Does the Minimum Lot Size Program Affect Farmland Values? Empirical Evidence Using Administrative Data and Regression Discontinuity Design in Taiwan

Hung-Hao Chang and Tzu-Chin Lin

This study empirically assesses the causal effect of the minimum lot size program on farmland values in Taiwan. A unique dataset of 4,032 parcels of farmland drawn from administrative foreclosure auction profiles between 2000 and 2008 and regression discontinuity design were applied to cope with the endogeneity issue of land use regulations. The results of the parametric and nonparametric estimations indicate that the minimum lot size program significantly increases farmland value by approximately 18% and 15%, respectively. Moreover, the program effect is more pronounced for farmland located in urban/suburban areas. In the absence of a tax effect and externality resulting from non-agricultural activities, the significant program effect on farmland values is likely to result from the effect of the program on farmland's option value for future development.

Key words: Minimum lot size program, farmland values, foreclosure auction data, regression discontinuity design, Taiwan.

JEL codes: Q15, R52.

Agricultural zoning is commonly employed to support farming, reduce urban sprawl, and protect the environment. Under such schemes, no intensive development can be allowed on land within agricultural zones. However, exceptions can be found for land that is used for family farm residences, or for structure facilities or easements for farm operation purposes. Zoning affects land price through its influence on the allocation of land parcels for alternative land uses (Fischel 1987). Various zoning regulations alter parcel attributes in different ways, thus resulting in different impacts on land value.[1] Based on economic theory, Henneberry and Barrows (1990) proposed four possible price effects associated with agricultural zoning: externality, neighborhood certainty, tax, and development. Agricultural zoning that prohibits nearby land use detrimental to farming, ensures that future land use patterns will remain compatible with farm operation, and confers preferential tax treatment can raise land value. In contrast, agricultural zoning that restricts farmland development rights, which generate a positive price effect, may decrease land value. The conflicting positive and negative effects will determine the net price capitalization of agricultural zoning.

A sizable amount of empirical evidence has documented the price effects of zoning regulations on farmland or undeveloped land. A positive price effect of zoning regulations on farmland has been documented in some studies; for instance, in the United

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[1] Grieson and White (1981) categorized various zoning methods into three broad types in terms of their restrictions: allowable use restriction, density restriction, and minimum land input requirement.

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States, Knaap (1985) presented evidence that land parcels inside Urban Growth Boundaries of Metropolitan Portland have higher values than land outside the boundaries. Moreover, the author found that only the parcels inside the boundaries were permitted development within a certain time horizon, and that this was primarily responsible for the observed price differences. Henneberry and Barrows (1990) found that zoning had a positive capitalization effect with regard to the value of parcels that were large and removed from urban areas, where little development potential was present.

On the other hand, some studies have documented a negative price capitalization of zoning regulations on farmland. For instance, Deaton and Vyn (2010) found that farmland close to the Greater Toronto Area Greenbelt experienced a significant decline in their values. Liu and Lynch (2011a) studied the Eastern Shore area of Maryland, where six of the nine studied counties reduced permitted housing density per acre in the 1990s or early 2000s. The authors found that the value of resource land (agricultural and forestry) was unaffected. However, the value of non-resource land dropped by 20–50%. The eventual price effect was suggested to be the aggregated effects of limiting non-farming activities, creating environmental amenities and promoting demand for estate homes on large lots. Further, Eagle et al. (2015) presented evidence concerning the long-term price effects that Canada's Agricultural Land Reserve (ALR) program had in Victoria, British Columbia. Twenty-six years after its imposition, the ALR residential farmland was worth 19% less than similar non-ALR farmland.

In an urban context, minimum lot size restriction is often justified as preventing residential density from rising too high, thereby reducing negative externalities such as noise, intrusion, etc. (e.g., Zabel and Dalton 2011). In the context of agriculture, a minimum lot size restriction is sometimes imposed to sustain agricultural zones. Minimum lot size restrictions impose a floor under the land input with regard to the production function, in combination with a constraint on use (White 1988). The payment for a parcel with the threshold size is analogous to the admission-fee element of a two-part tariff (Grieson and White 1981). A binding restriction of minimum lot size will prohibit houses to be built on small sites, which consequently reduces the prices of small size houses (Isakson 2004). In contrast, sites larger than the minimum size requirement enjoy the value of option. From this perspective, the value of an undeveloped parcel with development potential, such as the construction of farm easements on the land, is the sum of the value of an undeveloped parcel without development potential, plus the value of the development option (Geltner et al. 2007). In consequence, if the restriction of minimum lot size is binding, a price gap can be expected between groups of sites smaller and larger than the size requirement.

The objective of this paper is to investigate the impacts of the minimum lot size (MLS) program on farmland value using a case study in Taiwan as an illustration. The MLS program was implemented in Taiwan in 2000. Under the program, a farmhouse is only allowed to be erected on farmland equal to, or greater than, 0.25 hectares. Using an administrative profile of land foreclosure auctions of 4,032 parcels of farmland from 2000 to 2008, the Regression Discontinuity (RD) design was applied, and the farmland equations were estimated using the parametric and nonparametric estimation methods. The results indicated that the MLS program significantly increased farmland values by approximately 18% and 15% as predicted by the parametric and nonparametric models, respectively. Moreover, the effect is more pronounced for farmland located in the urban/suburban areas.

This article contributes to the existing literature on agricultural zoning in several aspects. First, this article focuses on parcels of farmland located within the agricultural zone. In Taiwan, all farmland should be located in agricultural zones and activities or constructions for non-agricultural purposes on land within agricultural zones are not allowed. As a result, the impacts of externalities generated from nonfarm activities, which are sometimes difficult to measure, do not need to be considered. In addition, all of the farmland in Taiwan has been exempt from property tax since 1987; thus, the tax effect on farmland price is absent. The exclusion of externalities and the absence of tax effects allowed us to concentrate on the extent to which the MLS program may affect farmland prices through its effect on the option value for future development on the land. Second, a national administrative land auction data set is used in this article. The data are transparent and reliable, as warranted by the courts. Using a large-scale administrative profile helps to ease the problem of potential measurement errors. Third, land use controls were commonly administered for specific geographic areas in most countries, and special research attention was usually paid to the price effects only within the areas that were affected by the programs. In contrast, the MLS program in Taiwan is a uniform agricultural zoning program implemented across the entire country, which allows us to examine the extent to which the MLS program may have different impacts among regions of various levels of economic development.

This article also contributes to existing studies that address the endogeneity problem of land use regulations. Previous studies have applied the Propensity Score Matching (PSM) method to control for the endogeneity bias (e.g., McMillen and McDonald 2002; Lynch, Gray, and Geoghegan 2007; Liu and Lynch 2011a, 2011b). This article adopts an alternative approach, the Regression Discontinuity (RD) design, to address the endogeneity issue. The RD design can be applied to a case when a dichotomous treatment depends on an observed continuous score. In contrast to other methods, the attractiveness of the RD design rests on its similarity to a formal randomized experiment, and the identification assumption is relatively weak (Lee and Lemieux 2010). To the best of our knowledge, the RD design has hitherto not been a popular approach in studies on land use regulations. The only exception is Grout, Jaeger, and Plantinga (2011), who examined the effect of the Portland, Oregon, Urban Growth Boundary (UGB) on property values. In that article, whether each plot of land is located inside or outside the UGB is determined by a score based on land characteristics, which are not directly observed by the researchers. By assuming that the UGB delineates a contiguous area, the authors used the distance of each parcel to the UGB as a proxy to measure the closeness to the boundary. In contrast to Grout, Jaeger, and Plantinga (2011), this article is a more straightforward application of the RD design since the eligibility rule of the MLS program in Taiwan depends on the observed land size.

Background on the Minimum Lot Size Program for Farmland in Taiwan

Until 2000, owners of farmland needed to be eligible farmers. Upon request, the local government would issue a “certificate of eligible farmer” subject to the farmer satisfying the following criteria. An eligible farmer needed to be at least 16 years old, without full-time nonfarm occupation, and without all of the farmland having been leased out. This strict regulation on farmland use was criticized as having caused a lack of economic competitiveness. Because of the occupational restrictions on purchasing farmland, any flow of large-scale capital investment into farming was difficult. It has been shown that the small scale of farm size in Taiwan is responsible for farm production inefficiency (Chiu 2003).

The Agricultural Development Act, the most important protocol for agricultural development in Taiwan, was revised in 2000, primarily in response to their entrance into the World Trade Organization, but also to enable farms to enjoy economies of scale. Two significant changes were made in this policy reform. First, the requirements for qualifying as an eligible farmer to purchase farmland were removed. Second, landowners who acquired agricultural land after January 1, 2000 and did not possess a farmhouse could apply to construct one, but subject to approval from the local city or county authorities. According to this policy reform, owners of agricultural land who satisfied the following requirements were allowed to construct a farmhouse on their land: 1) the owner is over 20 years of age; 2) the owner’s address is in the same city/county where the farmland is located; 3) the land is employed for farming; 4) the agricultural land on which farmhouses are constructed must be over 0.25 hectares in size. The primary reason for the government to impose the 0.25 hectares minimum for a farmhouse site was to protect the production environment, in that the 0.25 hectares is considered the minimum size acceptable for the convenient implementation of machinery and irrigation (Council of Agriculture 2008).

Data

Our dataset is unique in that it integrates the foreclosure land auction data drawn from the national administrative profile, as well as additional information on farming activity and the geographic characteristics at the county level. The following sections introduce the nature of each data source.

Administrative Foreclosure Farmland Auction Profile

The primary dataset is the foreclosure land auction profile. Due to the lack of transparent and reliable market information of farmland sales in the private land market in Taiwan, the foreclosure land auction market is an important source of information on farmland transactions. For readers who may not be familiar with the foreclosure land market in Taiwan, a brief background of the procedures followed in foreclosure auctions is provided. Foreclosure auctions occur primarily as the result of defaults of mortgage contracts. The foreclosure sales managed by local courts are carried out through sealed-bid auctions. The local courts make the date of the auctions and details of individual properties public beforehand, and announce the minimum bid requirements. This minimum bid is normally determined by a professional real estate appraiser to reflect fair market value. Interested buyers are required to submit their bids in sealed envelopes on the prescribed auction date. All bids are revealed to the public at the auction room, and each auction property is sold to the highest bidder. If the foreclosed property is not sold in the first round, it will be put up in further auction rounds at a price discount. The entire auction procedure is overseen by the courts. After a parcel of land is sold through court auction, there is no difference from any other land in the market in all respects; Asabere and Huffman (1992) confirmed this by showing that the price determinants of urban land using the foreclosure auction data are similar to those found in normal market sale data. Carroll, Clauretie, and Neill (1997) also found no price difference between residential properties sold through the foreclosure procedure and others in the private sales market in Las Vegas Valley.

The administrative foreclosure land auction profile in Taiwan was used herein; it collected all of the information for each foreclosed land transaction from 2000 to 2008. For each parcel of land sold in the foreclosure auction market, its geographic location, size and category for use (i.e., agriculture, construction, etc.), auction year, and bidding round of sale is documented. For research purposes, our sample was limited to parcels of farmland within the agricultural zone. Farmlands with existing farmhouses were further excluded because the data set lacks sufficient information to estimate the building value. Furthermore, we limited our sample to farmland smaller than 0.5 hectares for the following reason. In addition to the MLS program, another program related to farmland use, the so-called Special Loans to the Young and Beginning Farmers (SLYBF), was implemented in Taiwan in 1982. The purpose of the SLYBF program is to encourage young and beginning farmers to engage in farm production. Young and beginning farmers aged between 18 and 45 are eligible to apply to the SLYBF, and successful applicants can enjoy a low loan rate (1.5%) subsidized by the government on their first-time purchase of farmland larger than 0.5 hectares slated for farm production.[2] Since we had no information on the buyers in the auction profile, we could not identify the beneficiaries of the SLYBF program in our dataset. Given that the purpose of this study concerns the MLS program, we excluded plots of farmland larger than 0.5 hectares to rule out the potential effect of the SLYBF on farmland values. After deleting a few observations with missing values, the final sample consisted of 4,032 parcels of farmland with successful transaction records.[3] In total, 294 counties were included in the full sample, of which, 166 and 128 were located in urban/suburban and rural areas, respectively.[4]

Aggregated Geographic and Farm Characteristics Data

Although the administrative auction profile provided an objective measure of farmland values, it lacked detailed information on farming activities and geographic conditions for the areas where each parcel of land was located. According to the hedonic

[2] Detailed information on the SLYBF program can be found on the website of the Council of Agriculture in Taiwan, available at: https://talis.coa.gov.tw/ALRIS/LawDetail.asp?tID=2001.

[3] In total, 4,349 parcels of farmland were identified in the data set, of which, 317 of them (approximately 7%) were greater than 0.5 hectares. In the empirical analysis, we included farmland whose size is smaller or equal to 0.5 hectares only.

[4] The definition of rural and urban/suburban areas follows the categorization of Chang and Fu (2006); these authors applied a continuum score (similar to the Beale code used in the United States) to categorize Taiwan's entire 358 counties into seven subgroups of different economic development based on population density, the degree of industrialization, public facilities, geographic characteristics, etc. The authors further simplified the seven subgroups of counties into a binary classification for rural and urban/suburban area. Chang and Fu's approach has been a protocol of rural-urban classification used in official yearbooks published by the Council of Agriculture.

Table 1. Sample Statistics of the Selected Variables (Full Sample)

Variable	Definition	All (N = 4,032) Mean	All S.D.	If land area >= 0.25 (N = 1,166) Mean	S.D.	If land area <0.25 (N = 2,866) Mean	S.D.
Individual parcel farmland data							
Value	Value of each parcel of farmland (NT$10,000)	249	627	432	1,017	174	337
Land area	Farmland area (hectare)	0.18	0.14	0.37	0.07	0.11	0.07
Price	Farmland price per hectare (NT$10,000/hectare)	2123	3044	1205	2903	2497	3222
Auction 1	If sold in the first round auction (=1).	0.22	0.41	0.20	0.40	0.23	0.42
Auction 2	If sold in the second round auction (=1).	0.16	0.37	0.16	0.37	0.16	0.37
Auction 3	If sold in the third round auction (=1).	0.30	0.46	0.31	0.46	0.30	0.46
Auction 4	If sold in the fourth round or above (=1).	0.32	0.47	0.33	0.47	0.32	0.46
Year 2000	If year 2000 (=1).	0.08	0.27	0.08	0.26	0.08	0.27
Year 2001	If year 2001 (=1).	0.10	0.30	0.09	0.29	0.11	0.31
Year 2002	If year 2002 (=1).	0.22	0.41	0.19	0.40	0.23	0.42
Year 2003	If year 2003 (=1).	0.16	0.37	0.19	0.39	0.15	0.36
Year 2004	If year 2004 (=1).	0.16	0.37	0.18	0.38	0.15	0.36
Year 2005	If year 2005 (=1).	0.09	0.28	0.09	0.29	0.08	0.28
Year 2006	If year 2006 (=1).	0.07	0.26	0.07	0.25	0.08	0.27
Year 2007	If year 2007 (=1).	0.07	0.25	0.06	0.24	0.07	0.25
Year 2008	If year 2008 (=1).	0.05	0.22	0.05	0.22	0.05	0.22
Aggregated data at county level							
Slope	Average land slope (o^c).	5.46	8.55	6.19	9.10	5.16	8.30
Productivity	Average land productivity.	1.14	1.64	1.25	1.67	1.09	1.62
Landslides	Average size of landslide area (hectare).	269	723	357	864	233	654
Farm groups	Number of farmers' marketing groups.	16.92	19.15	16.86	17.33	16.95	19.84
Boundary	Area of the county (hectare)	6,364	5,912	7,061	7,268	6,081	5,236
R_farms	Share of farm households to total households (%).	17.68	15.16	19.05	15.37	17.12	15.04
R_full-time farms	Share of full-time farms to total number of farms (%).	19.02	8.71	19.05	8.64	19.01	8.73
R_rice farms	Share of rice farms to total number of farms (%).	44.51	29.23	44.21	29.83	44.63	28.99
R_fruit & veg farms	Share of fruit and vegetable farms to total number of farms (%).	39.65	27.95	40.06	28.59	39.49	27.68
R_other crop farms	Share of other crop farms to total number of farms (%).	14.31	12.17	14.05	12.35	14.41	12.10
R_livestock farms	Share of livestock farms to total number of farms (%).	1.53	1.44	1.68	1.51	1.48	1.41

price theory and empirical evidence drawn from previous studies on the determinants of farmland value (e.g., Lynch, Gray, and Geoghegan 2007; Deaton and Vyn 2010), farmland value is associated with the geographic and farming characteristics in the local area. Several variables that reflect geographic heterogeneity at the county level were specified, and they were included as explanatory variables in the parametric regression model. These variables were constructed by matching the natural environmental maps provided by the Construction and Planning Agency, and the counties' geographic locations using a Geographic Information System (GIS) technique. The

Table 2. Sample Statistics of the Selected Variables (Separate for Urban/suburban and Rural Area)

		Urban/suburban Area						Rural Area					
		All (N = 2,818)		If land >= 0.25 (N = 782)		If land <0.25 (N = 2,036)		All (N = 1,214)		If land >= 0.25 (N = 384)		If land <0.25 (N = 830)	
Variable	Definition	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Individual parcel farmland data													
Value	Value of each parcel of farmland (NT$10,000)	312	734	564	1,213	215	384	101	155	162	187	73	129
Land area	Farmland area (hectare)	0.18	0.14	0.37	0.07	0.10	0.07	0.19	0.14	0.36	0.07	0.11	0.07
Price	Farmland price per hectare (NT$10,000/hectare)	2754	4242	1571	3468	3207	5431	659	993	458	526	752	1135
Auction 1	If sold in the first round auction (=1).	0.23	0.42	0.20	0.40	0.24	0.43	0.21	0.40	0.22	0.41	0.20	0.40
Auction 2	If sold in the second round auction (=1).	0.18	0.38	0.19	0.39	0.17	0.38	0.13	0.34	0.12	0.32	0.14	0.34
Auction 3	If sold in the third round auction (=1).	0.30	0.46	0.32	0.47	0.29	0.45	0.30	0.46	0.28	0.45	0.31	0.46
Auction 4	If sold in the fourth round or above (=1).	0.30	0.46	0.30	0.46	0.30	0.46	0.36	0.48	0.38	0.49	0.36	0.48
Year 2000	If year 2000 (=1).	0.09	0.28	0.09	0.28	0.09	0.28	0.05	0.22	0.05	0.22	0.05	0.22
Year 2001	If year 2001 (=1).	0.10	0.30	0.09	0.28	0.10	0.30	0.11	0.32	0.10	0.30	0.12	0.32
Year 2002	If year 2002 (=1).	0.19	0.39	0.18	0.38	0.19	0.39	0.29	0.46	0.23	0.42	0.32	0.47
Year 2003	If year 2003 (=1).	0.17	0.38	0.19	0.39	0.16	0.37	0.15	0.36	0.20	0.40	0.13	0.34
Year 2004	If year 2004 (=1).	0.16	0.37	0.19	0.39	0.15	0.36	0.16	0.37	0.17	0.37	0.16	0.37
Year 2005	If year 2005 (=1).	0.09	0.29	0.10	0.30	0.09	0.28	0.08	0.27	0.09	0.28	0.07	0.26
Year 2006	If year 2006 (=1).	0.09	0.28	0.07	0.25	0.09	0.29	0.05	0.21	0.06	0.23	0.04	0.20
Year 2007	If year 2007 (=1).	0.07	0.26	0.06	0.24	0.08	0.27	0.05	0.21	0.05	0.22	0.05	0.21
Year 2008	If year 2008 (=1).	0.05	0.22	0.04	0.20	0.05	0.22	0.06	0.24	0.07	0.25	0.06	0.23
Aggregated data at county level													
Slope	Average land slope (o^c).	5.72	8.33	6.12	8.49	5.57	8.27	4.85	9.02	6.35	10.26	4.15	8.30
Productivity	Average land productivity.	0.72	1.36	0.84	1.43	0.68	1.34	2.10	1.80	2.07	1.81	2.11	1.80
Landslides	Average size of landslide area (hectare).	118	231	154	279	104	208	619	1199	769	1363	549	1109
Farm groups	Number of farmers' marketing groups.	10.91	11.41	11.80	11.70	10.56	11.28	30.89	25.23	27.15	21.81	32.61	26.50

Boundary	Area of the county (hectare)	5,071	2,933	5,438	3,178	4,930	2,821	9,367	9,125	10,367	11,123	8,904	8,000
R_farms	Share of farm households to total households (%).	10.87	10.92	11.77	11.36	10.53	10.73	33.47	11.37	33.87	11.27	33.29	11.41
R_full-time farms	Share of full-time farms to total number of farms (%).	15.41	5.44	15.58	5.40	15.35	5.46	27.40	9.09	26.11	9.66	28.00	8.75
R_rice farms	Share of rice farms to total number of farms (%).	46.88	28.79	47.46	29.16	46.66	28.66	38.99	29.51	37.60	30.12	39.63	29.23
R_fruit & veg farms	Share of fruit/vegetable farms to total number of farms (%).	40.28	26.49	39.80	26.85	40.46	26.36	38.20	31.03	40.59	31.88	37.10	30.58
R_other crop farms	Share of other crop farms to total number of farms (%).	11.66	7.06	11.46	7.14	11.74	7.03	20.45	17.96	19.33	17.83	20.97	18.01
R_livestock farms	Share of livestock farms to total number of farms (%).	1.18	0.93	1.28	1.03	1.14	0.88	2.36	1.98	2.49	1.94	2.30	2.00

geographic variables included variables that indicated if the county was covered by hilly land, and if it was located in a manufacturing area, water protection zone, or in a natural protection zone. In addition, two variables reflecting the average land slope and altitude of each county were included. The data were provided by the National Land Survey Center.

Regarding farming characteristics, several variables were specified for the average farming activities in each county of Taiwan. These variables included the number of farm households, the ratio of full-time farms to overall farms, and several other variables for the number of farms producing rice, fruit and vegetables, livestock, and other crops. The Council of Agriculture in Taiwan provided each county's averaged data. A detailed definition and sample statistics for all of the selected variables are presented in tables 1 and 2.

As presented in table 1, of the 4,032 parcels of farmland, 1,166 of them (29%) are larger than 0.25 hectares, while 2,866 of them (71%) are smaller than 0.25 hectares. The average auction value also differs between these two land groups. The average values are NT$4,320,000 for groups larger than 0.25 hectares, and NT$1,740,000 for those smaller than 0.25 hectares. Farmlands larger than 0.25 hectares were less likely to be sold in the first and second auction rounds, and were located in areas with higher slope and better land productivity, on average. To further investigate if the MLS program differs for farmland located in urban and rural areas, the data were further separated by urban/suburban and rural groups. As presented in table 2, 2,818 parcels of farmland were located in urban/suburban areas, while 1,214 parcels were located in rural areas. In addition, most of the farmland in the urban/suburban areas was less than 0.25 hectares ($2,036/2,818 = 72\%$). The average values of land in urban areas were higher than those in the rural areas (NT$3,120,000 vs. NT$1,010,000).

Empirical Strategy: The Regression Discontinuity Design

The Regression Discontinuity (RD) design is a program evaluation design used as an alternative to a randomized experiment. The RD design uses specific knowledge about the assignment rule that influences how individuals are assigned to, or selected for, treatment. More specifically, the RD design requires a known threshold (or cutoff point) in treatment assignment as a function of a continuous assignment variable; it is commonly applied to situations in which individuals are selected for treatment based on whether their value in a numeric rating (i.e., the running variable) falls above or below a certain threshold. The idea behind the RD design is that individuals with scores just below the cutoff (untreated group) make for good comparisons with those just above the cutoff (treated group). The magnitudes of the discontinuity of the outcome variable around the cutoff can be seen as the weighted average treatment effect (ATE), whereby weights are proportionally assigned to individuals who are closer to the threshold (Lee and Lemieux 2010). In an RD design, the participation status can depend, either completely or partly, on the value of an observed preprogram characteristic being above or below a specified threshold. Accordingly, the literature typically distinguishes between two types of RD designs: the sharp RD and fuzzy RD (Hahn, Todd, and van der Klaauw 2001). The RD design has been used to empirically evaluate the impact of a wide variety of social programs over the last two decades (see Lee and Lemieux 2010 for a survey).

The identification condition for a validated RD design only assumes that the outcome variable has to be a continuous function around the cutoff point in the absence of treatment. This assumption is considered to be relatively weak compared to identification assumptions imposed on other program evaluation methods, such as the "conditional independent assumption" used in the propensity score matching model.[5] Moreover, RD design has been considered to have the highest internal validity among quasi-experimental methods. However, since the RD design only estimates the treatment effect around the discontinuity point, its external validity is less impressive than other methods (Lee and Lemieux 2010).

In Taiwan, the MLS policy puts the restriction for constructing farmhouses and facilities at a minimum farmland area of 0.25 hectares. Therefore, the 0.25 hectare cutoff point becomes the criterion for the natural eligibility rule, making it straightforward to apply the sharp *RD* analysis. If the mean value of the farmland value is conditional to the size of the land (the running variable) being around 0.25 hectares, the ATE effect can be defined as:

$$(1) \qquad E(y_{1i} - y_{0i}|d_i = 1) = E(y_{1i}|d_i = 1, c^+) - E(y_{1i}|d_i = 1, c^-)$$

where y_{1i} and y_{0i} are the values of the ith parcel of land whose size is just larger and smaller than the cutoff point, respectively. Further, $\boldsymbol{d}_i$ is a binary indicator for the eligibility rule, and variables c^+, c^- are the two sides of the neighborhood around the cutoff point. With the selection of a sample close to the cutoff point, the magnitude of the program effect can be obtained using a regression method (Imbens and Lemieux 2008).

With regard to the model estimation of the RD design, two types of empirical strategies can be used: the parametric and nonparametric approach. Given a data set, the parametric approach focuses on finding the optimal functional form between the outcome and the assignment variable. Since it allows the inclusion of other covariates that are associated with the outcome variable, the parametric estimation can potentially offer greater precision compared to the nonparametric approach. In contrast, the nonparametric approach views the estimation of treatment status as a local randomization experiment and its analysis is limited to samples around the cutoff point (i.e., within the bandwidth). The nonparametric approach has the potential to substantially reduce the estimation bias by using a much smaller portion of data around the cutoff point. However, it may have less statistical power due to the smaller sample size used in the estimation (Lee and Lemieux 2010). When choosing between the parametric and nonparametric approach, one needs to consider the trade-off between bias and precision. Since it is impossible to know which case has a smaller bias without knowing the true function with a finite sample, we estimate the farmland value equation using both approaches in the empirical analysis.

[5] Heckman, Ichimura, and Todd (1998) proposed the Conditional Mean Independent Assumption (CMIA), which assumes that unobservable factors have the same impact on the outcome variable in the treated and untreated groups. Similar to the conditional independent assumption, the CMIA assumption is not empirically testable.

Parametric Estimation

After choosing a dataset near the cutoff point, the parametric reduced form of the farmland value equation can be specified as

$$(2)\qquad y_i = \alpha + f(r_i) + \tau^* d_i + x_i'\beta + \varepsilon_i$$

where r_i indicates the ith parcel of land whose size is normalized to be zero around 0.25 hectares (i.e., $r_i = land_i - 0.25$). Further, $f(r_i)$ is the low-order polynomial function for r_i, and $\boldsymbol{x}_i$ is a vector of the other exogenous determinants correlated with the value of the ith parcel of land. Although the identification condition of the RD design is irrelevant when including the exogenous variables, we include them in equation (2) to reduce the sampling variability in the estimator. Moreover, $\tau, \boldsymbol{\alpha}$, and $\boldsymbol{\beta}$ are parameters to be estimated, and ε_i is the random error. In this setup, coefficient τ then captures the ATE effect of the MLS regulation on farmland value. Consistent estimators of equation (2) can be obtained using the Ordinary Least Square method (OLS; Lee and Lemieux 2010).

Nonparametric Estimation

Unlike the parametric approach, the nonparametric approach aims to pick the right dataset to fit a given model. The nonparametric estimation chooses a small neighborhood (i.e., bandwidth) to the left and right of the cutoff point, and uses only data within the bandwidth to estimate the discontinuity in outcomes at the cutoff point. The most commonly used nonparametric regression analysis in the RD design is the local linear regression model, which searches for the optimal data range within which a linear regression can produce a consistent estimator (Hahn, Todd, and van der Klaauw 2001). We estimate two farmland value equations using the local linear regression for observations within the bandwidth (h) on either side of the cutoff point

$$(3)\qquad \underset{\alpha_1,\beta_1}{Min} \sum_{i0.25-h<r<0.25} \times (y_i - \alpha_1 - \beta_1 * (r_i))^2 K\left(\frac{r_i}{h}\right),$$

$$\underset{\alpha_2,\beta_2}{Min} \sum_{i0.25\le r<0.25+h} \times (y_i - \alpha_2 - \beta_2 * (r_i))^2 K\left(\frac{r_i}{h}\right)$$

where $\alpha_1, \alpha_2, \beta_1, \beta_2$ are estimated parameters, and $K(.)$ is the kernel function. The ATE is then equal to the differences between the two estimated parameters $ATE = \hat{\alpha}_2 - \hat{\alpha}_1$ (Hahn, Todd, and van der Klaauw 2001).

In applying the local linear estimation, it is necessary to choose the form of the kernel function and the value of the bandwidth (h). The data-driven optimal bandwidth proposed by Calonico, Cattaneo, and Titiunik (2014) was used herein. Compared to other suggested formulae of bandwidth (e.g., the cross-validation bandwidth and the plug-in bandwidth), the bandwidth suggested by Calonico, Cattaneo, and Titiunik (2014) provides the most robust data-driven inference in the nonparametric RD design.

Results

The empirical results are presented in several parts, starting with the findings of the MLS effect on farmland value. In what follows, we report the results of the robustness checks of our key finding.

Estimation of the Program Effect on Farmland Values

Graphical analysis provides a visual guidance of the program effect; most RD analyses begin with a presentation of the plot of the outcome variable against the running variable (e.g., Card, Dobkin, and Maestas 2008; Carpenter and Dobkin 2009). The purpose of depicting figures is to see if there is any "discontinuity" or "jump" in the outcome variable across the cutoff point of the running variable. We depict the sample distribution of the farmland values in the full sample ($N = 4,032$) in figure 1, and in urban/suburban ($N = 2,818$) and rural subsamples ($N = 1,214$) in the left and right panel of figure 2, respectively. In each figure, the Y and X axes represent the value of farmland (in NT$ 10,000) and the size of farmland (in hectares), respectively. Each dot point represents the mean value of farmland within each bin, and the dash and solid line represents the smoothed fitting value estimated by the nonparametric locally weighted regression method; the sample includes farmland smaller and larger than the cutoff at

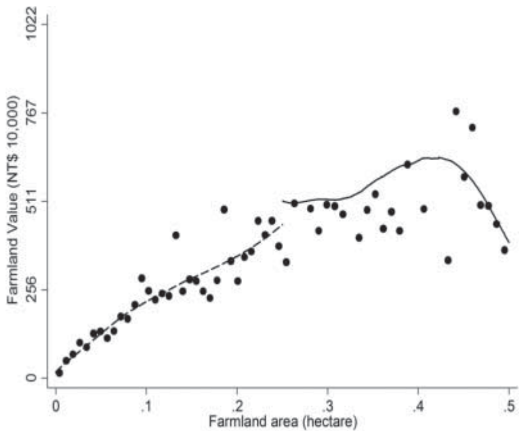

Figure 1. Distribution of the farmland values in the full sample

Note: The Y axis is the auction value of farmland (NT$10,000), and the X axis is the size of farmland area (hectare). The dashed and solid lines represent the smoothing fitted values of the relationship between the farmland value and farmland size based on locally weighted regression using the "lowess" command in STATA. The dot points represent the sample means of farmland values within each bin. In total, 4,032 parcels of farmland are included.

0.25 hectares, respectively.[6] The results in figure 1 provide visual evidence of "discontinuity" across the cutoff; this may provide a snapshot of the causal effect of the MLS program on farmland values. It also appears that the effect may be more pronounced for farmland in the urban/suburban areas since the magnitude of the "jump" seems to be more obvious in the left panel of figure 2. In contrast, a negligible "jump" is found for farmland in rural areas (the right panel of figure 2).

To further quantify the causal effect of the MLS program, the farmland value equation is estimated using the parametric OLS method with the clustered standard errors in the county level, and the results are reported in table 3.[7] A third-order polynomial function is specified for the running variable. The estimation results using the full sample and the subsamples in the urban/suburban and rural areas are reported in table 3. Perhaps the most interesting finding of table 3 is related to the coefficient of the variable "*Treat*," which captures the causal effect of the MLS program on farmland value. In the full sample, the estimated coefficient of the variable "*Treat*" is 45.80; it is statistically significant at the 1% level. This result shows that the MLS program significantly increased farmland value by NT$458,000. If it is evaluated based on the sample average of the farmland value (NT$2,490,000; see table 1), the magnitude of the effect is equal to approximately 18% of the sample average of the farmland value variable. Moreover, the effect is more pronounced for farmland located in the urban/suburban areas. The estimated coefficient of the variable "*Treat*" is 80.60, which is equal to approximately 26% of average farmland values in the urban/suburban areas (NT$3,120,000; see table 2). In contrast, there was no significant finding for land located in the rural areas.

In addition to the parametric estimation, we conducted the nonparametric analysis for the full, urban/suburban, and urban samples, respectively. The estimated average treatment effect (ATE), the associated standard errors, and the sample sizes corresponding to each bandwidth are reported in table 4. For each sample, a local linear regression model was estimated using the triangle kernel function, and the optimal bandwidth proposed by Calonico, Cattaneo, and Titiunik (2014).[8] The optimal bandwidth is 0.084, 0.101, and 0.076 for the full, urban/suburban, and rural samples, respectively. The associated sample derived from the nonparametric analysis includes 1,348, 937, and 311 parcels of farmland, respectively, in each sample group. In the full sample, the estimated ATE is 38.316, which is statistically significant at the 1% level (see panel A of table 4). The estimated ATE is 75.126 and −16.588 for the sample in urban/suburban and rural areas, respectively. However, only the finding in the urban/suburban area is statistically significant. If the estimated ATEs are further compared to the sample averages of the farmland value, the results of the nonparametric analysis show that the MLS program significantly increased farmland value by approximately 15% ($38.316/249 = 0.15$) and 24% ($75.216/312 = 0.24$) for land in the full and urban/suburban sample, respectively. To further show if the results are sensitive to the optimal bandwidth, the estimated results

[6] The "lowess" command in STATA was used to produce each figure.

[7] Since some of the explanatory variables were aggregated at the county level, clustered standard errors were used to account for the unobserved county heterogeneity. We thank one anonymous reviewer for this observation.

[8] In the preliminary analysis, different kernel functions were used for the estimation. The results are not sensitive to the kernel function selection.

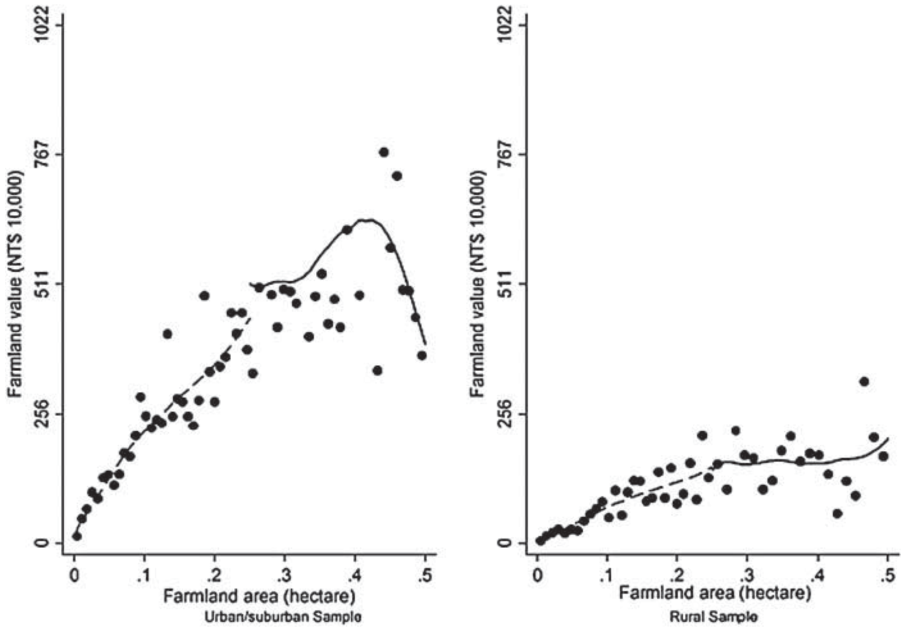

Figure 2. Distribution of the farmland values in the urban and rural samples

Note: The Y axis is the auction value of farmland (NT$10,000), and the X axis is the size of farmland area (hectare). The dashed and solid lines represent the smoothing fitted values of the relationship between the farmland value and farmland size based on locally weighted regression using the "lowess" command in STATA. The dot points represent the sample means of farmland values within each bin. The left and right panels present the results for the urban ($N = 2,818$) and rural ($N = 1,214$) sample, respectively.

using different bandwidths are presented in panel B of table 4. The results of using different bandwidths are robust; they all point to a positive effect on farmland values at the significance level of 10% or higher in both the full and urban/suburban samples. The estimated program effects using a nonparametric approach are qualitatively consistent with the ones derived from the parametric models.

Discussing the Effect on the MLS Program on Farmland Values

Henneberry and Barrows (1990) proposed four possible price effects of land regulations on farmland values: externality, neighborhood certainty, tax, and development. In the absence of the tax effect and externalities from non-agricultural activities in our case, the positive effect of the MLS program on farmland values may simply reflect the program effect on farmland's right for future development. In a farmland market without policy intervention, the relationship between the size of the farmland and its value shall be smooth and continuous. After controlling for other exogenous determinants, the differences in value among land plots will primarily reflect the difference in land size. Moreover, the difference in the price of land plots of similar size will be small, even negligible. Once the minimum size zoning regulation is implemented, plots of farmland smaller than the minimum size restriction will lose their options to develop in the future. In contrast, land over and above the minimum size requirement will still keep the right for future development. As a result, the price difference between these two groups of farmland (size just smaller and larger than minimum size) can reflect the option value. Moreover, farmland values are shown to generally increase as parcel size increases, but as the parcel size approaches 0.5 hectares decline is observed (see figure 1). This may reflect the possibility that buyers of farmland with a primary intention to build a farmhouse might regard the part of land far larger than 0.25 hectares to be surplus. To those buyers, a parcel of farmland of, for example, 0.45 hectares is much larger than the minimum size requirement but still not large enough to be subdivided into two parcels to build two farmhouses.

Table 3. Estimation Results of the Farmland Value Equations Using Parametric Models

	All Area ($N = 4{,}032$)		Urban/suburban Area ($N = 2{,}818$)		Rural Area ($N = 1{,}214$)	
Variable	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
Treat#	45.80***	19.00	80.60***	33.91	−26.18	28.73
(Land-0.25)	832.75***	297.43	1086.80***	404.54	197.11	142.43
$(\text{Land-0.25})^2$	−2072.30***	647.38	−2794.31***	915.98	−826.64***	291.26
$(\text{Land-0.25})^3$	898.41	3365.24	1042.34	4456.42	2012.27	2123.01
Auction 1	117.86***	30.68	175.87***	41.80	−14.35	10.27
Auction 2	124.95***	42.69	162.67***	56.84	13.18	17.76
Auction 3	28.12**	14.66	36.15*	22.57	28.62***	10.98
Year 2001	−24.23	30.63	−43.06	37.30	25.59	26.73
Year 2002	−16.72	36.70	−32.60	44.14	3.41	24.33
Year 2003	−28.53	39.95	−31.67	50.07	1.33	26.13
Year 2004	−48.26	37.10	−45.30	48.48	−9.18	24.43
Year 2005	−66.78*	40.65	−85.20*	51.05	7.22	34.38
Year 2006	−63.94	61.79	−52.15	78.17	−16.20	26.87
Year 2007	51.31	121.90	81.38	148.68	−35.60	24.76
Year 2008	−43.42	44.27	−18.29	57.48	−21.61	26.57
Slope	4.20	6.31	6.74	10.38	0.52	0.84
Productivity	1.16***	0.26	25.38*	14.23	6.46**	3.18
Landslides	−0.01***	0.00	−0.32**	0.15	0.01**	0.01
Farm groups	−1.14	1.15	−4.60**	2.02	1.10***	0.26
Boundary	−0.01*	0.00	−0.01	0.01	0.00**	0.00
R_farms	−7.16***	0.96	−6.30***	1.88	−3.23***	0.47
R_full-time farms	1.99	2.09	4.36	4.47	−0.93	0.58
R_rice farms	20.33**	10.58	66.30***	22.24	−0.41	2.26
R_fruit & veg farms	21.58**	11.03	68.61***	23.05	−0.79	2.30
R_other crop farms	22.67**	10.46	72.06***	22.30	−0.18	2.21
Constant	−1629.68	1063.81	−6226.55***	2245.14	261.46	224.86
Adjusted R^2	0.129		0.145		0.115	

Note: Asterisks ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively; # indicates that variable "*treat*" = 1 if farmland is >= 0.25 hectares, = 0 otherwise. Clustered standard errors in the county level are reported.

Our argument about the option value is reinforced by the significant program effect in the urban/suburban area. Given that residential housing prices are higher in urban areas than those in rural areas, farmhouses in urban areas are more valuable. Therefore, the option values for farmland greater than 0.25 hectares located in urban areas are worth more; this may result in a more pronounced effect of the MLS program on farmland values. In contrast, the insignificant effect found in rural areas may suggest a weak demand for building farmhouses. As a result, option values are not reflected in the values of farmland larger than 0.25 hectares in rural area.

Our argument, on the effect of the zoning policy on the right of future development, is similar to the one proposed by Plantinga and Miller (2001); they developed a theory to illustrate that farmland's potential rights for future development will be reflected in the current land price. Despite that the theory has highlighted the price effects of future development rights for farmland, not much empirical evidence has been provided to directly test the option values of farmland. For example, Liu and Lynch (2011a) examined the effects of Purchase of Development Rights on reducing farmland loss, while Deaton and Vyn (2010) investigated the spatial variation of price effects of a Greenbelt on farmland. These two studies touched on the policy effects of restraining the development potential of farmland, but did not directly estimate its option value for future development. In line with the theoretical discussion in Plantinga and Miller (2001), this article provides empirical evidence to assess the option value of farmland due to the implementation of the MLS program in Taiwan.

One prerequisite for rationalizing this argument is that the minimum size regulation

Table 4. Estimated Treatment Effects of the Farmland Value Equations Using Nonparametric Models

All Area				Urban/suburban Area				Rural Area			
Bandwidth	*N*	ATE	S.E.	Bandwidth	*N*	ATE	S.E.	Bandwidth	*N*	ATE	S.E.
Panel A: Using the optimal bandwidth#											
0.084	1,348	38.316***	16.327	0.101	937	75.126***	27.480	0.076	311	−16.588	15.297
Panel B: Sensitivity tests using different bandwidths											
0.060	850	41.039***	14.644	0.080	706	76.339***	28.060	0.050	185	−17.099	15.456
0.070	934	38.428***	12.734	0.090	812	77.562***	29.400	0.060	239	−17.480	14.860
0.080	1,078	36.948***	13.123	0.100	937	75.126***	27.480	0.070	279	−16.732	14.494
0.090	1,269	36.983***	16.237	0.110	1,041	70.553***	24.440	0.080	330	−15.750	14.185
0.100	1,408	33.425*	27.597	0.120	1,146	71.519***	21.180	0.090	374	−14.238	13.880

Note: Asterisks ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively; # indicates that optimal bandwidth is calculated using the method proposed by Calonico, Cattaneo, and Titiunik (2014). The ATE indicates the average treatment effect.

is binding, that is, the minimum size set by a zoning ordinance has to be larger than most of the farmland with farmhouses in the market prior to the introduction of the minimum size requirement. This argument is supported by the current farmland distribution in Taiwan. Based on the government report (Council of Agriculture 2008), more than half of the farmhouses built between 1995 and 2000 were built on plots smaller than 0.25 hectares, especially in the urban/suburban areas. Accordingly, it appears that this 0.25 hectares minimum lot size restriction is binding, and is expected to affect the value of farmland, particularly those lot sizes around 0.25 hectares.

Robustness Checks of Model Validation

To provide confidence in our empirical analysis of the MLS effect on farmland values, several empirical tests were conducted, and the results are reported in this section.

Robustness Tests Using Hypothetical Cutoffs and Different Polynomial Order Terms

A robustness test was conducted to determine if there is any program effect on hypothetical cutoffs other than the 0.25 hectares cutoff. Four different hypothetical cutoff points were selected: 0.1, 0.2, 0.3, and 0.4 hectares. The results using parametric estimation with clustered standard errors at the county level on the full sample of 4,032 parcels of land are presented in panel A of table 5. The results show that the estimated coefficients of the key variable "*Treat*" are statistically insignificant for all four selected hypothetical cutoffs. This indicates that there are no significant effects on farmland values at these hypothetical cutoff points.

A robustness test was also conducted by using the first-, second-, third-, and fourth-order polynomial functions. The results are presented in panel B of table 5. For the sake of presentation, only the estimated coefficient on the key variable "*Treat*" is presented. All four models point to a positive effect of the MLS program on farmland values, ranging from 42.96 to 48.43, and all of the estimated coefficients on the variable "*Treat*" are statistically significant at the 1% level. Therefore, our findings are robust using different polynomial terms.

Table 5. Results of the Robustness Checks in the Parametric Estimation

Cutoff (hectare)	0.1		0.2		0.3		0.4	
Variable	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
Panel A: Use Different Hypothetic Cutoffs of Farmland Size								
Treat#	−2.59	2.14	−4.06	4.54	−1.83	73.09	2.76	160.15
(Land-0.25)	1,722***	246	1,495***	400	863**	350	312	1,027
$(\text{Land-0.25})^2$	−1,785	1,178	−1,597***	510	−2,341**	1,096	−2,990	4,817
$(\text{Land-0.25})^3$	−1,273	3,468	−4,653	5,266	−1,968	4,209	−2,005	6,910
Other controls	Yes		Yes		Yes		Yes	
N	4,032		4,032		4,032		4,032	

	First order		Second order		Third order		Fourth order	
Variable	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
Panel B: Use Different Polynomial Order Terms								
Treat#	48.43***	22.82	49.69***	22.66	45.80***	19.00	42.96***	20.18
(Land-0.25)	1,124***	147	885***	179	833***	297	1,156***	480
$(\text{Land-0.25})^2$			−2,100***	641	−2,072***	647	−1,909	2,901
$(\text{Land-0.25})^3$					898	3,365	5,043	6,513
$(\text{Land-0.25})^4$							−73,566	51,268
Other controls	Yes		Yes		Yes		Yes	
N	4,032		4,032		4,032		4,032	

Note: Asterisks ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively; # indicates that the variable "*treat*" = 1 if farmland is >= 0.25 hectares, = 0 otherwise. Clustered standard errors in the county level are reported.

Table 6. Estimation Results of the Farmland Value Equations Using Pre-policy Period Data

	All Area		Urban/suburban Area		Rural Area	
	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
Treat#	−77.710	73.525	−80.003	83.498	15.287	38.017
(Land-0.25)	474.798*	280.823	439.548*	268.299	125.602	321.276
$(\text{Land-0.25})^2$	1284.439	944.163	1898.675	2952.257	−572.409	402.693
$(\text{Land-0.25})^3$	16737.350**	7521.047	22409.040	14690.040	82.068	4678.868
Other Controls	Yes		Yes		Yes	
Adjusted R^2	0.166		0.209		0.273	
N	733		583		150	

Note: Asterisks ** and * indicate significance at 5% and 10% levels, respectively. In total, 733 parcels of farmland in year 1999 were used; # indicates that the variable "*treat*" = 1 if farmland is >= 0.25 hectares, = 0 otherwise. Cluster standard errors in the county level are reported. The other controlled variables are the same as the ones specified in table 3, except the year dummy variables. Clustered standard errors in the county level are reported.

Estimation Results Using the Pre-policy Period Dataset

A sample of 733 parcels of farmland transacted in the foreclosure auction market in 1999, the year before the initiation of the MLS program, was used. Out of the 733 parcels of farmland, 583 and 150 of them were located in urban/suburban and rural areas, respectively. The estimation results using the parametric model are presented in table 6. The results show that the estimated coefficient on the key variable "*Treat*" is insignificant for all three models. This provides empirical evidence that the cutoff point of 0.25 hectares of farmland has no statistical effect on farmland values in the year without the implementation of the MLS program.

Testing the Smoothness of the Running Variable

One of the concerns in the RD's design is that decision makers may be able to manipulate the assignment rule, that is, if decision makers understand the assignment

Table 7. Estimation of Farmland Price Equations

	All sample		Urban/suburban area		Rural area	
Variable	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
Panel A: Parametric Estimation						
Treat#	214.81***	81.92	231.12***	105.24	−5.02	13.75
Other controls	Yes		Yes		Yes	
N	4,032		2,818		1,214	
Adjusted R^2	0.038		0.045		0.134	
	All sample		Urban/suburban area		Rural area	
	Estimator	S.E	Estimator	S.E	Estimator	S.E
Panel B: Nonparametric Estimation						
Optimal bandwidth#	0.04	–	0.04	–	0.06	–
ATE	126.94***	34.08	170.65***	43.86	−9.12	19.09

Note: Asterisks *** indicate significance at the 1% level; # indicates that the variable "*treat*" = 1 if farmland is >= 0.25 hectares, = 0 otherwise. Clustered standard errors in the county level are reported in the parametric model; # indicates that optimal bandwidth is calculated using the method proposed by Calonico, Cattaneo, and Titiunik (2014). The ATE indicates the average treatment effect.

mechanism and are able to manipulate their valuation of the running variable, they can place themselves just above (or below) the cutoff point. The specification test proposed by McCrary (2008) was conducted to test the potential manipulation problem. The idea behind McCrary's test is straightforward: if the decision maker has the ability to manipulate the rule, then a discontinuity would be seen with the running variable across the cutoff point. A graphical analysis of the density of the running variable across the cutoff point can provide a straightforward test. The density of the running variable (i.e., farmland size) is depicted in figure A.1 in the online appendix. The result is encouraging since a particular "discontinuity" is not observed in the running variable at the cutoff point.

Effects of the MLS Program on Farmland Price

In our analysis, the value of each parcel of farmland is defined as the outcome variable. Given that a larger size of farmland is likely to be more valuable in terms of total value, the positive program effect may possibly just reflect the size effect rather than the MLS program itself. To rule out this potential threat to the validity of our finding, we conducted a robustness check using the price per hectare of farmland as the outcome variable. The estimation results of the farmland price equations are presented in table 7 (visual evidence can be found in figures A.2 and A.3 in the online appendix). In the parametric analysis, the estimated coefficient of the key variable "*Treat*" is 214.81, 231.12, and −5.02 for the full, urban/suburban, and rural samples, respectively. However, the results of the rural sample are statistically insignificant. The results of the nonparametric analysis further confirm the positive and significant program effect in the full and urban/suburban samples (see panel B of table 7).

Other Determinants on Farmland Values

Although not the primary focus of this study, the effects of other exogenous determinants on farmland value are discussed briefly in this section. The discussions below are based on the estimation results of the parametric approach using the full sample of 4,032 farmland parcels (see column 1 of table 3).

The auction rounds, transaction years, characteristics of geographic conditions, and farm practices in the local area are significantly associated with farmland value. Compared to land determined at the fourth or higher auction round, land in the first and second auction rounds sold at a higher price of NT$1,178,600 and NT$1,249,500, respectively. In the foreclosure auction farmland market, if the foreclosed property is not sold in the first round, it will be put up in further auction rounds with a price discount. Therefore, it is not unexpected that the lower rounds of auctions that took place came with higher values. Land characteristics also matter in determining farmland values. The results show that land values are higher if the land is located in an area of higher land productivity. In contrast, farmland located in an area with a high proportion of landslides has, on average, a lower value. Farm production conditions in the local area also help to determine farmland values. The results show that higher farmland values are found in areas having farms with a greater intensity of rice, vegetables/fruits, or other crops. This result may reflect the possible positive association between environmental amenities and agricultural land value, in that crop production may generate environmental amenities and thus increase farmland value. Since the variables reflecting farm characteristics are aggregated at the county level, it calls for caution when explaining our findings regarding the association between farm characteristics and farmland values.

Conclusions

The literature has demonstrated that the price effects on land can reflect the benefits and costs of specific land use regulations imposed on the land. Using a national administrative dataset of foreclosure auction in Taiwan, this paper investigated the effect of a minimum lot size program on farmland value. It is evident that the zoning program can increase farmland value by 18% (15%), using the parametric (nonparametric) estimation method. Moreover, the effect is more pronounced for farmland located in urban and suburban areas. Due to the absence of a tax effect and externalities from nonfarm activities in our case, the program effect on land values can simply result from its effect on option values for future development.

In terms of policy relevance, some implications may be drawn. Prior to the year 2000, only farmers were allowed to hold farmland. This requirement in the buyers' qualification prevented competition from urban dwellers when purchasing farmland. In contrast, the required buyers' qualifications to own farmland and build a farmhouse after the year 2000 are no longer in place. This policy reform may invite buyers with much stronger purchasing power to compete with would-be farmers. After the policy reform, the farmland market is no long insulated, but rather is open to a price mechanism. The notable option values associated with farmland in urban/suburban areas may suggest a threat to the production environment. For instance, farmers interested in buying farmland with a significant option value are likely to be priced out of the market since owning a parcel of farmland has become an alternative to purchasing a house in nearby urban areas. As farmland tends to be cheaper than urban residential sites, farmland may be more likely to be filled with houses. However, the minimum lot size restriction raises the price of a farmhouse since at least 0.25 hectares has to be purchased to qualify as a building site.

Although this article reveals some interesting findings, some caveats remain. For instance, buyer information was not documented in our data set. If buyers' motivation to purchase farmland becomes known, then whether the evident significant program effect found in urban/suburban areas reflects the demand of local farmers or nearby urban non-farm residents can be further identified. If the demand for farmhouses is primarily driven by urban non-farm residents for investment purposes but not for farming, agricultural productivity and the agricultural environment may be adversely affected. In addition, the availability of the production history of each parcel of farmland in the auction market can be helpful. In general, production history is possibly associated with farmland value. If the data permit, this type of information can be accommodated in empirical analysis to determine the robustness of our findings.

Supplementary Material

Supplementary material is available at http://oxfordjournals.our_journals/ajae/online.

References

Asabere, P., and F. Huffman. 1992. Price Determinants of Foreclosed Urban Land. *Urban Studies* 29 (5): 701–7.

Calonico, S., D. Cattaneo, and R. Titiunik. 2014. Robust Nonparametric Confidence Intervals for Regression-discontinuity Designs. *Econometrica* 82 (6): 2295–326.

Card, D., C. Dobkin, and N, Maestas. 2008. The Impact of Nearly Universal Insurance Coverage on Health Care Utilization: Evidence from Medicare. *American Economic Review* 98 (5): 2242–58.

Carpenter, C., and C. Dobkin. 2009. The Effect of Alcohol Consumption on

Mortality: Regression Discontinuity Evidence from the Minimum Drinking Age. *American Economic Journal: Applied Economics* 1 (1): 164–82.

Carroll, T., T. Clauretie, and H. Neill. 1997. Effect of Foreclosure Statue on Residential Selling Price: Comment. *Journal of Real Estate Research* 13 (1): 95–102.

Chang, Y., and Y. Fu. 2006. *Taiwan Social Chang Survey*. Institute of Sociology, Academia Sinica, Taiwan.

Chiu, J. 2003. A Study of the Improvement of Basic Criteria for the Identification of Farm Size Structure. *Chinese Journal of Agribusiness Management* 9: 84–107.

Council of Agriculture. 2008. *Trend of Farmland Transactions and Farmhouse Building and Its Impacts on Farmland Use*. Council of Agriculture in Taiwan, Taipei, Taiwan.

Deaton, B., and R. Vyn. 2010. The Effect of Strict Agricultural Zoning on Agricultural Land Values: The Case of Ontario's Greenbelt. *American Journal of Agricultural Economics* 92 (4): 941–55.

Eagle, A., D. Eagle., T. Stobbe, and G. van Kooten. 2015. Farmland Protection and Agricultural Land Values at the Urban-rural Fringe: British Columbia's Agricultural Land Reserve. *American Journal of Agricultural Economics* 97 (1): 282–98.

Fischel, W. 1987. *The Economics of Zoning Laws: A Property Rights Approach to American Land Use Controls.* The Johns Hopkins University Press.

Geltner, D., N. Miller., J. Clayton, and P. Eichholtz. 2007. *Commercial Real Estate Analysis and Investments.* Mason, Ohio, USA: Thomson, South-Western.

Grieson, R., and J. White. 1981. The Effects of Zoning on Structure and Land Markets. *Journal of Urban Economics* 10 (3): 271–85.

Grout, C., W. Jaeger, and A. Plantinga. 2011. Land-use Regulations and Property Values in Portland, Oregon: A Regression Discontinuity Design Approach. *Regional Science and Urban Economics* 41: 98–107.

Hahn, J., P. Todd, and W. van der Klaauw. 2001. Identification and Estimation of Treatment Effects with a Regression-discontinuity Design. *Econometrica* 69 (1): 201–9.

Heckman, J., J. Hidehiko, and P. Todd. 1998. Matching as an Econometric Evaluation Estimator. *Review of Economic Studies* 65 (2): 261–94.

Henneberry, D., and R. Barrows. 1990. Capitalization of Exclusive Agricultural Zoning Into Farmland Prices. *Land Economics* 66 (3): 249–58.

Imbens, G., and T. Lemieux. 2008. Regression Discontinuity Designs: A Guide to Practice. *Journal of Econometrics* 142 (2): 615–35.

Isakson, H. 2004. Analysis the Effects of Large Lot Zoning. *Journal of Real Estate Research* 26 (4): 397–415.

Knaap, G. 1985. The Price Effects of Urban Growth Boundaries in Metropolitan Portland, Oregon. *Land Economics* 61 (1): 26–35.

Lee, D., and T. Lemieux. 2010. Regression Discontinuity Designs in Economics. *Journal of Economic Literature* 48 (2): 281–355.

Liu, X., and L. Lynch. 2011a. Do Zoning Regulations Rob Rural Landowners' Equity? *American Journal of Agricultural Economics* 93 (1): 1–25.

———. 2011b. Do Agricultural Land Preservation Program Reduce Farmland Loss? Evidence from a Propensity Score Matching Estimator. *Land Economics* 87 (2): 183–201.

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 (3): 502–9.

McCrary, J. 2008. Manipulation of the Running Variable in the Regression Discontinuity Design: A Density Test. *Journal of Economic Literature* 142 (2): 698–714.

McMillen, D., and J. McDonald. 2002. Land Values in a Newly Zoned City. *The Review of Economics and Statistics* 84 (1): 62–72.

Plantinga, A., and D. Miller. 2001. Agricultural Land Values and the Value of Rights to Future Land Development. *Land Economics* 77 (1): 56–67.

White, J. 1988. Large Lot Zoning and Subdivision Costs: A Test. *Journal of Urban Economics* 23 (3): 370–84.

Zabel, J., and M. Dalton. 2011. The Impact of Minimum Lot Size Regulations on House Prices in Eastern Massachusetts. *Regional Science and Urban Economics* 41 (6): 571–83.