy	-8.91	14.60	-23.11	23.03	17.43***	6.09
	Number of observations	3443		9445		6492	
	Adjusted R^2	0.2403		0.2403		0.2847	
Panel VI: Change timing from construction to plant opening	Dist_Ag Market	14.26	24.35	4.33	14.66	-36.85***	8.60
	Dist_Ag Mkt * Post_Dummy	-28.94*	15.87	-67.21**	22.15	9.20*	4.86
	Number of observations	3443		10880		6492	
	Adjusted R^2	0.2502		0.2704		0.2847	
Panel VII: Log-linear specification	Dist_Ag Market	0.0014	0.0088	0.0006	0.0030	0.0099***	0.0020
	Dist_Ag Mkt * Post_Dummy	-0.0062*	0.0035	-0.0088**	0.0040	-0.0042***	0.0015
	Number of observations	3443		10879		4864	
	Adjusted R^2	0.2276		0.325		0.4005	

Table 6. Robustness checks using alternative distance and timing cutoffs

Note: *, **, and *** indicates the coefficient is significant at 10%, 5% and 1% level, respectively. 50 county fixed effects are included in the model. The distance cutoffs used to construct matched samples based on proximity to agricultural market channels in panel I are 6 miles, 3 miles, and 10 miles for ethanol plants, grain elevators, and agricultural terminals, respectively. In panel II the distance cutoffs are 8 miles, 4 miles, and 12 miles for ethanol plants, grain elevators, and agricultural terminals, respectively. In panel III the distance cutoffs are 12 miles, 6 miles, and 18 miles for ethanol plants, grain elevators, and agricultural terminals, respectively.

		Ethanol Plant	
		Coef.	Std. Err.
Panel I: Exclude 2 nearest ethanol plants and agricultural terminals	Dist_Ag Market	44.14	35.48
	Dist_Ag Mkt * Post_Dummy	-48.68***	17.46
	Number of observations	3541	
	Adjusted R^2	0.243	
Panel II: Exclude 3 nearest ethanol plants and agricultural terminals	Dist_Ag Market	43.81	36.93
	Dist_Ag Mkt * Post_Dummy	-53.08***	19.52
	Number of observations	3541	
	Adjusted R^2	0.2426	
Panel III: Only use parcels within the Corn Belt boundary	Dist_Ag Market	23.61	51.68
	Dist_Ag Mkt * Post_Dummy	-49.23***	22.70
	Number of observations	3253	
	Adjusted R^2	0.2465	

Table 7. Robustness checks using alternative definitions of instruments

Table in the appendix:

Nominal farmland values ($/acre)	(I) Dist_Ethanol		(II) Dist_Ethanol* Post construction dummy	
	Coef.	Std. Err.	Coef.	Std. Err.
Assessed land value % of total assessed	0.3959	0.3967	-0.3078	0.5078
Total acres	0.0006	0.0028	0.0020	0.0034
Total acres squared	5.13E-06	0.0000	-3.17E-06	0.0000
National Commodity Crops Productivity Index	0.0004***	0.0001	0.0002**	0.0001
Prime farmland	0.7857**	0.3560	0.9595**	0.4387
Steep slope (>15 degrees)	-0.3574	0.3211	0.1460	0.4698
Building area % of parcel	0.5002	0.4272	0.5067	0.6605
Forest area % of parcel	-0.2076	0.7060	0.0401	0.7424
Wetland area % of parcel	5.7788	4.2820	26.04***	10.0750
Distance to highway ramp	0.0402	0.0420	-0.0077	0.0468
Distance to nearest city	-0.0217	0.0252	-0.0276	0.0266
Incremental distance to second nearest city	0.0960***	0.0238	0.0397	0.0249
Surrounding population within 25 miles	0.0031*	0.0017	-0.0010	0.0017
Gravity index of three nearest cities	0.0003	0.0010	0.0013	0.0011
Distance to railways	0.0853*	0.0448	0.2016***	0.0512
Distance to nearest grain elevator	0.3628***	0.0393	0.2061***	0.0489
Distance to nearest agricultural terminal	0.1671***	0.0195	0.0819***	0.0220
Capacity-weighted distance to other ethanol plants	0.1701***	0.0267	-0.0752***	0.0260
Capacity-weighted distance to other terminals	0.0002***	0.0000	0.0001***	0.0000
Avg_Dist_Ethanol * Post construction dummy	-7.04E-06*	0.0000	-2.91E-05***	0.0000
Avg_Dist_Terminal * Post construction dummy	-0.0056	0.0079	0.3103***	0.0105
Intercept	-18.5981***	2.5858	-8.1465***	2.8081
Year FE	yes		yes	
County FE	yes		yes	
Adjusted R^2	0.852		0.7707	
Number of observations	3343		3343	

Table A1: First stage regressions of the instrumental variables estimation

Figures:

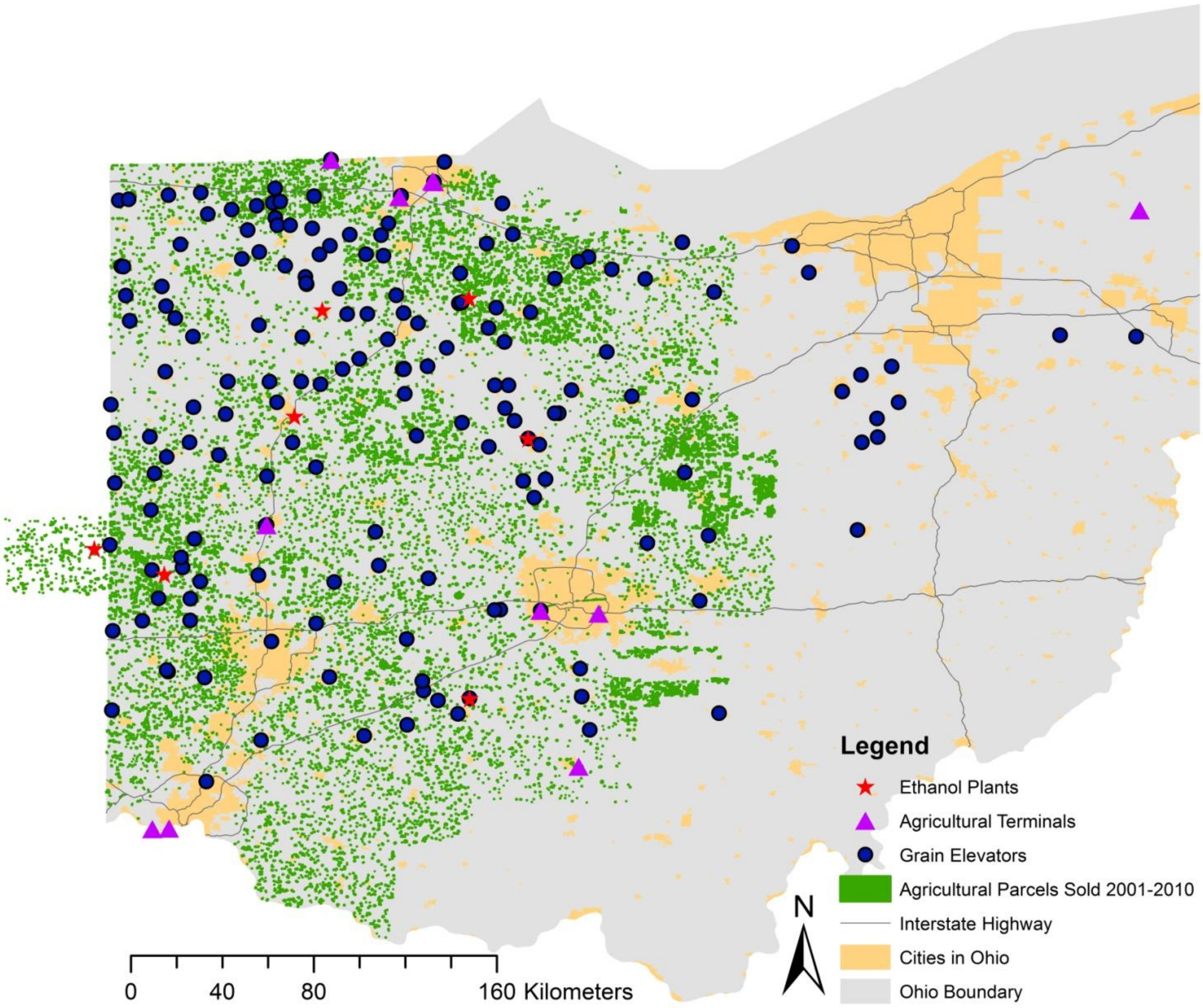


Figure 1: Agricultural land transactions from 2001 to 2010 and agricultural market channels in western Ohio

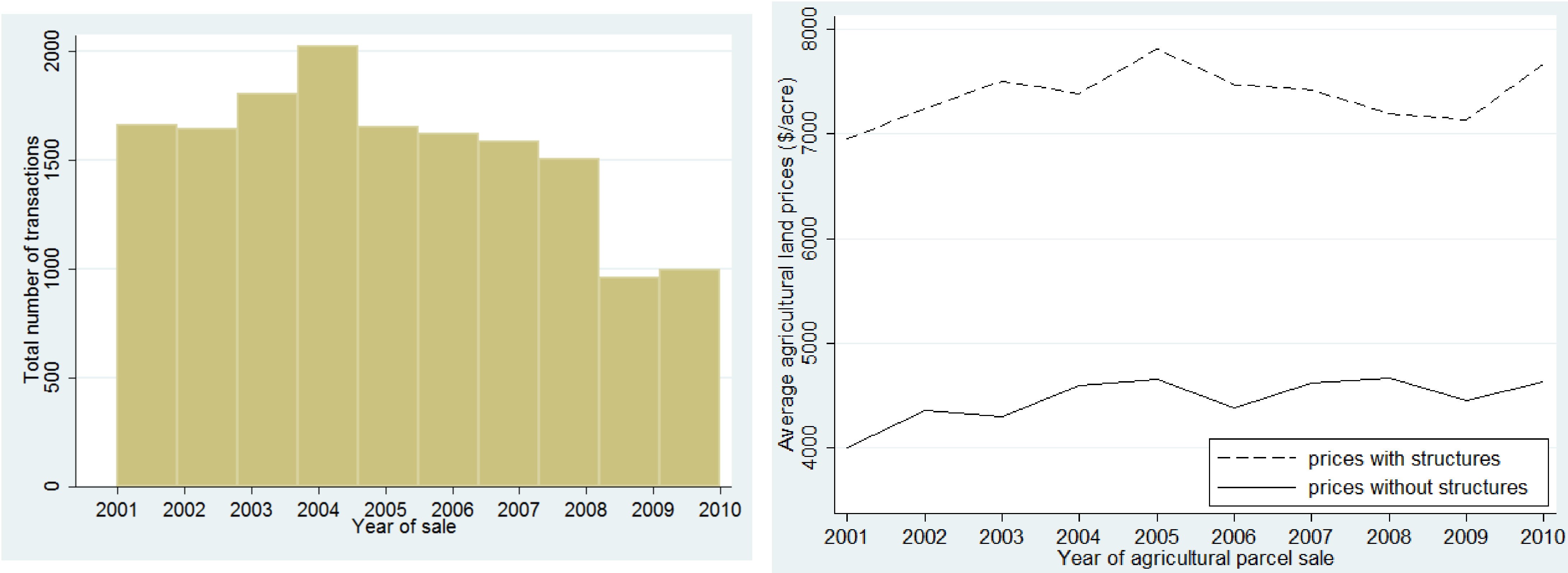
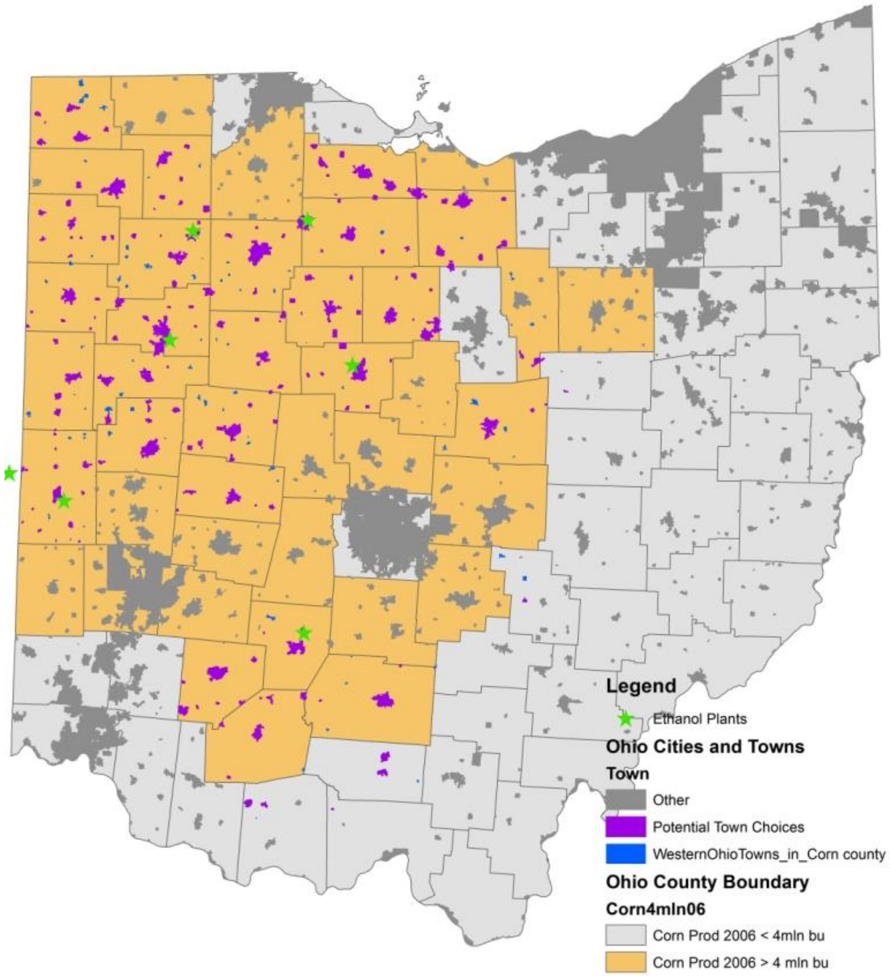


Figure 2: Number of agricultural land sales and average agricultural land values in western Ohio 2001-2010

Figures in the Appendix



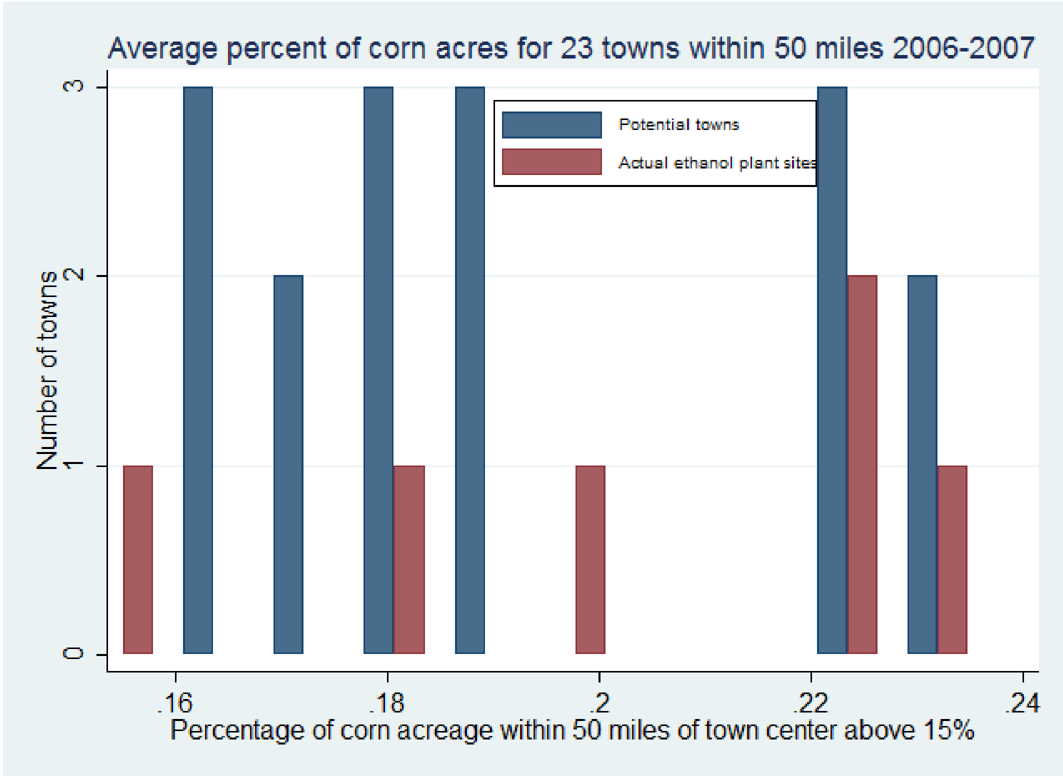


Figure A1: Alternative towns as sites for ethanol plants and percentage of corn acreage within 50 miles from actual ethanol plant and candidate towns

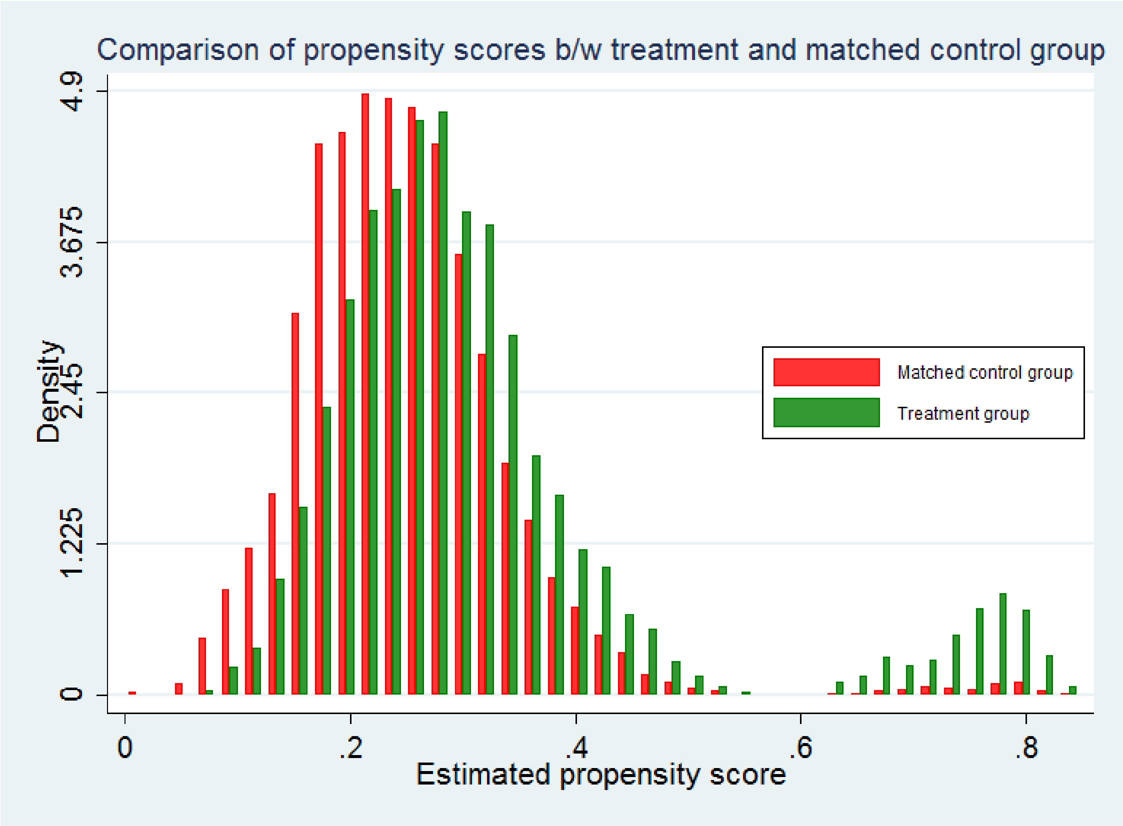


Figure A2. The comparison of propensity score between treatment and matched control groups for matching based on proximity to ethanol plants

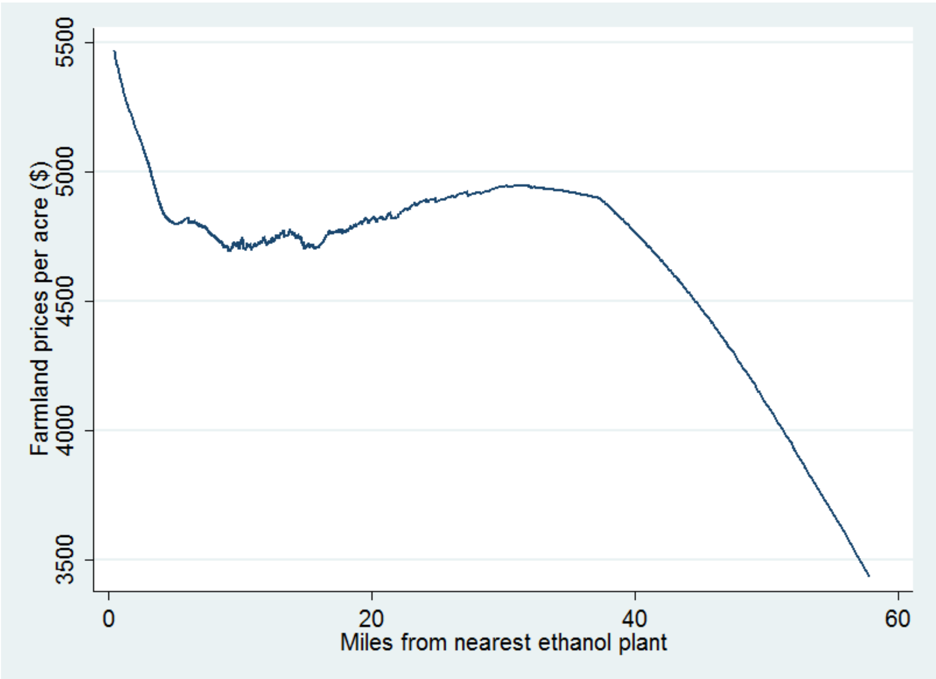


Figure A3: Nonparametric estimation of farmland values with respect to proximity to nearest ethanol plant