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

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Abstract

The recent housing market bust and subsequent economic 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. Parcel data on agricultural land sales from Ohio reveals that, although the number of agricultural land sales dropped precipitously after the housing market bust in 2007, there was no corresponding dip in the average sales price of agricultural land. Concurrent with the housing market bust, six new ethanol production facilities came into operation in Ohio in 2008. We hypothesize that changes in agricultural output markets, including increased demand for biofuels (and hence corn) and grain exports were capitalized into agricultural land values and that these effects offset the decline in the urban value of agricultural land parcels so that on average, agricultural and prices remained stable. 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, we test for structural change in the relative effects of proximity to agricultural delivery points (including ethanol plants, grain elevators and ports)before and after 2007, the year of the housing market bust and concurrent ethanol market expansion in Ohio. Specifically, we use propensity score matching (PSM) and difference-in-difference (DID) estimation on matched samples to isolate the effects of proximity to agricultural delivery points and test the hypothesis that the relative effect of proximity to these destinations has increased since 2007. We find preliminary evidence that the marginal value of being within close proximity to an ethanol plant was not significant in the earlier part of the decade, but became significant after 2007. Specifically, results from the DID estimation with the matched sample suggest that the marginal value of being located close to (between 5 and 13 kilometers) an ethanol plant was $419 per acre after 2007 and not significantly different from zero before this. In comparison, we find that the marginal value of being within close proximity of a grain elevator or agricultural terminal was positive throughout the decade and did not significantly change after 2007. Our results demonstrate the growing importance of the biofuels market for farmland values and show that proximity to ethanol plants has recently become a significant determinant of agricultural land values.

Keywords: Agricultural land values; Ethanol; Propensity score matching (PSM); Difference-in-difference (DID) regression; Housing market bust; Structural change

1 Introduction

The recent residential housing market bust and subsequent economic 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. Previous research has shown that in the Corn Belt states such as Ohio where corn and soybeans constitute a large share of agricultural production, there has been no corresponding decline in rural farmland values (Shane et al, 2009). Some descriptive studies have found that recent remarkable rise in farmland values is due in part to historically low interest rates, which attracted investment in agricultural land (Schnnitkey and Sherrick, 2010; Nickerson et al, 2012), as well as increasing demand for U.S. agricultural outputs due to a growing biofuels market (Wallander et al, 2011) and rising demand for U.S. grain exports (Gloy et al, 2011). However, most of the research is at an aggregate scale, which masks important differences in the influence of spatially distributed attributes on agricultural land values, including proximity to ethanol plants and other agricultural delivery points, as well as to urban areas.

Previous research on the determinants of agricultural land values has employed the standard hedonic pricing model, in which the price of a land parcel is regressed on the attributes of the parcel and its location to estimate the so-called implicit prices associated with these parcel-level attributes. However, this method suffers a number of limitations in terms of identification. In particular, many locational features, such as location of a parcel relative to an ethanol plant, are the result of a non-random process, implying that the estimates from a simple hedonic model with no control for systematic differences between those parcels that are located nearer versus farther away from an ethanol plant may be biased.

The purpose of this paper is to identify the marginal value of proximity to ethanol plants and other agricultural delivery points to test for structural change in these effects before and after 2007, the year of the housing market bust and concurrent ethanol market expansion in Ohio, We hypothesize that changes in agricultural output markets, including increased demand for biofuels (and hence corn) and grain exports, were capitalized into agricultural land values and that these effects offset the decline in the urban value of agricultural land parcels so that on average, agricultural land prices remained stable. We use parcel-level data on agricultural land sales from 2001 to 2010, a period which encompasses the housing market bust and the concurrent expansion of ethanol facilities, for a 50-county region of Ohio that encompasses great majority of grain production in Ohio. We address the sample selection bias imbedded in the standard hedonic approach by employing a quasi-experimental design approach. Specifically, we use propensity score matching (PSM) and difference-in-difference (DID) estimation to isolate the effects of proximity to agricultural delivery points and test the hypothesis that the relative effect of proximity to these destinations has increased since 2007. By controlling for unobserved time invariant heterogeneity over the matched samples, this DID estimator is subject to less bias than the standard hedonic estimates.

Our main result provides evidence that the marginal value of being within close proximity to an ethanol plant was not significant in the earlier part of the 2000 decade (from 2001 to 2006), but became significant after 2007. Specifically, results from the DID estimation with the matched sample suggest that the marginal value of being located close to (between 5 and 13 kilometers) an ethanol plant was $419 per acre after 2007 and not significantly different from zero before this. In comparison, we find that the marginal value of being within close proximity of a grain elevator or agricultural terminal was positive throughout the 2000 decade and did not significantly change after 2007. We also find that, regardless of relative location, the value of agricultural land parcels increased in the later part of the 2000 decade (2008-2010) relative to the earlier in the decade (2001-2006). We conclude that agricultural land values rose significantly from 2001-2010 in our Ohio study region and that these effects are spatially differentiated due to transportation costs to agricultural delivery points. Our results demonstrate the growing importance of the biofuels market for farmland values and show that proximity to ethanol plants has recently become a significant determinant of agricultural land values.

The remainder of the paper is laid out as follows. In the following section (section 2) we provide a brief synthesis of the literature on farmland values with a focus on recent papers that have attempted to examine the impact of expanding ethanol markets. This is followed by a discussion of the theoretical framework (section 3) and the econometric challenges and empirical strategy (section 4). Section 5 introduces the data, section 6 contains a discussion of the results and section 7 concludes.

2 Literature review

Numerous studies have analyzed the determinants of agricultural land values (e.g.Guiling et al (2009); Livanis et al (2006); Bastian et al (2002); Palmquist and Danielson (1989); Ma and Swinton (2011)). Most of them have employed the standard hedonic pricing method, which treats the agricultural land as a differentiated product whose price is modeled as a function of parcel attributes and location characteristics. Empirical applications have found a positive and significant relationship between farmland values and the soil quality measures (Huang et al, 2006; Palmquist and Danielson, 1989) or environmental amenities (Bastian et al, 2002; Pope, 1985; Henderson and Moore, 2006).

Studies have shown that in areas that are more urbanized or are experiencing faster population growth, the demand for land to be developed for urban uses is the most significant nonfarm factor affecting farmland values (Livanis et al, 2006; Hardie et al, 2001; Nickerson et al, 2012; Blank, 2007; Shi et al, 1997). The literature of urbanization spillover effects on rural lands is rapidly growing; however, most studies used a county level data, which generates a very coarse representation of the spatial extent and magnitude of urban influence. One exception is the study by Guiling et al (2009). They estimated a multi-level model which incorporated the county-level data and parcel characteristic, and found the distance where the urban influence on agricultural land values ended fell into the range of 20 to 50 miles, depending on the population and real income of the urban area.

In contrast, evidence of the potential impact of access to agricultural delivery points, such as proximity to ethanol plants or grain elevators, is limited. A recent report by USDA illustrated that a declining pattern of cropland values over farm distances to grain elevators, is evident in the Northern Plains where there is more variation in the distances (Nickerson et al, 2012). The surge in ethanol production has sparked a host of economic studies on ethanol industry (Henderson and Gloy, 2009), yet very few studies are relevant for understanding the impact on crop prices or farmland values (McNew and Griffith, 2005; Gallagher, 2006). For example, McNew and Griffith (2005) found evidence of higher corn price up to 68 miles away from ethanol plants. At this point there appear to be only three studies which directly studied the spatial effects of ethanol plants on farmland values. Specifically, Henderson and Gloy (2009) used survey data from Northern Plains and found evidence that, after controlling for urban influences at the county level, the cropland land market capitalized the surge in crop prices induced by ethanol market expansion. Blomendahl et al (2011) used price data from 961 sales of agricultural parcels from 2004 to 2008 in northwestern Nebraska, and didn't find support for the hypothesis that farmland values closer to ethanol plants were higher than comparable parcels farther away. Using farm-level data, Nehring et al (2006) estimated the impact of bio-fuel production and urbanization on quality-adjusted agricultural land prices in the Corn Belt region. However, these studies have at least inadequacies: first, the standard hedonic approach used by all three studies suffers from sample selection bias mentioned in the introduction; secondly, their measures of urban influences are only at county level; and finally, none of these studies explicitly examined the structural change in the relative effects of ethanol plants in the context of the housing market bust. Our study addresses these problems by constructing a counterfactual control group through a quasi-experimental design, and by utilizing a dataset which includes comprehensive parcel-level location characteristics for parcels sold before and after 2007, the year of the housing market bust and concurrent ethanol expansion.

3 Theoretical framework

Economic theory suggests that the value of agricultural land can be derived from the net present value of various returns (Guiling et al, 2009). Among various theories which try to explain the value of the land, Ricardo's famous capitalization model is by far most commonly used (Cavailhés and Wavresky, 2003). The capitalization formula is

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

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 δ_t (Henderson and Gloy, 2009). The returns R can be derived from agricultural uses, recreational uses or conversion to urban uses such as residential, commercial or industrial development. Any factor affecting the farmland returns R, either in terms of agricultural productivity, recreational profits 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 logarithm specification is defined as

$$R_{it}) = f(\mathbf{X_{it}}, \tau_t; \eta_{it}), \tag{2}$$

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

$$\mathbf{X_{it}} = \mathbf{A_{it}} + \mathbf{N_{it}} + \mathbf{U_{it}} + \mathbf{M_{it}}. \tag{3}$$

Combining equations (1), (2), and (3), we can get the following specification:

$$V_{it} = E_t \sum_s f(\mathbf{A_{is}}, \mathbf{N_{is}}, \mathbf{U_{is}}, \mathbf{M_{is}}; \delta_t). \tag{4}$$

The study region - Western Ohio - is fairly homogenous in soil type, slope of the land, climatic conditions and surrounding land uses, as a result we expect little variation in terms of recreational income 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.

The urban influence variables work through two channels, first, that proximity to population centers and increased access to customers could influence farmland values by increasing expected agricultural returns (Nickerson et al, 2012). In addition, agricultural land closer to urban fringe could sell for a premium, an option value that equals to the net present value of expected incremental returns above the current agricultural/recreational uses after conversion into urban development at a future date (Capozza and Helsley, 1989; Guiling et al, 2009). This option value gradually diminishes over the distance to the city center. The classical urban economic theory suggests the latter effect is more important, and thus predict the value of land declines as one moves away from the urban center (Capozza and Helsley, 1989). The recent housing market bust in 2007 resulted in a double-digit depreciation in urban residential housing prices in over half of American States, and Ohio, being one of the four states with highest foreclosure rate, is one of the most hit (Economist, 2008). This urban housing market downturn should greatly diminish the urban option conversion value of the agricultural land, and as a result, we should observe a declining relative significance of the urban influence variables $\boldsymbol{U_{it}}$ in determining the farmland values.

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 bio-fuels have increased demand for corn, which elevated corn and other agricultural commodity prices (Nickerson et al, 2012). The year of 2010 marks the first time that corn usage for ethanol production exceeds usage for feed stock (World Agricultural Outlook Board, 2012). Previous studies have identified increased corn basis prices in the vicinity of an ethanol plant (McNew and Griffith, 2005), and this 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 offset the benefits of increased grain exports to China for the agricultural terminal markets, is an empirical question.

4 Econometric challenges and empirical strategy

4.1 Potential bias in standard hedonic price estimation

With Rosen's (1974) seminal work as a backdrop, 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 in part 2 has employed the land value hedonics model. The most common specification is the log-linear form defined as

$$log(V_{it}) = \beta_0 + \beta_1 t + \beta'_{\mathbf{A}}\mathbf{A_{it}} + \beta'_{\mathbf{N}}\mathbf{N_{it}} + \beta'_{\mathbf{U}}\mathbf{U_{it}} + \beta'_{\mathbf{M}}\mathbf{M_{it}} + \epsilon_{it}, \quad (5)$$

where the agricultural land values are defined to be the real sale prices of the agricultural land without structures.

In this hedonic 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 a number of well-known econometric problems (De Vor and de Groot, 2009; Bajari et al, 2012). Foremost among those, when estimating average treatment effect, hedonic regressions impose problematic assumption about the distributional equality of the covariates for treatment and control subsamples (Kaza and BenDor, 2011), which will result in sample selection bias. Previous research has shown that the location of ethanol plant is not an exogenous incident. Instead the site-selection is a non-random process affected by the availability of feedstock nearby, the access to navigable rivers or railroads, and the extent of the product markets (Lambert et al, 2008). Arguably, agricultural parcels closer to the ethanol plants could have better soil quality and easier access to transportation network than those parcels farther away. These systematic differences, if not corrected, could result in erroneous estimates of the impact of proximity to ethanol plants on farmland values. If the distributional differences are large, the predictions for treatment and controls are essentially out of sample projections and therefore sensitive to functional form (Kaza and BenDor, 2011). Similar selectivity problem is reported by De Vor and de Groot (2009) when estimating the willingness to pay to avoid a disamenity in the residential housing context. In this paper, this log-linear hedonic price model is used as the benchmark.

4.2 Quasi-experimental design

To avoid the selection bias in hedonic approach, previous research has relied on instrumental variables, regression discontinuity (Greenstone and Gallagher, 2008), or other forms of quasi-experimental variation (Bajari et al, 2012). The popular regression discontinuity design does not apply to our application since this approach requires a sharp cut-off (Imbens and Lemieux, 2010); however, the proximity to agricultural delivery points is continuous. Instead, another quasi-experimental approach is employed. We use propensity score matching (PSM) and difference-in-difference (DID) estimation to isolate the effects of proximity to agricultural delivery points and test the hypothesis that the relative effect of proximity to these destinations has increased since 2007, the year of the housing market bust and concurrent expansion of the ethanol market in Ohio. We use PSM to construct treatment and control groups for each of three types of delivery points – ethanol plants, grain elevators and agricultural terminal ports – and use DID estimation to examine whether their relative influence on agricultural land values changed since 2007. Because these types of delivery points are heterogeneous, their locations may be determined by a different set of factors and therefore we estimate the effect of proximity to each type of delivery point separately in the three different models.

4.2.1 Propensity score matching

Propensity score matching (PSM) estimators, as a way to identify average treatment effect, has gained popularity in land use and agricultural economics literature in recent years (Bento et al, 2007; Towe et al, 2011; Lynch et al, 2007). The main advantage of matching is that by calculating the probability of one parcel receiving treatment given the set of observable conditioning variables, the researcher is able to construct the "counterfactual" control group. By doing that, the selection bias inherent in the standard hedonics is reduced. Following the seminal work by Rosenbaum and Rubin (1983), much of the work on PSM has focused on cases where the treatment is binary (Lynch et al, 2007).

Our application involves a two-step matching strategy. First, we will trim the pre-2007 sample to remove extremely dissimilar parcels with those sold after 2007 using 1 to 4 nearest neighbor matching technique(Lynch et al, 2007). Specifically, we consider the agricultural parcels sold after the exogenous housing market bust and concurrent ethanol expansion in 2007 as the treatment group and those sold before as part of the control group [1]. Propensity score (the probability of being sold after 2007) 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,

[1] Agricultural parcels sold in the year of 2007 are dropped in the estimation

surrounding land uses, and neighborhood population density. Then the distribution of estimated propensity scores among treated and control parcels is plotted. From this, we drop parcels with propensity scores not on support and those with propensity scores greater than 0.9 as recommended by Crump et al (2009). Similar sample trimming technique has been used by Busso et al (2010).

With the trimmed sample, we then construct the treatment and control group based on the proximity to a given type of delivery points. Because of the continuous nature of the distance to agricultural delivery point as the treatment variable, a cutoff value has to be determined to convert this continuous treatment into binary one, as required by the standard PSM. We first assume the treatment group to be parcels with distances less than a certain cutoff value, and then match these artificial treatment-group parcels with those farther away on a vector of parcel attributes and location characteristics as illustrated above, and finally check the balancing property, that is, conditioning on the true propensity score asymptotically balances the observed covariates Diamond and Sekhon (2012). The optimal cut-off value for the continuous treatment variable is determined such that at this cut-off, the balancing property is best satisfied [2]. Although the cutoff value is defined *a priori*, this selection process of the optimal cut-off based on balancing property exploits the quality of the data.

4.2.2 Difference-in-difference regression

For each of the three matched samples, a difference-in-difference (DID) estimation is used to test for a structural change over time in the influence of proximity to a given type of delivery point. Through the two-step propensity score matching illustrated above, we have established the counterfactual control groups pre- and post-2007, which differs with the treatment group only in one dimension, the proximity to this type of delivery point. Equation(6) can be used to model the sale price of agricultural land parcel i at year t:

$$P_{it} = \beta_0 + \beta_1 t + \beta_{\mathbf{2}}{}'\mathbf{X_{it}} + \beta_3\gamma_i + \beta_4\gamma_t + \beta_5\gamma_i * \gamma_t + \epsilon_{it}, \tag{6}$$

where P_{it} is the sales price, $\boldsymbol{X_{it}}$ is the vector of parcel attributes and location variables defined in equation (3). The location dummy variable γ_i is assigned a value of 1 if the agricultural parcel is located within the cut off distance of a delivery point (treated group) optimally chosen in second step PSM process and 0 if farther away. The time dummy variable γ_t is defined to be 1 if the sale of one particular agricultural parcel occurs after 2007 and 0 otherwise. The coefficient on the interaction term $\gamma_i * \gamma_t$ captures the structural

[2]Practically, we define *a priori* a cutoff value within which the parcels are regarded as part of the treatment group, and test whether the weighted mean of the covariates(X) is identical between units in the two treatment intervals, with weights being proportional to the number of times that one particular parcel was selected to match with a treated parcel. The optimal cut-off is selected with lowest average t-statistics from the group-means test.

change of the impact of proximity to a delivery point on agricultural land values after 2007 and serves as the difference-in-difference estimator.

4.2.3 Practical concerns and robustness check

By controlling for the systematic differences between the treatment and control groups through matching, and for unobserved time-invariant heterogeneity, our estimator is subject to less bias than the standard hedonic estimate. However, to the extent that other variables changed over this time period and are spatially correlated with the location of these agricultural delivery points, the DID estimator may still be subject to bias.

In particular, we need to address two issues. First, it is possible that the value of proximity to an ethanol facility was capitalized into farmland values before the plant opened. Previous research has demonstrated that the opening of a transit line in late 1993 in Chicago had been anticipated in the residential housing market as early as 1987 (McMillen and McDonald, 2004). Although the agricultural land sale market is comparatively a much thinner market, the expectations argument still works here. Another example that supports the expectations argument is that although the Valero ethanol plant at Bloomingburg, OH didn't begin operation until March 2008, the plans for that plant were conceived as early as late 2002 and the construction plan was announced in mid-2005 (Valero Plant Overview, 2012). To the extent that these expectations resulted the value of proximity being capitalized before 2007, our results will underestimate the effect of proximity to an ethanol plant. Secondly, arguably parcels close to the city (*urban parcels*) and those farther away (*non-urban parcels*) are subject to different driving forces, which may result in fundamental differences between the characteristics of these two groups. As a result, simple PSM matching which do not explicit differentiate these two subsets may not be fully justified. We address this problem by utilizing a special form of matching - direct matching, in which we first split the whole dataset into 5 subsets based on the quantiles of the distances from agricultural parcels to nearest city, and then conduct the standard PSM matching within each subset (distance band). By doing so, we reduce the likelihood of matches between urban parcels and non-urban parcels.

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, 2012). One robustness check is to use another matching technique, $Genetic\ Matching (GenMatch)$, which uses a weight matrix derived from the data that minimizes the differences between the distributions of the treatment and control groups. Technically, the distance metric between the attribute vectors of parcel i and j is defined as

$$d(\mathbf{X_i}, \mathbf{X_j}) = [(\mathbf{X_i} - \mathbf{X_j})'(\mathbf{S}^{-1/2})'\mathbf{W}(\mathbf{S}^{-1/2})(\mathbf{X_i} - \mathbf{X_j})]^{1/2}, \tag{7}$$

where $\boldsymbol{S}$ is the covariance matrix of $\boldsymbol{X}$ and $\boldsymbol{W}$ is the diagonal weight matrix.

The optimal weight matrix $\boldsymbol{W}$ can be derived from the data using a genetic algorthm, such that it minimizes the largest observed covariante discrepency of control and treatment group at each iteration (Sekhon, 2004; Kaza and BenDor, 2011). At the expense of computer time, $GenMatch$ is shown to have better property than other matching alternatives including PSM (Sekhon, 2004). Other robustness checks involve trying different cut-off values in the second step matching and different number of distance bands in the direct matching.

5 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 delivery points on farmland values in the context of residential housing boom-bust. Ohio is one of most impacted states in the recent housing market bust, and almost all land here is subject to some degree of urban influences. In addition, the bio-fuel industry in Ohio is gaining momentum over the last decade, with six ethanol plants in operation in Western Ohio. To analyze the structural break before and after the concurrent timing of the housing market bust and ethanol market expansion, we have assembled a detailed database of 21,342 arms-length agricultural land sale records for 50 western Ohioan counties [3] 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. We now briefly describe the key elements of our data in additional detail.

To form our dataset of agricultural land transactions, we combine 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, Hamilton and Randolph,IN. Only those agricultural parcels sold between 2001-2010 and with a valid arms-length indicator [4]are kept. Those valid agricultural sale records are merged with GIS parcel boundaries or are geocoded based on property addresses

[3]Randolph county, IN is also included in the dataset along with these 50 Ohioan counties.

[4]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.

using Google Maps API. The sales prices are adjusted for inflation [5], and 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. We are left with a filtered sample of 13,865 valid transactions that are plotted in Fig.1. As is evident from the figure, these data are widely distributed over virtually the entire region. The locations of three sets of agricultural delivery points - ethanol plants, grain elevators and agricultural terminal ports - are also shown in Fig.1. The ethanol plant located at Randolph county, Indiana is also included in the analysis since Randolph, IN shares border with Darke county, OH.

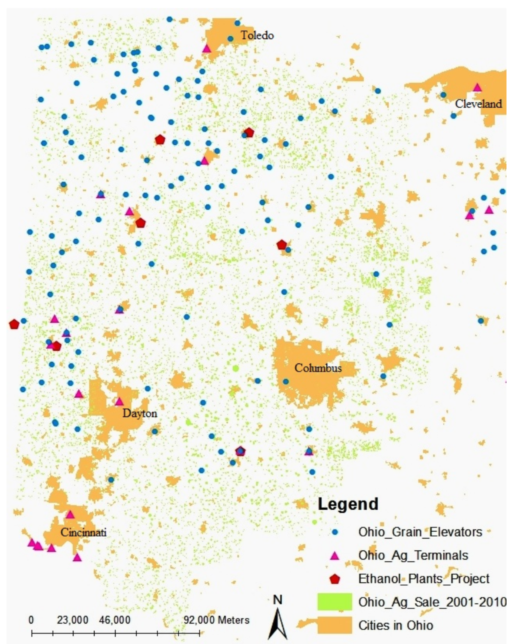

Figure 1: Agricultural land transactions from 2001 to 2010 and agricultural delivery points in western Ohio

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). 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

[5] The real sales prices are adjusted using the consumer price index (CPI) in the Cincinnati metropolitan area with year 2000 being the base year.

Table 1: Summary statistics for 13,865 agricultural land parcels, Western Ohio, 2001-2010

	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	4362.6990	3644.2720	1000.161	19988.09
Log of sale price per acre	Dollars	8.1169	0.6979	6.9079	9.9029
Assessed land value	Dollars	74190.6200	162980.2000	0	5878840
Assessed improvement value	Dollars	32269.2800	68910.3700	0	3937580
Assessed land value % of total assessed	%	0.7224	0.3121	0.003484	1
Total acres	Acres	44.2038	61.2890	0.14	2380.66
Sale year	Year	2004.8380	2.7608	2001	2010
Agricultural Productivity Variables					
National Commodity Crops Productivity Index	Number	5778.1530	1518.3360	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	19.1184	12.7587	0	56.8243
Total urban population within 25 miles	Thousands	290.0353	231.9361	64.7721	1187.3810
Distance to highway ramp	Kilometers	5.2218	3.2932	0	19.1050
Distance to nearest city	Kilometers	40.9684	20.3363	0.1983	105.6621
Number of cities within 25 miles	Number	1.8831	1.7276	0	7
Agricultural Market Influence Variables					
Distance to nearest ethanol plant	Kilometers	45.9917	22.5747	0.6792	111.7508
Production capacity of nearest ethanol plant	Million gallons	88.5604	25.0177	54	120
Number of ethanol plants within 25 miles	Number	1.1327	0.9094	0	4
Total production capacity of ethanol plants within 25 miles	Million gallons	96.1356	76.4837	0	304
Distance to nearest grain elevator	Kilometers	13.4455	11.3502	0.0405	88.4338
Number of grain elevators within 5 miles	Number	1.1851	1.4877	0	10
Distance to nearest agricultural terminal	Kilometers	52.4986	22.7373	0.2038	119.3951
Number of agricultural terminals within 25 miles	Number	1.1818	1.2215	0	4
Environmental Amenities Influence Variables					
Forest area % of parcel	%	0.1529	0.2586	0	1
Wetland area % of parcel	%	0.0034	0.0292	0	1
Pasture area % of parcel	%	0.1199	0.2408	0	1
Open water % of parcel	%	0.0026	0.0237	0	0.74627

Ohio Ethanol Council (2012), the Farm Net Services (2012) and the Ohio Licensed Grain Handlers List (2012). Using these data and ArcGIS software, we were able to create the the parcel attributes and location characteristics vector $\boldsymbol{X_i}$. See table 1 for summary statistics.

Most of variables in table 1 are self-explanatory; however, we do need to make three remarks. 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, we highlight the set of the urban influence variables $\boldsymbol{U_i}$ and the agricultural market influence variables $\boldsymbol{M_i}$ 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 delivery points. Moreover, the variables *total production capacity of ethanol plants within 25 miles* and *number of ethanol plants within 25 miles* are designed to capture the additional premium generated from the proximity of land parcels to multiple ethanol plants (Henderson and Gloy, 2009).

6 Results and discussion

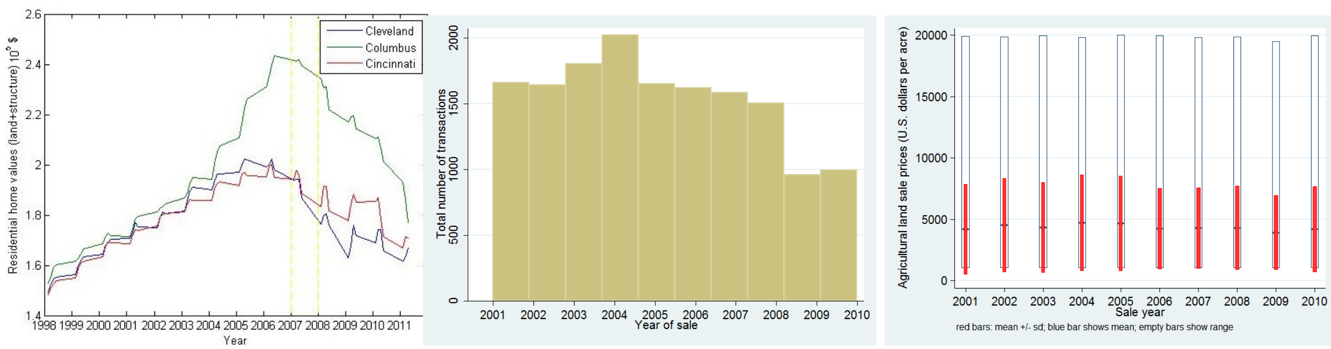

Figure 2: (a)Ohio Residential Home Values, (b) Number of agricultural land sales, (c) Real agricultural land prices

The recent housing market bust and subsequent economic 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 is plotted based on residential and agricultural land sales since 2001 from Ohio, which is almost entirely subject to some degree of urban influence and hence potential impacts of changes in urban land markets. Using Metropolitan Statistical Area (MSA) level data on residential land prices and structure costs (Lincoln Institute of Land Policy, 2012), Fig. 2(a) clearly reveals that Ohio residential home values have seen a significant decline after the housing market bust in 2007. The agricultural land market in Ohio has a totally different picture: although the number of agricultural land sales dropped precipitously after the housing market bust (See Fig. 2(b)), there was no corresponding dip in the average sales price of agricultural land. Instead, Fig. 2(c) suggests that the average real agricultural land sale prices stayed fairly constant around 5,000 dollars per acre over the past decade, which is consistent with the survey finding by Ward

(2011). As explained in previous sections, this phenomenon is in part due to the growing significance of agricultural markets, exemplified by the surging bio-fuels market (Wallander et al, 2011) and rising demand for U.S. grain exports (Gloy et al, 2011).

We hypothesize that changes in agricultural output markets, including increased demand for bio-fuels and grain exports were capitalized into agricultural land values and that these effects offset the decline in the urban value of agricultural land parcels so that on average, agricultural land prices remained stable. To further explore this issue, we first estimate the standard hedonic model as the benchmark model. In table 2, we show estimates of models of the effects of the housing market bust and concurrent ethanol expansion on real agricultural land sale prices for the whole dataset from 2001 to 2010 (with parcels sold in the year 2007 dropped). Two model specifications are explored in this hedonic analysis. By including 50 county fixed effects[6], model II not only improved the overall determination power (adjusted R^2), it also modified the significance and magnitudes of many explanatory variables. Out of 50 county fixed effects, 16 were significant, providing another evidence for the claim that model II outcompetes model I. Most of the estimates are intuitive and familiar: bad soil quality of presence of steep slope would decrease farmland values, while higher agricultural productivity or proximity to highway ramps would lead to an increase. The significant coefficient on *acres squared* implied a nonlinear relationship between the per-acre farmland values and total acreage. The effects of the variable *NCCPI* were absorbed into the location-specific county fixed effects, which suggested little heterogeneity of parcels within one county and also led to the superiority of model II over model I.

The key set of variables worth mentioning is the interactions of pre- or post- 2007 dummies with urban influence variables such as *distance to nearest city* and with agricultural market variables such as *distance to nearest ethanol plant*. The pre- (post-) 2007 dummy is defined to 1 (0)if the parcel is sold before 2007, and 0 (1) otherwise. The magnitude of the coefficient on the interaction term with *distance to nearest city* dropped from 0.0028 to 0.0020 after 2007, suggesting that although being close to urban center still was viewed as a good thing even after 2007, the positive benefits from this proximity diminished slightly. Consistently, the option value or value of consumer base imbedded in the variable *surrounding urban population* became insignificant after 2007. In the contrary, model II showed that the positive influence of proximity to agricultural delivery points were stronger after 2007. Specifically, the agricultural land prices were not significantly higher for parcels closer to an ethanol plant than those farther away before 2007; the model even suggested proximity to ethanol plants would dampen the farmland values. However, after 2007, this proximity became

[6]To save space, only the 16 county fixed effects that are statistically significant at 10 % level are shown in table 2.

Table 2: Hedonic estimation for the log of real sales prices of agricultural land without structures

Model	I		II	
	Coef.	Std. Err.	Coef.	Std. Err.
Intercept	8.4641***	0.0640	8.7337***	0.1409
Total acres	-0.0047***	0.0001	-0.0045***	0.0001
Total acres squared	0.0000***	0.0000	0.0000***	0.0000
National Commodity Crops Productivity Index	0.00002***	0.0000	0.00001	0.0000
Soil class 4 area % of parcel	-0.0049	0.0212	-0.0126	0.0230
Steep slope (>15 degrees)	-0.0143	0.0168	-0.0303*	0.0172
Distance to nearest city * Pre-2007 dummy	-0.0034***	0.0004	-0.0028***	0.0007
Distance to nearest city * Post-2007 dummy	-0.0028***	0.0007	-0.0020**	0.0009
Total urban population within 25 miles * Pre-2007 dummy	0.0003***	0.0000	0.0001**	0.0000
Total urban population within 25 miles * Post-2007 dummy	0.0002***	0.0001	0.00009	0.0001
Building area % of parcel	0.0412	0.0425	0.0631	0.0420
Distance to highway ramp	-0.0050***	0.0017	-0.0043**	0.0017
Distance to nearest ethanol plant * Pre-2007 dummy	0.0023***	0.0004	0.0008	0.0006
Distance to nearest ethanol plant * Post-2007 dummy	-0.0001	0.0006	-0.0010	0.0008
Distance to nearest grain elevator * Pre-2007 dummy	-0.0017***	0.0007	-0.0024*	0.0011
Distance to nearest grain elevator * Post-2007 dummy	-0.0044***	0.0012	-0.0037**	0.0015
Distance to nearest agricultural terminal * Pre-2007 dummy	-0.0034***	0.0003	-0.0048***	0.0006
Distance to nearest agricultural terminal * Post-2007 dummy	-0.0022***	0.0005	-0.0042***	0.0008
Forest area % of parcel	0.0372	0.0261	-0.0491*	0.0267
Wetland area % of parcel	-0.3781**	0.1874	-0.2180	0.1846
Year 2001	-0.2351***	0.0689	-0.2109***	0.0691
Year 2002	-0.1701**	0.0689	-0.1520**	0.0690
Year 2003	-0.1910***	0.0689	-0.1606**	0.0691
Year 2004	-0.1149*	0.0685	-0.0985	0.0689
Year 2005	-0.1003	0.0689	-0.0656	0.0690
Year 2006	-0.1047	0.0690	-0.0676	0.0694
Year 2008	0.018	0.0263	0.0049	0.0259
Year 2009	-0.0393	0.0290	-0.0344	0.0282
Butler County, OH			0.5115***	0.1295
Clermont County, OH			0.2861**	0.1342
Delaware County, OH			0.2533*	0.1417
Erie County, OH			0.2354*	0.1315
Fairfield County, OH			0.2220*	0.1252
Fayette County, OH			0.2505**	0.1212
Greene County, OH			0.3448***	0.1229
Hamilton County, OH			0.4156***	0.1629
Madison County, OH			-0.2213*	0.1286
Miami County, OH			-0.2335*	0.1276
Preble County, OH			-0.3362***	0.1211
Ross County, OH			-0.4173***	0.1292
Sandusky County, OH			-0.3338***	0.1223
Shelby County, OH			-0.3246**	0.1278
Williams County, OH			-0.2398*	0.1288
Wood County, OH			-0.3192*	0.1234
Adjusted R^2	0.1616		0.2137	
Observations	13865			

* significant at 10% level; ** significant at 5% level; *** significant at 1% level.
Pre-2007 dummy equals zero if sale year < 2007, equals one if sale year > 2007.
The agricultural sale transactions sold in 2007 are deleted.
To save space, the other 34 county fixed effects that are not statistically significant at 10% level are not shown.

a positive influence, although still insignificant. After 2007, a more evident declining pattern over distances from agricultural parcels to grain elevators emerged, mainly due to the increased demand for corn due to the unprecedented rise of the ethanol industry. In addition, we found a decreasing positive, though still large and significant, impact of agricultural outputs terminals on farmland values after 2007. This suggests that the competition from the newly constructed ethanol plants for grains was strong enough to offset the benefits of greater exports to countries like China, and this result is consistent with the argument made by Nickerson et al (2012). These results are preliminary since they did not control for the non-random location of agricultural delivery points nor did they control for unobserved differences across the samples drawn from the pre and post time periods. In addition, the Wald test of the equality of the regression coefficients revealed that only the coefficients on *distance to nearest ethanol plant* were statistically different before and after 2007. Nonetheless, they are suggestive and provide ample motivation to further investigate potential structural change in these effects using the DID estimation with matched samples.

Table 3 show the comparison of the means of the covariates before and after trimming the samples through a 1 to 4 nearest neighbor propensity score matching algorithm which treats the year 2007 as the treatment. Specifically, the treatment group was defined as parcels sold in the years 2008-2010, while the naíve control group as those sold between 2001 and 2006. 868 parcels with a propensity score not on support or higher than 0.9 were dropped, and hence we are left with 12969 parcels. Table 3 clearly revealed that without matching, there were systematic distributional differences between the naíve control group and the treatment group, which, as a result, would lead to biased estimates in the standard hedonic approach. In the contrast, these differences were removed through propensity score matching, which assures that the parcels in the treatment group were matched to parcels sold before 2007 with the most similar characteristics listed in table 3 (Lynch et al, 2007). After the first step PSM matching, we got a trimmed balancing sample of size 9880. 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.

The results about the balancing property of the second step PSM matching on distance to agricultural delivery point are presented in table 4. To make the matching work, a few adjustments were made compared to the first step PSM matching on the year of 2007 : first, due to the fact of too few observations in each county, the 51 county fixed effects were replaced by 6 JobsOhio Network Region dummies defined by Ohio Department of Development (2012). Secondly, parcels within 20 miles of nearest city and parcels within 5 kilometers of nearest ethanol plant were dropped when conducting the PSM matching on proximity to ethanol plants, while in contrast matching on proximity to grain elevators or agricultural terminals utilized

Table 3: Comparison of the means of the covariates across treatment and control groups after matching on the year of 2007

	Whole sample	Matched sample Treatment	Control	Naíve Control	Unmatched Control
Assessed land value % of total assessed	0.7125	0.7437	0.7395	0.7011***	0.6548***
Total acres	45.1638	49.4720	50.4100	43.5950***	38.9445***
Total acres squared	5936.4860	5451.0000	5941.9000	6113.3000***	8229.2670
Agricultural Productivity Variables					
National Commodity Crops Productivity Index	5783.0830	5872.2000	5866.6000	5750.6000***	5587.161***
Cropland area % of parcel	0.5634	0.6023	0.6024	0.5492***	0.4917***
Soil class 1 area % of parcel	0.2829	0.2748	0.2709	0.2858*	0.2890*
Soil class 2 area % of parcel	0.0798	0.0637	0.0624	0.0857***	0.1138***
Soil class 4 area % of parcel	0.1979	0.2021	0.2064	0.1963	0.2088
Representative slope	0.1790	0.1436	0.1461	0.1919***	0.2347***
Urban Influence Variables					
Building area % of parcel	0.0357	0.0446	0.0435	0.0324	0.0281***
Distance to urbanized area of over 25,000 people	20.0248	20.3340	20.4600	19.9120*	19.5549**
Total urban population within 25 miles	269.0390	253.7000	250.5400	274.6200***	282.7371***
Distance to highway ramp	5.2322	5.4208	5.4271	5.1635***	4.9751***
Distance to nearest city	42.3171	45.6120	45.7020	41.1170***	39.3887***
Number of cities within 25 miles	1.7793	1.6069	1.5915	1.8421***	1.9227***
Agricultural Market Influence Variables					
Distance to nearest ethanol plant	44.8900	40.5370	40.5210	46.4750***	51.1583***
Production capacity of nearest ethanol plant	88.0239	88.5570	88.4680	87.8300	87.3675*
Number of ethanol plants within 25 miles	1.1699	1.3380	1.3369	1.1087***	0.9176***
Total production capacity of ethanol plants within 25 miles	100.1081	116.4900	116.3600	94.142***	76.8339***
Distance to nearest grain elevator	12.9639	12.7710	12.6640	13.0340	13.4952***
Number of grain elevators within 5 miles	1.2199	1.2458	1.2634	1.2105	1.1084***
Distance to nearest agricultural terminal	53.0996	54.1830	54.1450	52.7050***	52.6005***
Number of agricultural terminals within 25 miles	1.1402	1.0300	1.0219	1.1804***	1.2450***
Environmental Amenities Influence Variables					
Forest area % of parcel	0.1454	0.1136	0.1134	0.1570***	0.2003***
Wetland area % of parcel	0.0032	0.0025	0.0024	0.0035*	0.0046**
Pasture area % of parcel	0.1144	0.0949	0.0984	0.1215***	0.1421***
Open water area % of parcel	0.0026	0.0032	0.0029	0.0024	0.0018
Number of observations	12969	3462	6418	9507	3089
	12969	9880			

* difference of the means of covariates in respective control group is statistically different from that in the treatment group at 10 % level; ** at 5 % level; *** at 1 % level.

Whole sample includes all the parcels with a propensity score on support, and this whole sample contains the treatment group, which is the set of all the parcels sold after 2007, and the naíve control group, all other parcels sold before 2007. Out of the 9507 parcels in the naíve control group, 6418 parcels constitute the matched control group through a 1 to 4 nearest neighbor propensity score matching algorithm.

To save space, the 50 county fixed effects included as part of the covariates in propensity score matching are shown here.

Table 4: Comparison of the means of the covariates across treatment and matched control groups after matching on proximity to a certain agricultural delivery point

Covariates	Ethanol Treatment	Plant Control	Grain Treatment	Elevator Control	Agricultural Treatment	Terminal Control
Assessed land value % of total assessed	0.8742	0.8587	0.7694	0.7703	0.7078	0.6699
Total acres	52.7500	51.8450	46.4610	46.8660	40.7410	39.7920
Total acres squared	5076.6000	4946.8000	4742.4000	4553.7000	4001.2000	4064.8000
National Commodity Crops Productivity Index	5531.5000	5632.3000	5870.3000	5880.6000	5298.4000	5281.0000
Soil class 1 area % of parcel	0.1980	0.2045	0.2241	0.2307	0.1864	0.2008
Representative slope	0.8742	1.1810	2.5796	2.4464	4.0021	4.0878
Total urban population within 25 miles	180	170	240	250	360	380
Distance to highway ramp	5.2248	4.8466	4.9368	4.9961	5.5642	5.7215
Distance to nearest city	58.1130	57.0820	45.4070	45.3350	37.2370	38.1520
Distance to nearest grain elevator	7.1353	6.6065			11.9440	12.4930
Distance to nearest agricultural terminal	51.0620	50.2520	51.7580	52.2410		
Distance to nearest ethanol plant			35.5920	35.0580	46.3060	45.8730
Forest area % of parcel	0.0483	0.0490	0.0763	0.0753	0.1051	0.1067
Wetland area % of parcel	0.0023	0.0020	0.0040	0.0035	0.0028	0.0026
Ohio Job Network Region - Cleveland	0.0015	0.0027	0.0590	0.0578		
Ohio Job Network Region - Toledo	0.1150	0.1093	0.4167	0.4019	0.4075	0.3399
Ohio Job Network Region - Columbus	0.3528	0.3677	0.2635	0.2478	0.3181	0.3329
Ohio Job Network Region - Dayton	0.5307	0.5203	0.2384	0.2731	0.2484	0.2973
Observation	652	1119	2983	4425	1096	2263
	1771		7408		3359	

Treatment group for proximity to ethanol plants are defined as parcels with distances to nearest ethanol plant between 5 and 13 km. For grain elevators and agricultural terminals the corresponding cutoff distances for being part of the treatment group are 7km and 22km.

the full sample. The optimal cut-off distances used to construct the treatment group for matching on proximity to ethanol plants, grain elevators, and agricultural terminals are 13km, 7km and 22km, respectively. These cut-off distances yielded 1771, 7408 and 3359 matched samples correspondingly. From table 4, we can see that after the second step PSM matching on the trimmed sample described above, the systematic differences of the covariates between parcels close to agricultural delivery points and those farther away were successfully removed, at the cost of reduced sample sizes.

For each of the three matched samples, we estimate a difference-in-difference (DID) model using the specification illustrated by equation (6). Table 5 shows the results for these three DID regressions. For the DID regression for the matched sample based on proximity to ethanol plant, the coefficient on the dummy variable γ_i indicating within a certain distance of the ethanol plant was not significant, suggesting that, after controlling for all the systematic differences of other location characteristics, there was no declining agricultural sales price gradient over the distance to nearest ethanol plant. This is likely due to the fact that the ethanol plants only started in 2008 and suggests that expectations in advance of these openings did not have a significant effect on farmland values. However, the positive and significant coefficient on the interaction term $\gamma_i * \gamma_t$ confirmed a positive structural change in the effects of ethanol plants in determining

Table 5: DID Regression on matched samples

Covariates	Ethanol	Plant	Grain	Elevator	Agricultural	Terminal
	Coef	Std Err	Coef	Std Err	Coef	Std Err
γ_i : Dummy_Close to certain ag delivery point	-0.0314	0.0383	0.0606***	0.0188	0.1070***	0.0304
γ_t : Dummy_Sold after 2007	0.1698***	0.0639	0.1649***	0.0348	0.1810***	0.0527
DID = γ_i*γ_t	0.1177**	0.0582	0.0210	0.0308	-0.0694	0.0515
Total acres	-0.0063***	0.0005	-0.0057***	0.0002	-0.0071***	0.0004
Total acres squared	0.00001***	0.0000	0.00001***	0.0000	0.00001***	0.0000
National Commodity Crops Productivity Index	0.00003***	0.0000	0.00002***	0.0000	0.00004***	0.0000
Soil class 1 area % of parcel	-0.0192	0.0597	0.0161	0.0296	0.0562	0.0421
Representative slope	-0.0001	0.0032	-0.0034***	0.0012	-0.0011	0.0017
Total urban population within 25 miles	-0.0001	0.0002	0.0001***	0.0001	0.0003***	0.0001
Distance to highway ramp	-0.0031	0.0041	-0.0028	0.0022	-0.0053*	0.0032
Distance to nearest city	-0.0043***	0.0013	-0.0036***	0.0005	-0.0045***	0.0007
Distance to nearest grain elevator	-0.0078**	0.0031			-0.0020	0.0017
Distance to nearest agricultural terminal	-0.0019**	0.0009	-0.0027***	0.0004		
Distance to nearest ethanol plant			0.0007	0.0004	0.0011	0.0007
Forest area % of parcel	-0.1704*	0.0999	-0.0191	0.0430	-0.0038	0.0634
Wetland area % of parcel	-0.2098	0.4385	-0.0529	0.2539	-0.2853	0.4123
Ohio Job Network Region - Cleveland	0.1440***	0.2063	-0.0299	0.0513		
Ohio Job Network Region - Toledo	-0.1664***	0.0432	-0.1158***	0.0433	-0.0191	0.0862
Ohio Job Network Region - Columbus			-0.0444	0.0419	-0.1055	0.0767
Ohio Job Network Region - Dayton	-0.1749***	0.0363	-0.1244***	0.0430	-0.1455	0.0827
Year 2001			0.0090	0.0320		
Year 2002	-0.0693	0.0620			0.0288	0.0497
Year 2003	-0.0343	0.0612	-0.0055	0.0311	0.0105	0.0482
Year 2004	0.0606	0.0608	0.0877***	0.0313	0.0657	0.0475
Year 2005	0.0751	0.0652	0.0974***	0.0319	0.0582	0.0480
Year 2006	0.0946	0.0592	0.1308***	0.0314	0.1333***	0.0486
Year 2008	-0.0753	0.0523	-0.0173	0.0292	-0.0160	0.0455
Year 2009	-0.1077*	0.0574	-0.0436	0.0319	-0.0705	0.0509
Intercept	8.6052***	0.1116	8.4050***	0.0708	8.2342***	0.1189
Adjusted R^2	0.1423		0.1394		0.1760	
Number of Observations	1771		7408		3359	

* significant at 10% level; ** significant at 5% level; *** significant at 1% level.

surrounding farmland values after 2007. Put it differently, the DID estimator revealed that being close to an ethanol plant was valued more comparatively after 2007. The coefficient on the DID estimator can be interpreted as the marginal value of being located close to (between 5 and 13 kilometers) to an ethanol plant after 2007. Numerically, this structural change on average would increase the log of real farmland sale price from 8.1169 to 8.2346 (8.1169+0.1177), which translated into a $419 increase in agricultural land sale prices. The coefficients on the dummies of proximity to grain elevators and agricultural terminals were both positive and significant, supporting our hypothesis that grain elevators and agricultural terminals can both cast a positive influence on surrounding agricultural land sale prices. The DID estimators for these two, however, were not significant. Nonetheless, The DID estimators both carried the expected signs. The positive (yet insignificant) DID estimator for grain elevators showed that the positive benefits of being close to a grain elevator for agricultural land prices may have increased after 2007. This increase can at least be attributed to the greater demand for corns induced by the rise of ethanol industry and the constructions of new ethanol plants. Other factors that may also play a role included higher transportation costs due to rising gasoline prices and greater export demands from China. However, these economy-wide factors were at least to some extent absorbed in the year trend dummies. On the contrary, the negative (yet insignificant) DID estimator for agricultural terminals provided evidence for our hypothesis that the competition of grains from newly constructed ethanol plants would offset the positive trend due to greater exports to China, and these factors combined would lead to a decreasing influence of agricultural terminals in shaping farmland values. This decline was picked up by this negative DID estimator. This is consistent with the Wald test for the interaction terms in the hedonic estimation shown in table 2. The coefficient on the dummy variable γ_t indicating the concurrent timing of the housing market bust and openings of all seven ethanol plants were positive and significant across the three regressions. This coefficient picked up all the macroeconomic factors influencing the agricultural land sale prices between 2008 and 2010, out of which the increased demand for grain imports from China and the national trend in biofuels industry were the most important two ones. Other variables in the DID regressions are analogous to those in the standard hedonic results shown in table 2, and hence the discussion of them were omitted. Combining the results from the three DID regressions, we found some evidence supporting the hypothesis that after 2007, the influences of the agricultural market forces such as proximity to ethanol plants and grain elevators have seen a positive structural change. Being close to an ethanol plant would be valued more in determining agricultural land sale prices after 2007. In comparison, we find that the marginal value of being within close proximity of a grain elevator or agricultural terminal was positive throughout the decade and did not significantly change after 2007.

To further illustrate the benefits resulting from the propensity score matching, we ran the same DID

Table 6: Comparison of the structural change between regression on matched samples and regression on sample without matching

Model	Variable	Ethanol Coef	Plant Std Err	Grain Coef	Elevator Std Err	Agricultural Coef	Terminal Std Err
Panel I:	γ_i : Dummy_Proximity	-0.0314	0.0383	0.0606***	0.0188	0.1070***	0.0304
Matched	γ_t :Dummy_Bust	0.1698***	0.0639	0.1649***	0.0348	0.1810***	0.0527
Sample	DID = γ_i * γ_t	0.1177**	0.0582	0.0210	0.0308	-0.0694	0.0515
Number of Observations		1771		7408		3359	
Panel II:	γ_i : Dummy_Proximity	0.0406	0.0300	0.0430***	0.0150	-0.0116	0.0257
Original	γ_t :Dummy_Bust	0.0724***	0.0262	0.0575**	0.0275	0.0909***	0.0264
Sample	DID = γ_i * γ_t	0.0918*	0.0471	0.0726***	0.0275	-0.0947**	0.0429
Number of Observations		13865		13865		13865	

* significant at 10% level; ** significant at 5% level; *** significant at 1% level.

regressions on the whole unmatched samples as if they were matched, with the cut-off distance a certain type of agricultural delivery points same as that defined in table 5. Besides the replicated results from table 5 in table 6 panel I, table 6 panel II showed the DID results for the whole sample. Comparison of panel I and panel II revealed that without controlling for the systematic differences between parcels nearer to the agricultural delivery points and those farther away before and after 2007, the DID regression on the unmatched original samples would lead to inaccurate (inflated in this case) inference about the potential structural change in the influences of proximity to agricultural delivery points in determining farmland values after 2007. This, in return, further validates the necessity and benefits of matching. With that said, our estimator is subject to less bias than the standard hedonic estimates, because it controls for the systematic differences between parcels nearer versus farther away from an agricultural delivery point by matching and for the time-invariant unobserved heterogeneity using DID regression.

7 Conclusion

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). Parcel-level data on agricultural land sales since 2001 from Ohio reveals that, although the number of agricultural land sales dropped precipitously after the housing market bust in 2007, there was no corresponding dip in the average sales price of agricultural land compared to its residential counterpart. To our knowledge, our study is the first in identifying the potential structural change of the effects of the agricultural market forces in shaping agricultural land prices during a period that witnessed both the housing market bust and a concurrent expansion of the ethanol market. This also serves as the first formal attempt to test the general belief that the rise of ethanol industry has helped the farm sector withstand the downturn (Nickerson et al, 2012). By controlling for distributional differences using propensity score matching and for time-invariant heterogeneity using difference-in-difference regressions, our estimator is subject to less bias than the standard hedonic estimates.

Our main result provides evidence that the marginal value of being within close proximity to an ethanol plant was not significant in the earlier part of the 2000 decade (from 2001 to 2006), but became significant after 2007. Specifically, results from the DID estimation with the matched sample suggest that the marginal value of being located close to (between 5 and 13 kilometers) an ethanol plant was $419 per acre after 2007 and not significantly different from zero before this. In comparison, we find that the marginal value of being within close proximity of a grain elevator or agricultural terminal was positive throughout the 2000 decade and did not significantly change after 2007. We also find that, regardless of relative location, the value of agricultural land parcels increased in the later part of the 2000 decade (2008-2010) relative to the earlier in the decade (2001-2006). We conclude that agricultural land values rose significantly from 2001-2010 in our Ohio study region and that these effects are spatially differentiated due to transportation costs to agricultural delivery points. Our results demonstrate the growing importance of the biofuels market for farmland values and show that proximity to ethanol plants has recently become a significant determinant of agricultural land values.

Ohio, one of most impacted states in the recent economic crisis and an agriculturally important Corn Belt state with three big cities, provides an ideal laboratory to study the structural change in the proximity to agricultural delivery points on farmland values. Our parcel-level analysis not only re-highlights the needs of disaggregated data analysis, but also illustrates the necessity of addressing potential selection bias. In the context of current heated debate about whether there are bubbles in agricultural land markets, our study of competing determinants of agricultural land prices can provide a timely contribution in evaluating the economic fundamentals of the farmland values.

References

Bajari, P., J.C. Fruehwirth, K.I. 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*, forthcoming.

Bastian, C.T., D.M. McLeod, M.J. Germino, W.A. Reiners and B.J. Blasko. 2002. "Environmental Amenities and Agricultural Land Values: A Hedonic Model Using Geographic Information Systems Data," *Ecological Economics*, 40, 337-349

Bento, A., C. Towe and J.Geoghegan. 2007. "The Effects of Moratoria on Residential Development: Evidence from a Matching Approach," *American Journal of Agricultural Economics*, 89, 1211-1218.

Bishop, K.C. and C. Timmins. 2011. "Hedonic Prices and Implicit Markets:Estimating Marginal Willingness to Pay for Differentiated Products Without Instrumental Variables," Working paper, Duke University.

Blank, S.C. 2007. "Farmland Values as an Indicator of Regional Economic Performance?" Agricultural and Resource Economics Update, University of California. Available online: http://giannini.ucop.edu/media/are-update/files/articles/v10n6_1.pdf

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(2), 223-232.

Busso, M., J. Gregory and P.M. Kline. 2010. "Assessing the Incidence and Efficiency of a Prominent Place Based Policy," NBER Working Paper No. 16096.

Capozza, D.R. and R.W. Helsley. 1989. "The Fundamentals of Land Prices and Urban Growth" *Journal of Urban Economics*, 26(3), 295-306.

Cavailhés, J. and P. Wavresky. 2003. "Urban Influences on Periurban Farmland Prices," *European Review of Agricultural Economics*, 30, 333-357.

Crump, R., J. Hotz, G. Imbens and O. Mitnik. 2009. " Dealing with Limited Overlap in Estimation of Average Treatment Effects," *Biometrika* 96(1), 187-199.

De Vor, F. and H.L.F. de Groot. 2009. "Impact of Industrial Sites on Residential Property Value: A Hedonic Pricing Analysis for the Netherlands," A Tinbergen Institute Discussion Paper.

Diamond, A. and J.S. Sekhon. 2012. "Genetic Matching for Estimating Causal Effects: A General Multivariate Matching Method for Achieving Balance in Observational Studies," Working Paper, available at: http://sekhon.berkeley.edu/papers/GenMatch.pdf.

Dobos, R.R., H.R. Sinclair, Jr. and K.W. Hipple. 2008. "User Guide National Commodity Crop Productivity Index (NCCPI) Version 1.0," available at: ftp://ftp-fc.sc.egov.usda.gov/NSSC/NCCPI/NCCPI_user_guide.pdf

Economist. 2008. "A Helping Hand to Homeowners," Available at: http://www.economist.com/node/12470547?story_id=12470547

Farm Net Services, Farm Equipment and Agriculture Business Directory. 2012. "Ohio Grain Elevators," available at: http://www.farmnetservices.com/farm/Grain_Elevators/OHIO_GRAIN_ELEVATORS/660.html

Gallagher, P.W. 2006, "Energy production with biomass: what are the prospects?", *Choices: The Magazine of Food, Farm, and Resource Issues*, 21(1), 21-25.

Gloy, B.A., C. Hurt, M.D. Boehlje, and C. Dobbins. 2011. "Farmland Values: Current and Future Prospects," Center for Commercial Agriculture Staff Paper. Department of Agricultural Economics Purdue University. West Lafayette, IN.

Greenstone, M. and J. Gallagher. 2008. "Does Hazardous Waste Matter? Evidence from the Housing Market and the Superfund Program." *The Quarterly Journal of Economics*, 123(3), 951-1003.

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

Hardie, I., T. Narayan and B. Gardner. 2001. "The Joint Influence of Agricultural and Nonfarm Factors on Real Estate Values: An Application to the Mid-Atlantic Region," *American Journal of Agricultural Economics*, 83(1), 120C132.

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

Henderson, J. and S. Moore. 2006. "The capitalization of wildlife recreation income on farmland values," *Journal of Agricultural and Applied Economics*, 38(3), 597-610.

Hite, D., W. Chern, F. Hitzhusen and A. Randall. 2001. "Property-value Impacts of an Environmental Disamenity: The Case of Landfills," *Journal of Real Estate Finance and Economics*, 23, 185-202.

Huang, H., G.Y. Miller, B.J. Sherrick and M.I. Gomez. 2006. "Factors Influencing Illinois Farmland Values," *American Journal of Agricultural Economics*, 88(2), 458-470.

Imbens, G. and T. Lemieux. 2010. "Regression Discontinuity Designs: A Guide to Practice," *Journal of Economic Literature*, 48, 281-355.

Kaza, N. and T. BenDor. 2011. "Land Value Impacts of Aquatic Ecosystem Restoration," Working paper, Univerisity of North Carolina at Chapel Hill, available at: http://www.unc.edu/k̃aza/documents/eep_acsp.pdf

Kohlhase, J.E. 1991. "The Impact of Toxic Waste Sites on Housing Values." *Journal of Urban Economics*, 30, 1-26.

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(1), 117C135.

Lincoln Institute of Land Policy, 2012. "Land and Property Values in the U.S.," available at: http://www.lincolninst.edu/subcenters/land-values/metro-area-land-prices.asp

Livanis, G., C. Moss, V. Breneman, and R.Nehring.2006. "Urban Sprawl and Farmland Prices," *American Journal of Agricultural Economics*, 88, 915-29.

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.

Lynch, L., W. Gray and J. Geoghegan. 2007. "Are Farmland Preservation Program Easement Restrictions Capitalized into Farmland Prices? What Can a Propensity Score Matching Analysis Tell Us?" *Review of Agricultural Economics*, 29, 502-509.

Ma, S. and S.M. Swinton. 2011. "Valuation of Ecosystem Services from Rural Landscapes Using Agricultural Land Prices," *Ecological Economics*, 70(9), 1649-1659.

McMillen, D.P. and J. McDonald. 2004. "Reaction of House Prices to a New Rapid Transit Line: Chicago's Midway Line, 1983-1999," *Real Estate Economics*, 32(3), 463-486.

McNew, K. and D. Griffith. 2005. "Measuring the Impact of Ethanol Plants on Local Grain Prices" *Review of Agricultural Economics*, 27(2), 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 U.S. Farmland Values and Ownership," EIB-92. U.S. Dept. of Agriculture, Economic Research Service.

Ohio Dept. of Agriculture, Grain Warehouse Program. 2012. "Ohio Licensed Commodity Handlers," available at: http://www.agri.ohio.gov/divs/plant/grain/plnt-gs-GrainHandlers.pdf

Ohio Dept. of Development, JobsOhio Network. 2012. available at: http://ohiolmi.com/maps/MapJobsOhioNetwork.pdf

Ohio Dept. of Transportation, ESRI/Statewide Digital Data (Environmental Systems Research Institute Data). 2012. "Active Rails, Airports, Cities and Townships," available at: http://www.dot.state.oh.us/Divisions/Planning/TechServ/prod_services/Pages/ESRIDwnLds.aspx

Ohio Ethanol Council. 2012. "Ohio Ethanol Industry Quick Facts," available at: http://ohethanol.com/ohio_ethanol

Palmquist, R. and L.E. Danielson. 1989. "A Hedonic Study of the Effects of Erosion Control and Drainage on Farmland Values," *American Journal of Agricultural Economics*, 71(1), 55-62.

Palmquist, R.B. 2005. "Property Value Models," In *The Handbook of Environmental Economics*, Vol. 2, ed. K. Goran-Maler and J. R. Vincent. Elsevier.

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.

Pope, C.A. III. 1985. "Agricultural Productive and Consumptive Use Components of Rural Land Values in Texas,"*American Journal of Agricultural Economics*, 67(1), 81-86.

Rosen, S. 1974. "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition," *Journal of Political Economy*, 82(1), 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, 41C55.

Shi, Y., T. Phipps, and D. Colyer. 1997. "Agricultural Land Values Under Urbanizing Influences," *Land Economics*, 73, 90-100.

Sekhon, J.S. 2011. "Multivariate and Propensity Score Matching Software with Automated Balance Optimization: The Matching Package for **R**," *Journal of Statistical Software*, 42(7), 1-52.

Schnnitkey, G.D. and B.J. Sherrick. 2010. "Income and Capitalization Rate Risk in Agricultural Real Estate Markets," *Choices: The Magazine of Food, Farm, and Resource Issues*, 26(2).

Shane, M., W. Liefert, M. Morehart, M. Peters, J. Dillard, D. Torgerson and W. Edmondson. 2009. "The 2008/2009 World Economic Crisis: What It Means for U.S. Agriculture," WRS-09-02, U.S. Dept. of Agriculture, Economic Research Service.

Towe, C., H.A. Klaiber, D. Wrenn, D. Newburn and E.G. Irwin. 2011. "Exploiting Spatial and Temporal Variations in Residential Subdivision Development to Identify Urban Growth Spillovers," Selected paper presented at AAEA & NAREA Joint Annual Meeting, Pittsburgh, PA, July 24 26, 2011.

U.S. Census TIGER/Line. 2012. "Census Block Shapefiles with 2010 Census Population and Housing Unit Counts," available at: http://www.census.gov/geo/www/tiger/tgrshp2010/pophu.html

U.S. Dept. of Agriculture, Natural Resources Conservation Service. 2012. "GeoSpatial Data Gateway," available at: http://datagateway.nrcs.usda.gov/GDGHome.aspx

U.S. Department of Energy, Energy Information Administration. 2011. "Monthly Energy Review: Table 10.3 Fuel Ethanol Overview," Avaialble at: http://205.254.135.7/totalenergy/data/monthly/pdf/sec10_7.pdf.

Valero Plant Overview. 2012. "Valero Renewables-Bloomingburg Plant Overview," available at: http://www.valero.com/OurBusiness/OurLocations/Plants/Pages/Bloomingburg.aspx

Wallander, S., R. Claassen, and C.J. Nickerson. 2011. "The Ethanol Decade: An Expansion of U.S. Corn Production, 2000-09," EIB-79, U.S. Dept. of Agriculture, Economic Research Service.

Ward, B. 2011. "Western Ohio Cropland Values and Cash Rents 2010 - 11," The Ohio State University Extension, Fact Sheet, Agricultural and Natural Resources. available at: http://ohioline.osu.edu/ae-fact/pdf/11-AED-911.pdf

World Agricultural Outlook Board. 2012. "World Agricultural Supply and Demand Estimates (WASDE-503) Table 12," U.S. Dept. of Agriculture, avaialble at: http://usda01.library.cornell.edu/usda/current/wasde/wasde-02-09-2012.pdf