The Influence of Wind Energy and Biogas on Farmland Prices

Olena Myrna, Martin Odening and Matthias Ritter *

Department of Agricultural Economics, Humboldt-Universität zu Berlin, Phillippstr. 13, 10115 Berlin, Germany;
olena.myrna@agrar.hu-berlin.de (O.M.); m.odening@agrar.hu-berlin.de (M.O.)
* Correspondence: matthias.ritter@agrar.hu-berlin.de; Tel.: +49-(0)30-2093-46851

Abstract: In the context of the rapid development of renewable energy in Germany in the last decade, and increased concerns regarding its potential impacts on farmland prices, this paper investigates the impact of wind energy and biogas production on agricultural land purchasing prices. To quantify the possible impact of the cumulative capacity of wind turbines and biogas plants on arable land prices in Saxony-Anhalt, we estimate a community-based and a transaction-based model using spatial econometrics and ordinary least squares. Based on data from 2007 to 2016, our analysis shows that a higher cumulative capacity of wind turbines in communities leads to higher farmland transaction prices, though the effect is very small: if the average cumulative capacity of wind turbines per community doubles, we expect that farmland prices per hectare increase by 0.4%. Plots that are directly affected by a wind turbine or part of a regional development plan, however, experience strong price increases.

Keywords: farmland prices; wind energy; biogas; hedonic pricing model; spatial econometrics

1. Introduction

During the past decade, a significant increase in wind energy and biogas production has been observed in Germany. This was triggered by the development of the energy industry and subsidisation of renewable energy projects, stipulated by the German Renewable Energy Sources Act (*Erneuerbare-Energien-Gesetz*, EEG). In 2017, the number of onshore and offshore wind turbines reached 28,675, producing about 50.8 Gigawatt of electric power [1]. As of 2016, more than 9200 biogas plants were installed in Germany [2], with a cumulative capacity of about 4.2 Gigawatts [3]. Feed-in tariffs for renewable energy projects stipulated by the EEG played a decisive role in investment decisions. Even though the expected profitability of the projects was not achieved in many places [4], an expansion of wind parks and biogas plants is still foreseen.

Along with the expansion of renewable energy source (RES) projects, an increase in farmland prices has been observed in recent years [5]. This increase was triggered by the growing attractiveness of investments in farmland, the declining supply of and increasing demand for agricultural land, and the boom in food prices beginning in 2008 [5,6]. Moreover, conversions of agricultural land play a role in the land market. Developers often lease or buy agricultural land for commercial use [7], such as for renewable energy projects, which may influence farmland prices. For example, in biogas production, arable land plots that could alternatively be used to cultivate other crops for the food industry are used to produce "feed" for biogas plants [8]. This could lead to additional competition and a higher demand for agricultural land.

A relationship between wind energy expansion and the market for farmland also exists. Although farmers usually do not operate wind turbines, they provide the required land for their installment and are paid compensations that significantly exceed usual lease prices for agricultural land. Moreover,

there is empirical evidence that land prices are spatially correlated. This spatial relationship can be explained by the fact that prices of neighbouring properties can influence property values. For example, plots adjacent to wind parks can increase farmland values, because they could be potentially used for the enlargement of wind parks. In addition, it can be assumed that plots that are suitable for wind turbine construction, according to the regional planning of federal states, also have higher prices [9].

While there has been observed co-movement of the expansion of renewable energy and the increase in farmland prices, it remains unclear if there is causality between the two processes. Several recent studies have considered the impact of renewable energy policies by analysing the impact of the proximity and scope of wind turbines and biogas plants on farmland values. For example, Vyn and McCullough [10] examined whether the presence of wind turbines impacted nearby residential property prices and agricultural land values in Somerset County, Pennsylvania. Shultz et al. [11] applied a similar approach to another region. Both studies found no significant effect of wind turbine proximity on the value of farmland. Another methodological approach to the estimation of the influence of wind energy on farmland prices was applied by Ritter et al. [9] for the case of Brandenburg, Germany. The presence of a significant positive relationship between the scope of wind energy and the level of farmland sales prices was found. Using a spatial econometric approach, Habermann and Breustedt [12] found that agricultural biogas production, measured as the share of farmland cultivated with energy crops, significantly increases rental farmland prices in Western Germany, whereas increases in farmland prices and other values of farmland were not found. In a later study, Emmann et al. [13] applied ordinary least squares regression to analyse data collected from 246 farmers in six randomly selected rural districts in the German state of Lower Saxony and showed that biogas production led to increased farmland lease values. In a study based on data in northern Germany, Hennig and Latacz-Lohmann [14] concluded that biogas density could have a significant impact on rental prices of arable land, but only in regions with high livestock densities.

Based on the above-mentioned studies, there has been no consensus regarding a positive, negative, or lack of influence of RES on farmland prices. In this context, the paper aims to answer this research question: do wind energy and biogas production influence farmland values?

The primary objective of the first model ("community-based model") is to estimate the influence of the cumulative capacity of wind turbines and biogas installations that have been built in Saxony-Anhalt on the average annual per hectare arable land price by community. Data on average yearly farmland prices in 215 communities in Saxony-Anhalt within 10 years are analysed using a spatial lag model with fixed effects. The primary objective of the second model ("transaction-based model") is to estimate the influence of the capacity of wind and biogas production facilities on transaction prices. The latter model also aims to determine whether the presence of a wind turbine on arable land plots and a location adjacent to wind turbine plots influence farmland prices. Plots suitable for wind turbine installation, according to regional planning, are also considered in the analysis.

The remainder of the paper is organised as follows. The following section describes the development and current state of the agricultural land market and energy transition in the study region of Saxony-Anhalt. In Section 3, the data preparation process, applied methods, results, and interpretation of results are described. The conclusions are drawn at the end of the paper.

2. Agricultural Land Market and Energy Transition in Saxony-Anhalt

The focus of the paper is on the German federal state of Saxony-Anhalt (ST). The choice of this region is justified by the fact that agriculture and renewable energy are among the most important industries in the structure of the economy of ST. About two-thirds of the area of the region consists of agricultural land, namely, 1.174 million hectares of agricultural land, of which 1 million ha (85%) is arable land [15]. Since 2015, more than half of the electricity generated in ST came from RES [16].

After the end of WWII, Saxony Anhalt, Brandenburg, Mecklenburg-Vorpommern, Saxony, and Thuringia were part of the German Democratic Republic, which was characterised by a state-controlled, centrally planned economy. After the reunification of Germany, privatisation began. In order to

facilitate the process of agricultural land privatisation, the *Treuhand* agency was established, which was succeeded by *Bodenverwertungs- und -verwaltungs GmbH* (BVVG) in 1992. Since 1994, the agency had 1.2 million hectares, or about 20% of the total agricultural area in the new federal states to be sold at the specific auctions. As of 2016, 156,000 ha have yet to be privatised by 2030 [17].

Figure 1 shows average farmland prices in ST between 2007 and 2016. During this period, BVVG prices dropped only two times, namely in 2008 and 2016. In all other years, prices steadily increased. Between 2007 and 2016, not only did BVVG land prices increase, but the average price per hectare for all agricultural land also increased three-fold [18–25]. The trend of increasing farmland prices can be explained by the declining supply of, and increasing demand for, agricultural land, as well as the recent boom in food prices [5,6].
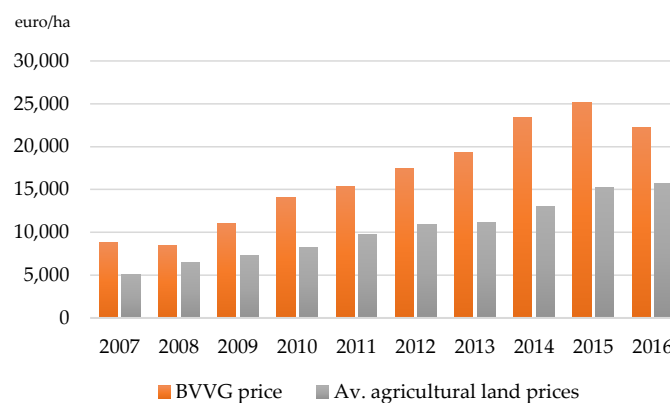
Figure 1. The development of annual BVVG (*Bodenverwertungs- und -verwaltungs GmbH*) and average agricultural land prices in Saxony-Anhalt, 2007–2016 [18–25].

The decline of BVVG prices in 2016 in Saxony-Anhalt is noteworthy because regular land prices were still increasing in that year. This increase can be explained by new privatisation guidelines adopted by the BVVG in 2016 that had the objective of reducing the price gap between regular sales and BVVG sales. For example, the maximum plot size was limited to 15 hectares, so that smaller farmers could also afford to bid for land.

The state of ST is one of the leading German regions in the field of energy transition. In 2016, for the first time, more than half of ST's generated electricity came from renewables. Wind energy contributed the most to RES (56.9%), followed by biomass (26.3%) (as long as biomass has the second greatest share) [16]. The region aims to have 100% of its electricity generated from RES by 2030.

Energy transition in Germany was supported by policymakers whose intention was to cut carbon dioxide emissions and reduce dependency on non-renewable energy sources. Since the 1970s, this has resulted in the implementation of several policies for energy transition [26]. The EEG was adopted in 2000 and amended in 2004, 2009, 2012, 2014, and 2017. The act established the legislative framework to encourage the growth of renewable electricity generation using a feed-in tariff scheme that led to the prompt development of all RES, including wind power and biomass [27]. The recently amended EEG 2017 stipulated a fundamental change in the policy for all RES by introducing a tendering system for most RES, namely onshore and offshore wind, solar energy projects, and biogas plants. With this change, subsidies now depend on an amount awarded by technology-specific auctions [28].

3. Methods and Results

3.1. Data Preparation

In order to reach the aim of the study, two models are estimated. The community-based model aims to estimate the effect of the cumulative capacity of wind turbines and biogas plants on the average yearly price of farmland by community. The transaction-based model, in turn, aims to estimate the effect

of the same variables and the impact of additional wind energy-related plot-specific characteristics on transaction prices.

The models are estimated with data obtained from the *Gutachterausschuss für Grundstückswerte in Sachsen-Anhalt*. The dataset includes information about all farmland sales in ST from 1991 to 2016. For the first dataset of this study, sales contracts from 2007 to 2016 are selected. This period is chosen because it is associated with renewable energy expansion in ST. As farmland plots are located mainly in rural areas, property sales in three cities, namely Magdeburg, Halle (Saale), and Dessau-Roßlau, are removed from the sample. The sample includes 11 counties (*Landkreise*) consisting of 215 communities (*Gemeinden*).

Given that the data is rather heterogeneous, the following adjustments are made to achieve higher homogeneity. First, sale prices of arable land and plots with information related to wind turbines were selected. Second, the data are adjusted for family circumstances. Plots sold to relatives or friends usually have lower prices than those sold using market mechanisms. Observations missing soil quality values were replaced by the mean (63 index points). Since soil quality is indicated by an index measuring the productivity of soil and ranging from 1 (low productivity) to 120 (high productivity), observations with soil quality equal to 0 or higher than 120 are removed from the sample. Further outliers are not removed to save important information related to wind energy. The values of land plots with wind parks are much higher than the average. Therefore, the removal of outliers could lead to the loss of observations that fall within the focus of the study.

The dataset is merged with an additional dataset containing information about the cumulative capacity of wind turbines and biogas plants that were connected to the 50 Hertz Transmission Network Operator, the year of commissioning, and the community where the wind turbines and biogas plants are located as of December 2016. The wind energy and biogas datasets contain information on 2765 wind turbines in ST, with a total capacity of 4861 MW in 145 districts from 1993 to 2016, as well as 445 biogas plants with a total capacity of 420 MW, installed in 155 communities from 1997 to 2016. Since larger communities in general have more space for wind turbines and biogas plants, the cumulative number and capacity of wind turbines and biogas plants per community are normalised to the average area of a community (9381.46 ha).

Figure 2 shows the spatial distribution of (a) wind turbines and (b) biogas plants in ST. There are clear differences among communities; those situated in the northwest and center have a much higher number of wind turbines than communities in the east. In terms of the distribution of biogas plants, there are several communities with higher concentrations of plants, namely in the north and center of ST. The figure also shows average per hectare prices for each community from 2007 to 2016. At first glance, a higher price is seen in communities with larger wind turbine concentration. On the other hand, for biogas plants, the relationship between higher average land prices and a higher number of biogas plants is not obvious. However, these average prices are not adjusted for other variables such as soil quality, which is a main driver of farmland prices.

Overall, the final first dataset consisted of 32,599 observations. Approximately 3000 transactions occurred in which there was no physical wind turbine or biogas plant at the time of the transaction.
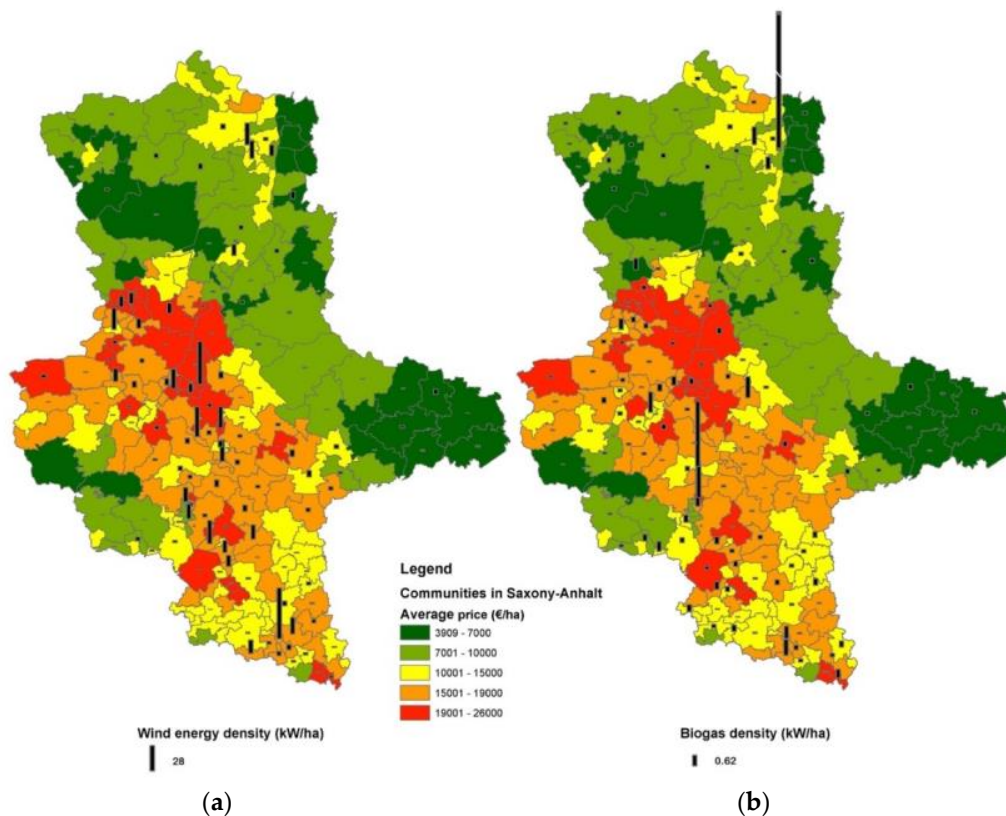
Figure 2. Average arable land prices and the number of wind turbines (**a**) and biogas plants (**b**) in communities of Saxony-Anhalt, 2007–2016.

3.2. Community-Based Model

For the community-based model, the first dataset is further modified. Using the remaining 32,599 observations that represent farmland transaction prices, a weighted average per hectare price, size, and soil quality of agricultural land in 215 communities over 10 years (2007 to 2016) is calculated. Some communities have no farmland plots sold in some years, so the average price, size, and soil quality are linearly interpolated. Missing values are calculated as an average of the respective previous value and the following one in the same community. If the previous or following value is also missing, the next respective value is used. We use this interpolation method because we find that land prices follow a linear trend during the observation period, at least locally. An alternative to interpolating missing values would be to drop these communities completely to obtain a balanced panel, which is necessary for further spatial analysis [29].

The final dataset used to fit the community-based model consists of observations in 215 communities over 10 years, so that the total size of the panel equals 2150 observations.

The essential price determinants chosen for the model can be divided into two groups: land characteristics (average plot size, average soil quality, and year when the plot was sold) and wind- and biogas-related variables, such as the cumulative capacity of wind turbines and biogas plants.

Hedonic land price models are plagued by considerable heterogeneity and subject to potential omitted variable bias [30]. Thus, one should include all relevant economic variables that may explain variation of land prices. Our approach to reduce potential omitted variable bias is to include time dummy variables that implicitly capture many economic shifters. Likewise, we pursue a spatial econometric approach to account for unobserved heterogeneity and spatial dependence among land prices.

As follows from Table 1, the average price per hectare ranges between 1602.74 euro and 42,474.37 euro, with a mean of 12,206.15 euro. Sold plots are, on average, three hectares. It is

expected that larger plots will have a higher price, because farming activities can be more conveniently conducted with larger plots. For example, cultivation of several remote plots would lead to additional costs of transporting machinery and labor from one plot to another [17].

Table 1. Descriptive statistics of determinants of farmland prices in the community-based model, 2007–2016 (N = 2150).

	Mean	Std. Dev.	Min.	Max.
Average annual price per community, euro/ha	12,206.15	7216.48	1602.74	42,474.37
Average annual size per community, ha	3.05	3.35	0.01	62.20
Average annual soil quality per community, index	62.77	18.20	20	99
Normalised cumulative capacity of wind turbines built in the community up to the observation date, kW	26,555.4	56,286.33	0	516,237.7
Normalised cumulative capacity of biogas plants installed in the community up to the observation date, kW	3344.92	28,497.41	0	414,988.8

Average soil quality varies between 20 and 99 with a mean of 62.77. Higher soil quality is expected to have a positive effect on land prices, since it is associated with higher crop yields, so we expect a positive sign of the regression coefficient [9]. Furthermore, as farmland prices have been increasing over the last 10 years, the presence of a time trend is expected. We use year dummy variables, which represent a temporal evolution of purchasing prices compared to the reference year 2007. The first year in the dataset was selected as a reference to check if the time trend is correctly represented in the sample and to avoid a dummy variable trap.

The number of wind turbines and biogas plants and their capacities are predictably interrelated. Higher numbers of turbines or plants generate more kilowatts of electric power. Therefore, only RES capacity was included in the community-based model. The average capacity of wind turbines per community is 26,555 kW. It ranges from 0 in communities where no wind turbine was installed in the respective year to 516,237 kW in a community where 205 turbines had already been built. The average capacity of biogas plants is 3344 kW, and varies between 0 in communities with no biogas plant and 414,988 kW in a community where 31 biogas plants had already been built.

In order to avoid misspecification bias, it is important to correctly specify the functional form of the model. Flexible functional forms, such as those offered by the Box-Cox procedure, can be more suitable than simpler forms (such as linear, log-linear, and log-log), especially in models where spatial effects are added to address possible omitted variable bias [10]. To keep the coefficients economically meaningful, the suggestions from the multivariate Box-Cox procedure have been rounded to values closest to 0 (logarithmic transformation), 1 (linear), or −1 (inverse). According to the test results, all variables included in the regression were log-transformed, except for soil quality.

Since the prepared dataset is panel data, either a fixed (FE) or random effects (RE) model must be chosen, as they allow adding spatial lag or error to the models later on. The application of the Hausman test [31], which is based on the difference between the FE and RE estimators, rejected the hypothesis that RE adequately models the individual-level effects (Prob > chi2 = 0.0000). Therefore, FE estimators were selected as an appropriate method.

After the selection of the method of panel data analysis, we proceed to the issue of spatial autocorrelation. The correlation between communities can be an important issue in panel data analysis, since it can lead to inefficient estimates of parameter coefficients. In the present analysis, we tested the FE estimates using the Moran's I test [32] to determine whether spatial autocorrelation affects the parameter coefficients. The test reports that we can reject the null hypothesis that there is zero spatial autocorrelation present in the model at alpha = 0.05.

There are several spatial lags that can be included in the model [33]. As we had no theoretical reasons for adding spatial lags of independent variables to the model, we selected the most appropriate model among a spatial lag model, spatial error model, and spatial autoregressive model, with spatially autocorrelated errors. The Lagrange Multiplier test [34] indicated significant spatial lag of the dependent

variable. As the model focuses on average community-level farmland prices, the contiguity matrix was chosen and created to fit the spatial lag model with fixed effects. The latter was done using the quasi-maximum likelihood estimator. A transformation was applied to remove fixed effects from the equation [35]. Therefore, the community-based model is as follows:

$$\ln(P_{it}) = \rho \sum_j W \ln(P_{it}) + b_1 \ln(A_{it}) + b_2 Q_{it} + \sum_k c_k Year_{kit} + d_1 \ln(WE_{it}) + d_2 \ln(BM_{it}) + u_{it} \quad (1)$$

where P_{it} denotes a vector of the average sales of farmland prices at time t; W is a spatial weighting contiguity matrix; A_{it} represents area of plots sold in ha; Q_{it} indicates a soil quality index; $Year_{kit}$ is a year dummy that represents temporal development of purchase prices compared to the reference year 2007; WE_{it} is wind turbine capacity installed up to the relevant year in the particular community; BM_{it} is biogas plant capacity installed up to the relevant year in the particular community; ρ is a spatial correlation coefficient; u_{it} is an error term; i is an observation number ranging from 1 to 215; and t is a time period ranging from 1 to 10, denoting the years 2007 to 2016, respectively.

3.3. Results of the Community-Based Model

After the estimation of the spatial model with fixed effects, the results were obtained (Table 2). In the model, independent variables can statistically significantly predict average farmland community sales prices, and independent variables accounted for 65% of the explained variability in farmland sales prices. The estimated coefficients are not affected by multicollinearity, according to the variance inflation factors.

The estimated value of the spatial autocorrelation parameter ρ is estimated to be significant; however, it is not large, and ρ is theoretically bound by −1 and 1, with $\rho = 0$ indicating that there is no autocorrelation. In the current case, $\rho = 0.15$ and corresponds to the presence of a relatively low level of spatial autocorrelation.

In interpreting the regression coefficients for plot size and soil quality, emphasis is placed on the average direct effects, since a spillover or indirect effect of average plot size and soil quality per community is of little practical importance, and does not fall directly within the focus of the present study. LeSage and Pace (2009) [36] provide an explanation of direct impacts, indirect impacts, and total impacts. As shown in the results, an increase in plot size increases the sales price. The own-community direct effect increases the average farmland price per hectare by 0.106%. This confirms our expectation and can be explained by the fact that arable land cultivation and other farming activities are more convenient to conduct if there is one large plot at the farmer's disposal.

The statistically significant direct effect of average soil quality measures the impact arising from changes in soil quality on average farmland sales prices. A one-unit increase in average soil quality within the community increases the average farmland price per hectare by 0.9%. Similar results showing a positive impact of plot size and soil quality on farmland prices in ST have been found and discussed by Hüttel et al. [6,17,37,38]. Some differences in coefficients between our study and those of Hüttel et al. can be explained by the fact that despite being based on data in ST, different time periods were considered and different data preparation and estimation methods were used.

Table 2. Regression results from the community-based model ($N = 2150$).

Variable	Direct Effect	Indirect Effect	Total Effect	Variance Inflation Factor
Average price, euro/ha				
Average size, ha (log)	0.106 ***	0.018 ***	0.124 ***	1.05
Average soil quality	0.009 ***	0.001 ***	0.011 ***	1.27
Capacity of wind turbines (log, shift)	0.001	0	0.001	1.05
Capacity of biogas plants (log, shift)	−0.001	0	−0.001	1.05
2007	Reference			
2008	0.073 **			

Table 2. *Cont.*

Variable	Direct Effect	Indirect Effect	Total Effect	Variance Inflation Factor
2009	0.182 ***			
2010	0.234 ***			
2011	0.379 ***			
2012	0.498 ***			
2013	0.610 ***			
2014	0.717 ***			
2015	0.823 ***			
2016	0.833 ***			
Pseudo R-squared	0.653			
Rho	0.15			
Mean VIF				1.32

Notes: ** $p < 0.01$, and *** $p < 0.001$.

Statistically significant effects of the capacity of wind turbines and biogas plants in ST on average community farmland prices are not found. It may be the case that the relatively low average capacity of wind turbines and biogas plants per community contributed to relatively large standard errors that resulted in the lack of statistical significance. Moreover, regional differences in wind energy and biogas might already be captured through community fixed effects. The presence of insignificant results concerning the effect of wind turbines are in line with other papers published earlier. However, one should note that in the case of wind energy, although Vyn and McCoullough [10] and Shultz [11] also found no significant effect of wind energy on property prices, they used entirely different variables to account for wind energy influence, and considered different countries and time periods.

The absence of an effect of biogas on farmland prices is in line with Habermann and Breustedt [12], who also found no significant effect on farmland prices in eastern Germany. Appel et al. [39], however, concluded that the EEG caused rising farmland rental prices due to higher competition, but they analysed only one county in ST and applied a different methodology, an agent-based simulation model AgriPoliS.

While the results of the model indicate a general lack of significant effects of wind- and biogas-related variables on the average farmland prices examined in this study, this does not prevent wind energy and biogas from effecting transaction prices. Thus, an alternative transaction-based model is examined and discussed in Sections 3.4 and 3.5, which investigates the impact of the capacity of wind turbines and biogas plants, as well as additional wind energy-related dummies on transaction farmland sales prices.

3.4. Transaction-Based Model

To estimate the transaction-based model, the first dataset is used. In addition, several dummy variables are defined that capture information about BVVG sales, plots appropriate for wind turbine construction included in regional development planning, plots where wind turbines have already been installed, and plots adjacent to a wind turbine plot. This information was specified by the data provider. Unfortunately, due to the lack of information about exact locations of biogas plants, the second model could not be extended to estimate the influence of the same biogas-related dummy variables.

The effect of wind energy and biogas on land prices is analysed with a hedonic price function. In the regression model, we focus on the analysis of farmland sales prices and essential determinants, such as the area of plots sold and the soil quality index. As shown in Table 3, the per hectare price varies between 11.75 euro and 858,723.4 euro, with a mean value of 11,136.89 euro. The plots sold are an average of three hectares. The average soil quality is between 6 and 105, with a mean value of 64.94. As in the first model, it is expected that larger and more productive plots will have a higher purchasing price. Year dummy variables were also included to show purchasing price development compared to the reference year 2007.

Table 3. Descriptive statistics for the transaction-based model ($N = 32,599$).

	Mean	Std. Dev.	Min	Max
Sales price, euro/ha	11,136.89	13,841.94	11.75	858,723.4
Area, ha	2.96	9.30	0.0001	469.51
Soil quality, index	64.94	22.59	6	105
Seller BVVG, dummy	0.12	0.33	0	1
Appropriate plots for wind turbine construction under regional plans (24 plots), dummy	0.001	0.03	0	1
Plots with wind turbines (79 plots), dummy	0.002	0.05	0	1
Adjacent plots to the plots with wind turbines (32 plots), dummy	0.001	0.03	0	1
Normalised cumulative capacity of wind turbines installed in the community up to the observation date, kW	22,463.56	38,215.16	0	516,237.7
Normalised cumulative capacity of biogas plants built in the community up to the observation date, kW	1525.09	13,959.19	0	414,988.8

Additionally, the dummy variable indicating 4041 plots sold by BVVG is defined. The sample includes two-thirds of the total BVVG sales within the same time period [40]. It was expected that the decreasing supply of farmland would result in increasing prices compared to the other farmland, which had already been privatised.

In the case of farmland, properties of plots may influence prices of neighbouring plots, which would indicate spatial autocorrelation. In order to address the problem of spatial autocorrelation, county dummies are included in the model. The reference county is Wittenberg, where farmland prices are the lowest in ST.

As mentioned earlier, it is expected that the capacity of wind turbines in a community impacts transaction per hectare farmland prices. This effect is measured by the cumulative capacity of wind turbines built up to the observation date in the community, normalised by the community average area. The average normalised capacity of wind turbines is 22,463 kW, and varies between 0 and 516,237 kW. The average normalised capacity of biogas plants per community is 1525 kW, and ranges between 0 and 414,988 kW.

Additionally, dummy variables containing wind energy-related information are defined. The sample contains information on 79 plots where wind turbines were already installed. Moreover, since renewable energy is a rapidly developing industry, we expect that the enlargement of existing wind farms is potentially possible and that land plots in the direct neighbourhood play a role in the development of new wind farms. Therefore, the sample contains information about 24 plots that were included in regional development plans as appropriate sites for installing a wind turbine, as well as 32 adjacent plots to wind parks.

Since hedonic models can be affected by heteroscedasticity that can lead to inefficient parameter estimates, residuals were made more closely normal and less heteroscedastic using the multivariate Box-Cox procedure. The results of the procedure show the need to log-transform all variables except for soil quality. Heteroscedasticity was also addressed by generating robust standard errors. In addition, the presence of multicollinearity was examined by the variance inflation factor.

To fit the model, the ordinary least squares regression was used. The transaction-based model is as follows:

$$\ln(P_i) = a_i + b_1 \ln(A_i) + b_2 Q_i$$
$$+ \sum_t c_t Year_{ti} + \sum_k d_k LK_{ki} + d_1 \ln(WE_i) + d_2 \ln(BM_i) \qquad (2)$$
$$+ d_3 D_{BVVG,i} + d_4 D_{WT,i} + d_5 D_{WTN,i} + d_6 D_{PLAN,i} + u_i$$

where P_i represents transaction farmland sales per hectare prices; A_i is the area of plots sold in hectares; Q_i is a soil quality index; $Year_{ti}$ is a year dummy that represents a temporal development of purchase prices compared to the reference year 2007; LK_{ki} is a county dummy that includes all 11 counties of ST; WE_i is the wind turbine capacity installed up to the relevant year in the particular community; BM_i is the capacity of biogas plants installed up to the relevant year in the particular community; $D_{BVVG,i}$ indicates farmland plots sold by BVVG; $D_{WT,i}$ indicates farmland plots where at least one wind turbine

was built; $D_{WTN,i}$ indicates farmland plots that are adjacent to wind parks; $D_{PLAN,i}$ indicates plots are suitable for wind turbine construction according to regional development plans; u_i is an error term; i is an observation numbered 1 to N; and a_i is the constant or intercept across the sample.

3.5. Results of the Transaction-Based Model

The multiple linear regression found that independent variables could statistically significantly predict farmland sales prices. Independent variables accounted for 60.4% of the explained variability in farmland sales prices (Table 4). The estimated coefficients were not affected by multicollinearity, according to the variance inflation factors.

The results show that for a 1% increase in plot size, a 0.033% increase in farmland sales price is predicted, holding all other variables constant. Similarly, for a one-unit increase in soil quality, we expect an 1.2% increase in farmland sales prices. These results are consistent with those in the first model, as well as with conclusions drawn by Hüttel et al. [6,17,37,38].

The 4041 examined farmland plots sold by the BVVG had almost 47.6% higher prices than other farmland sales. This result can be explained by the decreased area of land that remains to be privatized, and increased competition in the regional land market. Moreover, this result is in line with statistics presented in Figure 1 and results in similar research, such as Hüttel et al. [17].

Table 4. Regression results for transaction-based model ($N = 32,599$).

Variable	Coef.	Variance Inflation Factor
Price, euro/ha (log)		
Size, ha (log)	0.033 ***	1.03
Soil quality	0.012 ***	1.76
Capacity of wind turbines (log, shift)	0.004 ***	1.17
Capacity of biogas plants (log, shift)	0.000	1.22
BVVG	0.476 ***	1.02
Plans	0.323 *	1.02
Wind turbine	1.797 ***	1.00
Plot adjacent to a wind turbine	0.569 **	1.02
2007	Reference	
2008	0.121 ***	1.95
2009	0.201 ***	1.94
2010	0.253 ***	1.81
2011	0.374 ***	1.92
2012	0.516 ***	1.94
2013	0.652 ***	1.88
2014	0.817 ***	1.88
2015	0.932 ***	1.87
2016	0.998 ***	1.75
Wittenberg	Reference	
Stendal	0.167 ***	1.77
Salzlandkreis	0.437 ***	3.20
Saalekreis	0.366 ***	2.68
Mansfeld-Südharz	0.159 ***	2.64
Jerichower Land	0.114 ***	1.61
Börde	0.531 ***	2.92
Burgenlandkreis	0.384 ***	2.57
Anhalt-Bitterfeld	0.279 ***	2.02
Altmarkkreis Salzwedel	0.111 ***	1.74
Harz	0.440 ***	2.83
Constant	7.44 ***	-
R^2	0.604	-
Mean VIF	-	1.86

Notes: * $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$.

For every 1% increase in the capacity of wind turbines per community, there is an expected 0.004% increase in farmland sales prices, holding all other variables constant. We conclude that the cumulative capacity of wind turbines per community built up to the transaction date has a local effect on farmland purchasing prices. The effect is in line with conclusions drawn by Ritter et al. [9] in the case of Brandenburg; however, in the case of Brandenburg, the effect was larger. The larger effect can be explained by the higher number of wind turbines installed in Brandenburg compared to ST. Our results also show that the presence of a local effect of wind turbines on farmland prices is confirmed by the dummy variables that capture information about wind energy-related plots in ST. We can conclude that the presence of a wind turbine on a land plot leads to 179.7% higher prices. Plots adjacent to those with wind turbines are 56.9% more expensive than those that are not. In addition, plots that are appropriate for building a wind turbine are 32.2% more expensive. Both findings are related to the conclusion in Palmquist and Danielson [41] that adjacency in the case of farmland research matters. In our study, the results indeed show that proximity to wind turbines are expected to lead to higher land prices.

Both plots adjacent to and appropriate for wind turbines are associated with the probability to build a wind turbine. This could mean that it is more likely that adjacent plots will be used for enlarging already existing wind parks rather than plots included in regional planning that are not adjacent to wind parks. The positive effect of wind turbines built or potentially built on farmland prices can also be explained by the fact that there is only a small amount of land in Germany that is suitable for building wind turbines, and in the course of the rapid development of RES, such land theoretically will become scarcer. The coefficient of the capacity of biogas plants is approximately 0 and is not significant at the 0.05 level. This confirms the result of the community-based model and relevant papers in eastern Germany [12].

The coefficients of year and county dummies indicate that farmland prices have increased during the whole period covered by the study. From 2007 to 2016, prices increased an average of 175% with local differences. For example, farmland prices are 53% higher in Boerde compared to Wittenberg.

The existence of limitations in this study should not be ignored. The results of dummy variables were based on a small sample, namely 79 plots with wind turbines built up to the date of the land sale transaction, 32 plots adjacent to wind turbines, and 24 plots suitable for wind turbine construction according to regional development plans. However, the majority of plots characterised by the same features may not have been sold during the period of interest. For example, if a property's value became substantially higher as a result of becoming a competitive plot appropriate for wind turbine construction or for being adjacent to a plot with wind turbines, the owner may have refused to sell it.

4. Conclusions

In the context of the rapid development of renewable energy in Germany in the last 10 years, and the increased concerns about its possible impact on farmland prices, a hedonic pricing approach was applied to analyse the influence of renewable energy on farmland prices. For the first time, the effects of two RES, namely wind energy and biogas production (which provide about three-quarters of all of the renewable energy produced in ST), were jointly considered. Furthermore, we used a comprehensive dataset, which consists of all farmland sales in ST from 2007 to 2016. The comparison of models using aggregated data and transaction data allows for a better understanding of the RES impact on the farmland market.

The estimation of the two models showed that in the case of ST from 2007 to 2016, the capacity of wind turbines in communities had a positive local impact, albeit rather small, on farmland sales prices. The estimation did not allow a conclusion about the presence of the effect of the capacity of wind turbines on average community-level farmland prices, or about the presence of any local impact of the capacity of biogas plants located in ST.

For individual plots that are directly affected by wind energy that were examined in this study (i.e., 79 plots with wind turbines, 32 adjacent plots, and 24 plots suitable for wind turbine construction

according to regional development plans), a strong positive impact on land prices was found. The study also found that land plot size and soil quality influence agricultural land prices. Land sold by means of BVVG public auctions was generally more expensive than the average land sale price.

Due to comparable results in the German federal state of Brandenburg and a similar situation in other states, we believe that our results can be generalised for Germany as a whole. The findings have implications for the assessment of wind energy and biogas expansion, as well as for understanding factors of farmland market development. The criticism that the EEG and subsidies for renewable energy projects have an effect in the form of increasing agricultural land prices cannot be observed for biogas projects. In turn, wind parks have an impact on the local agricultural land market. In addition, possible enlargements of wind parks play a role in land prices. In this context, areas suitable for wind turbines, according to regional planning and adjacent plots, increase land values. However, one cannot attribute increasing farmland prices to the subsidisation of renewable energy or conclude that renewable energy expansion is a major factor influencing farmland prices.

The estimation procedure and results found in the present research allow several suggestions for further research. The availability of additional data, namely data containing the exact locations of all wind parks and biogas plants, adjacent plots, and regional development plans, would allow the application and examination of other approaches to measure wind energy and biogas effects on farmland prices, as in Vyn and McCullough [10] and Shultz et al. [11]. Analysing spatial effects based on distances from farmland to wind parks or biogas plants can help obtain more precise results on their effects on farmland prices. Furthermore, data regarding other renewable energy sources could be added. Then, RES could be divided into two groups. The first group could include sources that are directly related with agriculture, such as biogas, bioenergy, and biofuel production, since they require large farmland plots to be at their disposal. The second group of RES could include wind energy, solar energy, photovoltaics, etc., which do not need large land plots or "feed" produced by the agricultural industry and therefore do not have such a close link to the agricultural land market.

Conflicts of Interest: The authors declare no conflict of interest. The founding sponsors did not have a role in: the design of the study; the collection, analyses, or interpretation of data; the writing of the manuscript; or the decision to publish the results.

References

1. Deutsche Windguard. Status des Offshore-Windenergieausbaus in Deutschland. Available online: https://www.offshore-stiftung.de/sites/offshorelink.de/files/documents/Factsheet_Status_Offshore-Windenergieausbau_2017_0.pdf (accessed on 13 November 2018).

2. Statista. Installierte Elektrische Leistung der Biogasanlagen in Deutschland in den Jahren 1999 bis 2017. Available online: https://de.statista.com/statistik/daten/studie/167673/umfrage/installierte-elektrische-leistung-von-biogasanlagen-seit-1999/ (accessed on 13 November 2018). (In Megawatt)

3. Statista. Anzahl der Biogasanlagen in Deutschland in den Jahren 1992 bis 2017. Available online: https://de.statista.com/statistik/daten/studie/167671/umfrage/anzahl-der-biogasanlagen-in-deutschland-seit-1992/ (accessed on 13 November 2018).

4. Ritter, M.; Deckert, L. Site Assessment, Turbine Selection, and Local Feed-in Tariffs through the Wind Energy Index. *Appl. Energy* **2017**, *185*, 1087–1099. [CrossRef]

5. Ciaian, P.; Kancs, D.; Swinnen, J.F.M.; Van Herck, K.; Vranken, L. Key Issues and Developments in Farmland Sales Markets in the EU Member States and Candidate Countries, Working Papers 120247, Factor Markets, Centre for European Policy Studies. Available online: https://ideas.repec.org/p/ags/famawp/120247.html (accessed on 19 November 2018).

6. Hüttel, S.; Odening, M.; Balmann, A. Agricultural Land Markets—Recent Developments and Determinants. *GJAE* **2013**, *62*. Available online: http://www.gjae-online.de/news/pdfstamps/freeoutputs/GJAE-715_2013.pdf (accessed on 13 November 2018).

7. Li, R.Y.M. Changes from the Visible Hand to the Invisible Hand: The Land Market in Hong Kong Before and After the Asian Financial Crisis. In *Law, Economics and Finance of the Real Estate Market a Perspective of Hong Kong and Singapore*; Springer: Berlin/Heidelberg, Germany, 2014; pp. 1–169.

8. Torrijos, M. State of Development of Biogas Production in Europe. *Procedia Environ. Sci.* **2016**, *35*, 881–889. [CrossRef]

9. Ritter, M.; Hüttel, S.; Walter, M.; Odening, M. Der Einfluss von Windkraftanlagen auf landwirtschaftliche Bodenpreise. *Berichte über Landwirtschaft-Zeitschrift für Agrarpolitik und Landwirtschaft* **2015**, *93*, 1–15. [CrossRef]

10. Vyn, R.; McCullough, R. The Effects of Wind Turbines on Property Values in Ontario: Does Public Perception Match Empirical Evidence? *CJAE* **2014**, *62*, 365–392. [CrossRef]

11. Shultz, C.; Hall, J.; Strager, M. Production of Wind Energy and Agricultural Land Values: Evidence from Pennsylvania. Working Paper No. 15–11, Department of Economics, West Virginia University. Available online: https://business.wvu.edu/files/d/13f8b90e-982f-45cb-86d0-d1c20eff8ef4/15-11.pdf (accessed on 13 November 2018).

12. Habermann, H.; Breustedt, G. Einfluss der Biogaserzeugung auf Landwirtschaftliche Pachtpreise in Deutschland. *GJAE* **2011**, *60*, 85–100.

13. Emmann, C.; Guenther-Lübbers, W.; Theuvsen, L. Impacts of Biogas Production on the Production Factors Land and Labour—Current Effects, Possible Consequences and Further Research Needs. *Int. J. Food Syst. Dyn.* **2013**, *4*, 38–50. [CrossRef]

14. Hennig, S.; Latacz-Lohmann, U. Impacts of bioenergy promotion on farmland rental rates in Northern Germany. *ERAE* **2016**, *44*, 231–254. [CrossRef]

15. European Commission (December 2014): Factsheet on 2014–2020 Rural Development Programme for Saxony-Anhalt (Germany). Available online: https://ec.europa.eu/agriculture/sites/agriculture/files/rural-development-2014-2020/country-files/de/factsheet-saxony-anhalt_en.pdf (accessed on 17 March 2018).

16. Statistical Office of Saxony-Anhalt. Windkraft Wird Wichtigster Energieträger: Mehr als die Hälfte des Erzeugten Stroms aus Erneuerbaren Energien. Available online: https://www.stala.sachsen-anhalt.de/Internet/Home/Veroeffentlichungen/Pressemitteilungen/2017/11/275.html (accessed on 13 November 2018).

17. Hüttel, S.; Wildermann, L.; Croonenbroeck, C. How Do Institutional Market Players Matter in Farmland Pricing? *Land Use Policy* **2016**, *59*, 154–167. [CrossRef]

18. Bodenmarkt. Verkäufe von Agrarland in Sachsen-Anhalt 2007. Available online: http://www.bodenmarkt.info/g/BM-Ex/daten/3-1/3-1-1-4/BMsDE_ST08_06_26.pdf (accessed on 13 November 2018).

19. Bodenmarkt. Verkäufe von Agrarland in Sachsen-Anhalt 2008. Available online: http://www.bodenmarkt.info/g/BM-Ex/daten/3-1/3-1-1-5/BMsDE_ST09_06_25.pdf (accessed on 13 November 2018).

20. Bodenmarkt. Verkäufe von Agrarland in Sachsen-Anhalt 2009. Available online: http://www.bodenmarkt.info/g/BM-Ex/daten/3-1/3-1-1-6/BMsDE_ST10_05_26.pdf (accessed on 13 November 2018).

21. Bodenmarkt. Verkäufe von Agrarland in Sachsen-Anhalt 2010. Available online: http://www.bodenmarkt.info/g/BM-Ex/daten/3-1/3-1-1-7/BMsDE_ST11_05_31.pdf (accessed on 13 November 2018).

22. Bodenmarkt. Verkäufe von Agrarland in Sachsen-Anhalt 2012. Available online: http://www.bodenmarkt.info/g/BM-Ex/daten/3-1/3-1-1-9/BMsDE_ST13_05_21.pdf (accessed on 13 November 2018).

23. Bodenmarkt. Verkäufe von Agrarland in Sachsen-Anhalt 2014. Available online: http://www.bodenmarkt.info/g/BM-Ex/daten/3-1/3-1-1-11/BMsDE_ST15_09_22.pdf (accessed on 13 November 2018).

24. Bodenmarkt. Verkäufe von Agrarland in Sachsen-Anhalt 2016. Available online: http://www.bodenmarkt.info/g/BM-Ex/daten/3-1/3-1-1-13/BMsDE_ST17_08_23.pdf (accessed on 13 November 2018).

25. BVVG. Informationen für Presse, Funk und Fernsehen (2008–2017). Available online: www.bvvg.de (accessed on 13 November 2018).

26.　Leiren, M.D.; Reimer, I. EU Coercion or Voluntary National Decision Making? The Shift towards Auctions in German Renewable Energy Policy. Paper to Presented at the Panel 'Climate and Energy: EU Renewable Energy in Comparison' in the Section 'Energy Policy, Politics and Governance' at the General ECPR Conference 2017, Oslo. Available online: https://ecpr.eu/Filestore/PaperProposal/ea8df7c6-f2a3-44d3-8343-baaeaaa0aab8.pdf (accessed on 13 November 2018).

27.　Federal Ministry for Economic Affairs and Energy. Act on the Development of Renewable Energy Sources. 2014. Available online: https://www.bmwi.de/Redaktion/EN/Downloads/renewable-energy-sources-act-eeg-2014.pdf?__blob=publicationFile&v=1 (accessed on 13 November 2018).

28.　Gesetz für den Ausbau Erneuerbarer Energien (Erneuerbare-Energien-Gesetz—EEG 2017). Available online: https://www.gesetze-im-internet.de/eeg_2014/BJNR106610014.html (accessed on 13 November 2018).

29.　Gelman, A.; Hill, J. Missing-data imputation. In *Data Analysis Using Regression and Multilevel/Hierarchical Models*; Cambridge University Press: Cambridge, UK, 2006; pp. 529–544.

30.　Nickerson, C.J.; Zhang, W. Modelling the Determinants of Farmland Values in the United States. In *The Oxford Handbook of Land Economics*; Duke, J.M., Wu, J., Eds.; Oxford University Press: New York, NY, USA, 2014; pp. 111–138.

31.　Baltagi, B.H. *Econometric Analysis of Panel Data*; Wiley & Sons: Chichester, UK, 2005.

32.　Moran, P.A. Notes on Continuous Stochastic Phenomena. *Biometrika* **1950**, *37*, 17–23. [CrossRef] [PubMed]

33.　Drukker, D.M.; Peng, H.; Prucha, I.R. Creating and Managing Spatial-Weighting Matrices with the Spmat Command. *Stata J.* **2013**, *13*, 242–286. [CrossRef]

34.　Anselin, L.; Bera, A. Spatial dependence in linear regression models with an introduction to spatial econometrics. In *Handbook of Applied Economic Statistics*; Ullah, A., Ed.; Marcel Dekker: New York, NY, USA, 1998; pp. 237–289.

35.　Lee, L.-F.; Yu, J. Estimation of Spatial Autoregressive Panel Data Models with Fixed Effects. *J. Econom.* **2010**, *154*, 165–185. [CrossRef]

36.　LeSage, J.P.; Pace, K.R. Introduction to Spatial Econometrics. Taylor&Francis Group, LLC. 2009. Available online: http://enistat.lecture.ub.ac.id/files/2013/02/James_LeSage_Robert_Kelley_Pace-Introduction_to_Spatial_Econometrics_Statistics___A_Series_of_Textbooks_and_Monographs-Chapman_and_Hall_CRC2009.pdf (accessed on 13 November 2018).

37.　Hüttel, S.; Odening, M.; Kataria, K.; Balmann, A. Price Formation on Land Market Auctions in East Germany—An Empirical Analysis. *GJAE* **2013**, *62*, 99–115.

38.　Hüttel, S.; Ritter, M.; Esaulov, V.; Odening, M. Is There a Term Structure in Land Lease Rates? *ERAE* **2016**, *43*, 165–187. [CrossRef]

39.　Appel, F.; Ostermeyer-Wiethaup, A.; Balmann, A. Effects of the German Renewable Energy Act on Structural Change in Agriculture. The Case of Biogas. *Util. Policy* **2016**, *41*, 172–182. [CrossRef]

40.　BVVG. Informationen *für* Presse, Funk und Fernsehen vom 11. January 2018. Available online: https://www.bvvg.de/Internet/waktuell.nsf/vbroinfo/dPDFPM113_webaktuell/$File/pm113.pdf (accessed on 20 November 2018).

41.　Palmquist, R.B.; Danielson, L.E. A Hedonic Study of the Effects of Erosion Control and Drainage on Farmland Values. *Am. J. Agric. Econ.* **1989**, *71*, 55–62. [CrossRef]