German Journal of Agricultural Economics Vol. 74 (2025), 1-33

Original Research Article

https://doi.org/10.52825/gjae.v74i.2537

Submitted: 12 Nov. 2024 | Accepted: 08 Jun. 2025 | Published: 12 Aug. 2025

Costs of Farmland Fragmentation: Evidence from Farmland Transactions in Eastern Germany

Lars Isenhardt[1,*], Stefan Seifert[1], Theelke Wiltfang[2], and Silke Hüttel[1]

[1]Georg-August University of Göttingen, Germany

[2]Independent Researcher, Germany

*Correspondence: Lars Isenhardt, lars.isenhardt@uni-goettingen.de

Abstract: Farmland fragmentation in use is related to higher operation cost and reduced productivity, while ownership fragmentation increases transaction costs, both leading to inefficient land use and diminished overall farm performance. This paper aims to quantify the costs of farmland ownership fragmentation using a market-based approach. We hypothesize that buyers and sellers in the farmland market have a lower valuation and demand for spatially separated farmland. To test this hypothesis, we analyze a rich dataset of 24,528 arable land transactions from the eastern German Federal State of Brandenburg from 2000 to 2022 that includes information on whether the traded land was spatially fragmented. Using a doubly robust approach combining matching and regression, we find that package transactions of spatially separated parcels achieve on average 6.7% lower prices than transactions of single parcels with the same size and comparable characteristics. The quantified markdown for packages suggests that market participants associate costs with fragmentation and consider these into their valuation for farmland.

Keywords: Fragmentation, Land Market, Farmland Pricing, Matching, Hedonic Model

1 Introduction

Land use fragmentation refers to the spatial distribution of plots under cultivation; farmland ownership fragmentation summarizes spatially distributed small, non-contiguous parcels across owners. Both often have been discussed as the result of historical land reforms and restitution processes (Hartvigsen, 2014) and in the context of inheritance practices (Gatterer et al. 2024) and urbanisation trends (Zheng et al., 2022).

Such farmland fragmentation is widely associated with inefficiencies and increased costs for land users and owners (Veršinskas et al., 2020): fragmented farmland use is associated with higher production costs and lower operation efficiency as smaller and spatially distant plots increase transportation costs and reduce economies of scale (Valtiala et al. 2023; Ptacek et al. 2024), and ultimately farm productivity (Latruffe, Piet, 2014). Given such distance costs, farms prefer land in proximity and their willingness to bid and pay for land declines with distance and with fragmentation (Graubner, 2018; Graubner, Hüttel, 2024). Fragmented ownership implies higher transaction and administration costs, e.g., to find solvent tenants (Humpesch et al., 2023). Fragmentation may also weaken landowners' bargaining position in the land market; for example, parcels too small to be cultivated independently may have to be leased out (Sklenicka et al., 2014). At a broader scale, ownership fragmentation involving numerous stakeholders can impede the implementation of land-based initiatives such as land improvement (Sklenicka, 2016), nature conservation (Veršinskas et al., 2020), and renewable energy projects (Winikoff, Parker, 2023). Land ownership fragmentation may thus contribute to an underutilization of common resources (Buchanan, Yoon, 2000). Empirical evidence that quantifies the costs of farmland fragmentation remains, however, limited.

This paper aims to quantify the costs of farmland ownership fragmentation using a market-based approach based on observed farmland prices. Observed market prices capture the expectations of bidders about future returns and the associated cost of spatially separated parcels. We hypothesize that buyers and sellers in the farmland market have a lower valuation and demand for spatially separated farmland. Markdowns for spatially separated parcels compared to contiguous parcels with identical size and characteristics would provide evidence that market participants consider the costs of fragmentation in their willingness to pay and bid for farmland. We test this hypothesis by quantifying price differences between transactions of spatially separated parcels (package transactions) and transactions of single or contiguous parcels of land (single transactions).[1] Our empirical analysis uses 24,528 arable land transactions in the eastern German Federal State of Brandenburg. This region is marked by highly fragmented farmland ownership, with over 170,000 private non-agricultural landowners holding 52% of the farmland and on average of seven parcels per owner (Jänicke, Müller, 2025). Around 30% of transactions involve packages of spatially fragmented parcels.

Across different study regions, analyses of farmland price formation consistently identify transaction size as key price determinant, though empirical findings on the size-price relationship remain mixed and context-dependent (Ritter et al., 2020; Schaak et al., 2023). The role of fragmentation in this relationship, however, remains unclear. Assembling spatially separated parcels into one package may offer transaction cost savings, productivity gains argued to drive the size-price relationship may be limited to transactions of single contiguous parcels. Further, because farmland markets are thinly traded with overall limited supply and price formation being governed by the underlying local market structure (Balmann et al., 2021), each transaction is unique.

To isolate the valuation for fragmentation while accounting for the specifics of farmland markets, we apply a doubly robust approach: we use non-parametric matching to pair package transactions with single transactions that are comparable in transaction size, soil quality, location, and time. Using the matched sample, we run a parametric hedonic price regression to quantify the price effect attributable to package transactions. Our results indicate that package transactions of spatially separated parcels receive on average 6.7% lower prices than comparable single transactions. The observed markdown for packages suggests that market participants associate costs with fragmentation and consider these into their valuation for farmland.

This paper contributes to the literature on costs of farmland ownership fragmentation using a market-based approache based on farmland prices. It offers the first systematic approach that explicitly discusses and quantifies the market valuation for spatially fragmented farmland. Our findings inform policymakers about the benefits of land consolidation and improve market transparency by highlighting fragmentation as a determinant of farmland prices. Our robust and tractable approach provides a framework for market-based valuation, which can support land consolidation efforts. Our results also underscore the importance of informing future sellers and buyers at the farmland market whether prices were formed in a package, or in a single transaction.

The paper is structured as follows: Section 2 introduces the study region and data. Section 3 outlines our empirical strategy. We present our results in Section 4; Section 5 discusses our results and concludes.

[1] Package transactions consist of at least two spatially separated parcels. Our data does not provide information on the exact number of parcels included in a transaction or their distances from each other.

2 Study Region and Data

2.1 Study Region

The German Federal State of Brandenburg, our study region, is located in eastern Germany and surrounds the German capital, Berlin. Nearly 45% of Brandenburg's area is used for agriculture, with 77% arable land and 23% grassland. Farming conditions are characterized by low precipitation (long-term average 1991-2022: 580 mm/year) compared to the German average (800 mm/year) (DWD, 2022b), and low average soil quality with mostly sandy soils with poor water storage capacity (Schmitz, Müller, 2020).

As in other eastern German Federal States and states with a post-communist transition economy history (Hartvigsen, 2014), Brandenburg's land ownership structure and agricultural sector have been shaped by the communist era between 1945 and 1989, followed by subsequent restitution and privatization (Wilson, Wilson, 2001; Wolz, 2013). Following World War II, the land of farms exceeding 100 ha and those owned by active Nazi members were expropriated between 1945 and 1949, known as the first land reform in Eastern Germany. This land was redistributed to private individuals, mostly agricultural workers, small-scale farmers, and refugees, resulting in an average farm size of 8 ha with approximately 560,000 landowners. In 1952, aiming to increase agricultural productivity, the Socialist Party initiated the consolidation of private farms into collective farms known as agricultural production cooperatives (LPGs). The collectivization processes continued until the fall of the Iron Curtain in 1989, resulting in a large-scale farm structure comprising around 580 state farms and 4,000 corporate farms and cooperatives. Following Germany's reunification, land was returned to the members and to former owners who had been expropriated after 1949. This process was managed by the *Treuhandanstalt* until 1992; thereafter, jurisdiction over this land was transferred to the state agency *Bodenverwertungs- und Verwaltungs GmbH* (BVVG) with the mandate to transfer the land to private ownership. In 2007, the BVVG adopted a highly efficient tendering mechanism in addition to direct sales to privatize land at market prices (Seifert, Hüttel, 2023). Until 2023, BVVG transferred in total around 900 thousand hectares of agricultural land to private ownership at market price, accounting for around 10% of the total farmland in eastern Germany (BVVG, 2023).

Brandenburg's farmland ownership remains highly fragmented. In 2020, more than 170,000 private persons owned 52% of the total farmland, with an average of seven parcels per owner (Jänicke, Müller, 2025). Field sizes average at 12 hectares (Wesemeyer et al., 2023).

In total, around 5,400 farms operated in Brandenburg in 2023. The average farm size is 242 ha, i.e., around four times the German average (MLUL BB, 2023). The farm structure includes small privately-owned farms and larger agricultural holdings and cooperatives with average farm sizes of 134 ha and 688 ha, respectively (MLUL BB, 2023). With the privatization process, the share of rented land decreased from 81.3% in 2005 to 64.9% in 2023 (EU average: approx. 50%; Eurostat, 2024). Privately owned farms show a lower share at 59.1% compared to farms operated as legal entities at 66.8%.

The farmland market in Brandenburg is thinly traded, with only 1.4% of the total agricultural area traded annually between 2005 and 2022 (MLUL BB, 2023). Farmland prices developed dynamically: Between 2005 and 2022, prices more than tripled from around 2,501 €/ha in 2005 to 12,180 €/ha in 2022. Given Germany's rather liberal farmland market regulation (Vranken et al., 2021), investigating Brandenburg's land market provides a suitable case for analysis.

2.2 Farmland Transaction Data

We rely on detailed transaction data for arable land from 2000 to 2022 in Brandenburg provided by the Committee of Land Valuation Experts (*Oberer Gutachterausschuss, OGA*) (see Appendix A for the data profile). On behalf of the federal state, the OGA documents all farmland transactions to track land market activity and to ensure market transparency. For each transaction, we observe the sales price, key land characteristics (e.g., transaction size and a soil quality index[2]), characteristics of the transaction (e.g., contract date), and location information including the geocoordinate.

The data also includes information on whether a transaction consists of a single parcel or if it includes more than one parcel.[3] We define a package transaction as a transaction with at least two spatially separated parcels and refer to transactions involving one parcel or contiguous parcels as single transactions. In package transactions, our data does not enable us to identify the number of parcels and their distance to each other. Recorded characteristics of package transactions relate to the “price-determining” or “largest” parcel (e.g., transaction coordinate). We illustrate package transactions involving spatially separated parcels based on selected transactions with information on all included parcels identified in the transaction’s records in Appendix Figure A1.

Our initial data set comprises 51,216 transactions. We consider arm’s-length transactions; 145 transactions with prices of 500 €/ha or less, and with total prices of 1 € or less are removed as they likely do not reflect regular market activity. We also consider only transactions of parcels that can be operated independently, e.g., without requiring further rights of way, which excludes another 6,913 observations. Following the OGA’s definition of regular land market activity, we remove 4,203 transactions smaller than 0.25 ha. We drop 811 transactions located in Brandenburg’s four independent cities (Brandenburg an der Havel, Cottbus, Frankfurt (Oder), Potsdam) due to a suspected urbanization impact on prices potentially correlated with the choice of selling a single parcel or a package of parcels. Further, we drop 7,417 transactions by public sellers including the privatization agency BVVG as price formation may differ from the remaining market due to the use of public tenders and the tendency to package a large number of parcels of heterogeneous qualities in one offer (Seifert, Hüttel, 2023). We exclude data from eight counties in the early years of the observation period, during which parcel transactions seem to be erroneously recorded (see Appendix A1 for details). A further 3,487 observations are excluded due to missing information. This mainly concerns unobserved soil qualities, which are not recorded for transactions of farmland intended for a future non-agricultural use, such as public infrastructure investments. Lastly, we also remove 370 transactions identified as outliers using the minimum covariance determinant estimator (Rousseeuw, van Driessen, 1999).

Our final dataset for the analysis comprises 24,528 transactions with a total transaction volume of 104,624 hectares generating revenues of 671 million € in 2015 terms (GDP deflator by Destatis, 2022). Thereof, 17,112 are single transactions (53,567 ha, 352 million € in 2015 terms), and 7,416 package transactions (51,057 ha, 320 million € in 2015 terms).

2.3 Farmland Price Determinants

We augment the transaction data by incorporating information on factors that affect the expected returns from land ownership that are likely to be reflected in the observed sales prices

[2] The soil quality index reflects the natural yield capacity of farmland. It is used for the fiscal valuation of agricultural land in Germany. The parameters of soil structure up to a depth of one meter, terrain conditions, climatic conditions, water availability and other natural conditions are included in the index (Schmitz, Müller, 2020).

[3] The data differentiations transaction composition as: 1 = entire parcel affected, 2 = parcel partially affected, 3 = additional parcels also affected, 4 = additional parcels affected with parcels being spatially separated.

(Nickerson, Zhang, 2014). For each transaction, we consider the land's productivity, local farming conditions, and the local farming structure as key elements.

We capture expectations about the returns of land ownership by the transaction size, soil quality, and water availability. An increasing parcel size may offer economies of scale, suggesting higher expected returns from farming and thus higher prices (Ritter et al., 2020); returns to scale may, however, not be available for the buyer of a package. For very large transaction size, competition may be reduced due to the financing constraints of the potential buyers. A price premium may be observed for smaller parcels (Brorsen et al., 2015) due to a wider range of potential buyers, including, for instance, non-agricultural buyers intending a non-agricultural post-sale land use, such as horse keeping.

Climate change affects yields and yield stability by impacting the local drought exposure and water availability and thus may affect expected returns from farming and finally farmland values (Ortiz-Bobea, 2020). To account for water availability, we use the long-term average annual precipitation in the 30 years before the transaction extracted from a 1 km grid at the transaction coordinate (DWD, 2022b). To account for droughts, we indicate the lands' drought exposure in the three years before the transaction using the average de Martonne drought index over this period calculated on a 1 km grid at the transaction coordinate (DWD, 2022a).

The expectation of higher returns from a non-agricultural land use, often tied to the location of land, may likewise influence farmland prices (e.g., Delbecq et al., 2014). We use multiple variables to capture such effects: to account for potential urban sprawl effects around Berlin, we use a dummy variable that reflects location in a municipality bordering the city-state of Berlin. A second dummy indicates adjacency to a settlement if the parcel's most distant point is within 500 m of a settlement to account for option values from a potential conversion to building land by. Additionally, we consider the distance to the next upper or middle centers[4] (BBSR, 2019) to account for urban proximity and infrastructure access (Seifert et al., 2021). We also use the shares of utilized agricultural area (UAA) and settlement area at the municipal level to indicate the local land use structure and demand for land. To account for land demand for animal husbandry, we include information on the capacity-weighted livestock density (LSU) using georeferenced data on farmsteads, types of husbandry, and stable sizes in Brandenburg (LfU, 2022).

With the German Renewable Energy Act in 2000, Brandenburg became a hotspot region for renewable electricity generation. Higher expectations on returns from using land for renewable energy production have been shown to increase land rents (e.g., Hennig, Latacz-Lohmann, 2017) and farmland values (e.g., Haan, Simmler, 2018). To account for the impact of renewable energy sources, we utilize plant-level data recorded by the German regulatory office for electricity (*Marktstammdatenregister, BNetzA, 2022)*. We derive capacity weighted-kernel density maps (Hart, Zandbergen, 2014) that reflect the installed capacity of each wind and biogas plant in each year in Brandenburg, and extract the respective installed density at the location of the transaction.

2.4 Pre-Assessment

Table 1 lists the descriptive statistics for package transactions (left) and single transactions (right). Parcel packages account for around 30% of all transactions in our sample. We observe minor unconditional price differentials between transactions of parcel packages (0.58 €/m²) and single parcels (0.59 €/m²) (see Table 1). Over our observation period, no clear patterns are visible (e.g., -0.057 €/m² in 2002 and -0.018 €/m² in 2022).

[4] The distance-based hierarchy of upper and middle centers is based on the principles outlined in Germany's Spatial Planning Act, which aims to ensure balanced access to essential facilities throughout the country (BBSR, 2019).

Table 1. Descriptive statistics by transaction composition status

n= 24,528	**Packages** n_t = 7,416				**Single** n_c= 17,112			
	Mean	SD	Q1	Q99	Mean	SD	Q1	Q99
Dependent variable								
Deflated price [€/m²]	0.58	0.43	0.11	2.01	0.59	0.44	0.10	2.04
Price [€/m²]	0.59	0.46	0.10	2.10	0.59	0.47	0.09	2.14
Land characteristics								
Transaction size [ha]	6.88	6.11	0.39	29.5	3.13	4.13	0.26	21.34
Soil quality [index]	32.95	9.87	16.00	61.00	32.32	10.52	14.00	62.89
Agro-climatic conditions								
Precipitation [cm]	56.38	3.67	47.75	65.12	56.87	3.38	48.41	64.89
Drought index [count]	2.87	0.37	2.02	3.74	2.89	0.36	2.02	3.70
Location								
Metro region [0/1]	0.04	0.20	0.00	1.00	0.05	0.22	0.00	1.00
Adjacency to settlement [0/1]	0.15	0.36	0.00	1.00	0.28	0.45	0.00	1.00
Distance to next center [km]	38.63	15.08	10.21	81.47	36.73	15.3	8.62	79.63
Share UAA [%]	55.8	19.25	18.41	89.8	53.75	18.89	16.18	89.01
Share settlement [%]	5.86	5.32	1.61	29.83	6.40	5.75	1.57	31.59
LSU density [LSU/cell]	3.47	2.10	0.12	9.17	3.56	2.37	0.08	10.31
Renewable energies								
Wind density [MW_{el}/cell]	4.92	11.24	0.00	51.57	4.49	10.04	0.00	49.18
Biogas density [MW_{el}/cell]	1.01	1.40	0.00	6.88	0.91	1.26	0.00	5.95

Notes: due to data privacy regulations, minima and maxima are not reported.
Source: own calculation based on data sources indicated in text

Packages and single transactions exhibit, on average, similar soil quality of around 32 index points with similar ranges between 14 and 62, respectively. The transaction size is 6.88 ha on average for packages, which is twice as high as for single transactions (3.13 ha). The 99th quantile of transaction size indicates a wider range for package transactions (29.5 ha) compared to single transactions (21.34 ha).

Approximately 28% of the single transactions are adjacent to settlements, compared to around 15% for package transactions. We observe small differences in the distance to the nearest regional and administrative center (38 km for packages, and 36 km for single transactions), the share of UAA at the municipality (55.4% vs 53.7%), and the share of settlement (5.86% and 6.40%). Small differences in average wind and biogas densities suggest that package transactions are located in regions with higher intensity of wind power and biogas installations.

The data shows some spatio-temporal dynamics in the shares of package transactions: respective shares vary across Brandenburg's districts, ranging from 17% in Elbe-Elster to 45% in Teltow-Fläming (see Figure 1). In some counties, the total traded volume of package transactions exceeds that of single transactions while comprising fewer transactions (see Appendix A, Figure A3 and Table A2). Over our sample period, 2000–2022, the annual share of package transaction in Brandenburg ranges from 25.2% to 40.8% (see Appendix A, Figure A4), without a clear time trend.

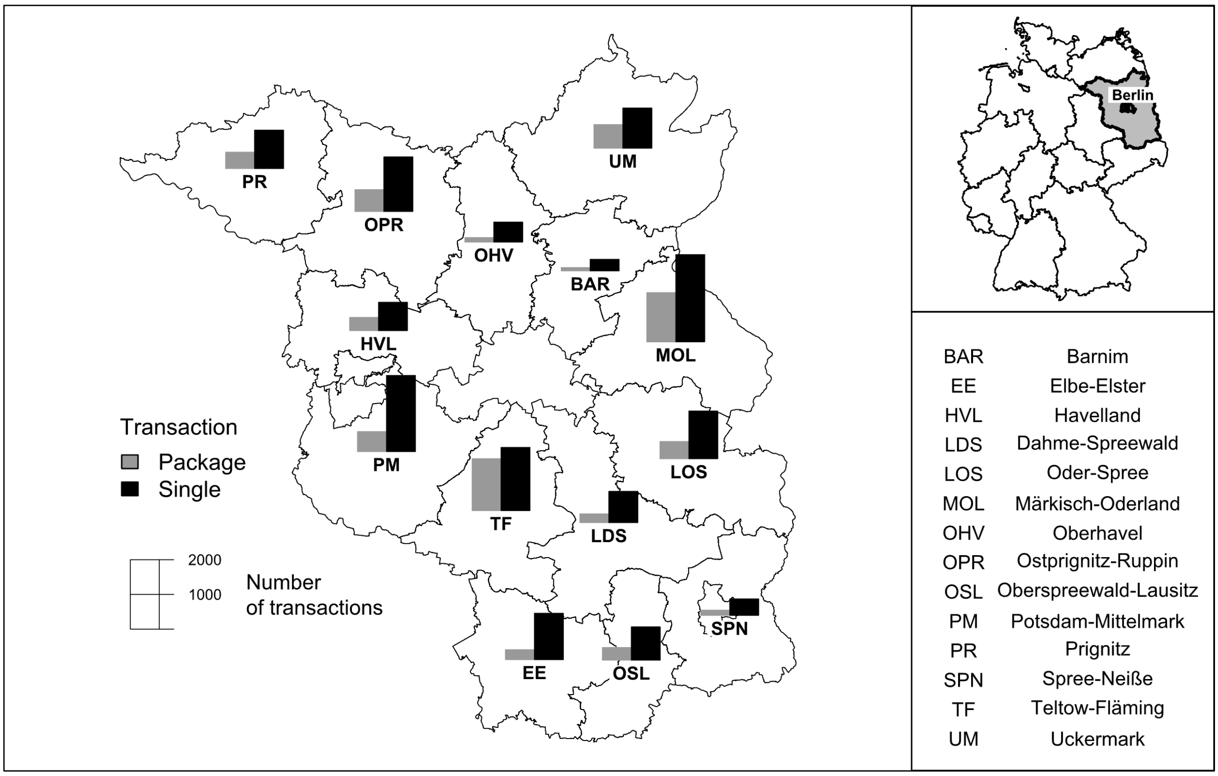

Figure 1. Number of transactions by composition in Brandenburg, Germany

Source: own illustration based on data from the Committee of Land Valuation Experts in Brandenburg

3 Empirical Strategy

To quantify the price differences between package transactions and single transactions, we consider that whether a parcel is sold in a single transaction or in a package may not be random but depend on the land's characteristics and market sentiment. For instance, in regions with excess demand and strong competition for agricultural land, buyers might be more willing to buy a package of spatially separated parcels if parcels of the package would otherwise be sold to another buyer. Without further control, such a relationship between our effect of interest and the sales' characteristics could bias our estimates.

To mitigate such potential bias, we aim to compare transactions with similar land characteristics traded in the same local market and at the same time. We follow the procedure proposed by Ho et al. (2007) and adopt a doubly robust approach that combines non-parametric matching in a first step with a parametric post-matching regression in the second step. Matching in the first step serves as a pre-processing to identify a set of single transactions similar in farmland characteristics, market location, and time of trade to the package transactions. In the second step, we conduct a parametric hedonic regression using the matched sample to quantify price effect attributable to package transactions. The second step adjusts for remaining imbalances in the variables used for matching and for other price-determining factors not included in the matching. The resulting estimate of the package effect is “doubly robust”; that is, it is consistent if either the matching procedure or the parametric outcome model are correctly specified (Ho et al., 2007: 215). This reduces model dependence in the parametric regression.

3.1 Matching

The matching uses a non-parametric two-nearest neighbor matching to identify for each package transaction the two nearest single transactions with the most similar covariate values. The similarity between two transactions is assessed through the Mahalanobis distance, which combines information in a unitless measure accounting for the potential correlation of these variables (Rubin, 1980). Matching on Mahalanobis distance creates pairs of transactions with similar covariate values (i.e., following the idea of matching a "perfect" twin), addressing critiques on other approaches such as propensity score matching (King, Nielsen, 2019). The two-nearest neighbor matching based on the Mahalanobis is particularly suitable for our approach: matching on few key characteristics ensures similarity in the main price determinants while retaining a sufficiently large pool for matching twice. Two-nearest neighbor matching further reduces the dependence of the identified effects on individual transactions.

In the matching, we consider transaction size x_s, soil quality x_q, and longitude and latitude of the transaction coordinate as covariates. Matching on transaction size and soil quality ensures similarity in the main land productivity characteristics (Nickerson, Zhang, 2014). Matching on the coordinates should ensure that matched transactions are traded in the same market environment, including similar supply and demand structures as well as competition for farmland (Balmann et al., 2021). The geographical proximity may further increase similarity in location-specific factors impacting farmland price formation. This includes both factors observed and unobserved by us, such as weather characteristics, topographic features or the degree of urban sprawl. Matching on coordinates, rather than exact matching on administrative units, helps to mitigate problems of defining the relevant market and allows matching across administrative borders. To ensure that potential matches take place in times of similar market sentiment, and to account for the price surge in our observations period (Hainbach et al., 2024), we only match package transactions with single transactions from the same year, or one year apart.

To avoid a potential bias from extreme single transactions, we allow the matching of a single transaction only up to three times (Stuart, 2010). This prevents an overuse of control units and a high dependence on a few control units while limiting the effect of a single potential match on the final outcome. We assess the matching quality based on the standardized difference in means and the Euclidian distance between package transactions and their matched single transactions.

3.2 Hedonic Regression

In the second step, we base our analysis on the hedonic pricing framework (Rosen, 1974), where the price of land is expressed as a function of the implicit prices of its characteristics. These implicit prices reflect the average market valuation of the land's characteristics, determined by the observed matches of the buyer's willingness to pay and the seller's willingness to accept. The observed farmland price p_i for a transaction i, resulting from a search and bargaining process, with land characteristics x_i', is expressed as:

$$ln(p_i) = h(x_i'\beta) + \delta^{package} d_{i,package} + \epsilon_i \quad (1)$$

where $h(.)$ denotes the hedonic price function, β the vector of implicit prices of the land characteristics, and ϵ the error term. We assume that this relationship varies between non-fragmented and package transactions through the indicator variable $d_{i,package}$, where $d_{i,package} = 0$ for single transactions, and $d_{i,\text{package}} = 1$ for package transactions; $\delta^{package}$ indicates the price effect attributable to being a package transaction. The parameter estimate of $\delta^{package}$, $\hat{\delta}^{package}$, indicates the average price effect attributable to a transaction being a package, i.e., the market valuation for fragmentation in a package.

We estimate Equation (1) using the natural logarithm of the price p in € per m^2 of the transaction i deflated to 2015 values as the dependent variable. In the hedonic part, $h(.)$, we adjust for price-determinants of farmland considering land characteristics, location, agro-climatic conditions, and renewable energy intensity. For the land characteristics and agro-climatic conditions, we follow Seifert et al. (2025) and use a flexible functional form to allow for potential non-linear relationships. Transaction size (x_s) and soil quality (x_q) enter flexibly as square roots, in their quadratic form, and as interactions of the linear terms. Precipitation (z_{pre}) and drought index (z_{dro}) are included in linear and quadratic form. We use dummy variables to indicate the location in the metropolitan area of Berlin (d_{berlin}) and adjacency to a settlement (d_{settle}). The distance to the next high or middle center (x_{dist}) enters in linear and squared form. We describe the local land use by the shares of agricultural land (x_{uaa}) and settlements (x_{settle}) at the municipal level in linear terms. We account for land demand from animal husbandry and for renewable energy production from wind and biogas plants using respective spatial kernel densities in linear term. To capture remaining unobserved temporal and spatial heterogeneity, we add county dummy variables (d_l) indicating the location in one of the 14 counties, and year dummy variables (d_t) for the respective year of sales. We add a dummy variable indicating the time of transaction in the third quarter of a year (d_{Q3}) to account for a potential seasonality resulting from higher cash flows of farms after the harvest season (Seifert et al., 2021). Omitting the transaction-specific subscript i, the hedonic specification is

$$\begin{aligned} h(.) = \quad & \alpha + \beta_1\sqrt{x_s} + \beta_2 x_s^2 + \beta_3\sqrt{x_q} + \beta_4 x_q^2 + \beta_5\left(x_s \times x_q\right) + \\ & \beta_6 z_{pre} + \beta_7 z_{pre}^2 + \beta_8 z_{dro} + \beta_9 z_{dro}^2 + \\ & \beta_{10} d_{berlin} + \beta_{11} d_{settle} + \beta_{12} x_{dist} + \beta_{13} x_{dist}^2 + \beta_{14} x_{UAA} + \beta_{15} x_{settle} + \\ & \beta_{16} x_{LSU} + \beta_{17} x_{biogas} + \beta_{18} x_{wind} \\ & \textstyle\sum_l \gamma_l^{county} d_l + \sum_t \gamma_t^{year} d_t + \gamma_{Q3} d_{Q3} \end{aligned} \tag{2}$$

where α denotes the intercept; β's and γ's are parameters to be estimated for price-determining factors and spatiotemporal dummy variables, respectively.

We estimate the second step regression using weighted least squares. Weights for the matched single transactions reflect the matching frequency from the pre-processing step scaled to the sum of the uniquely matched single transactions (Ho et al., 2011). Weights for the package transactions are one. Unmatched single transactions receive a weight of zero.

To illustrate the magnitude of the package effect, we simulate the monetary difference between a single and a parcel transaction for different transaction sizes and transaction compositions. Using the coefficient estimates from the hedonic regression, we predict prices and revenues for a hypothetical sale of two parcels sold separately or as a package. We vary the composition between the two parcels considering parcel sizes from 0.5 to 17.5 hectares and investigate how different composition of the package affect price outcomes. We use Märkisch-Oderland (MOL), the county with the highest transaction volume, and the year 2022 as the baseline for prediction; all other variables are fixed at the matched weighted sample mean.

Because our observations might be non-independent within clusters (Abadie et al., 2023), we base statistical inferences on clustered standard errors. To determine the appropriate level of clustering, we implement the test by MacKinnon et al. (2023). That is, we sequentially test from fine clustering (i.e., no clustering, each observation is a cluster) to coarser clustering (municipal level, county level). Based on the test result, we report 95% confidence intervals using cluster-robust standard errors clustered at the municipal level. We implement our approach using R, version 4.3.1; the matching procedure is implemented using the MatchIt package v.4.5.4 (Ho et al., 2011).

3.3 Effect Heterogeneity

The package price effect may vary with transaction size and financial volume due to economies of scale (Valtiala et al., 2023; Ritter et al., 2020; Schmidt et al., 2024), and due to the land market sentiment in which a transaction occurred. We therefore analyze potential heterogeneity in the package effect for different transaction sizes, across space, and over time.

First, addressing the role of transaction size we investigate the package-effect for different transaction sizes by interacting the package indicator $d_{package}$ with dummy variables for the deciles of the transaction size observed in our matched sample. We use 10 dummy variables $d_{d,size}$ that equal one for a transaction in the d^{th} decile of the observed transaction size distributions. The regression Equation is:

$$ln(p) = h(.) + \sum_{d=1}^{10} \delta_{d,size}^{package}\left(d_{package} \times d_{d,size}\right) + \sum_{d=1}^{10} \beta_{d,size} d_{d,size} + \epsilon \qquad (3\text{-}1)$$

where $\delta_{d,size}^{package}$ gives the average log price difference between the transactions of packages and matched single transactions for decile group d, conditional on characteristics included in $h(.)$.

Second, parcel sizes and landownership structures may, however, vary also notably across our study region (Balmann et al., 2021; Jänicke, Müller, 2025). The probability to observe a package transaction and potential price differentials between single and package transaction may thus be linked to a lot's location. We investigate spatial heterogeneity of the package price effect by interacting the package indicator $d_{package}$ with dummy variables indicating location in one of the 14 counties such that

$$ln(p) = h(.) + \sum_{l=1}^{14} \delta_{l}^{package}(d_{package} \times d_l) + \epsilon \qquad (3\text{-}2)$$

where $\delta_{l}^{package}$ indicates the average log price difference between single and package transactions in county l.

Third, given the considerable price surge in our study region during the observation period, we also investigate the temporal heterogeneity of the package price effect. We perform a rolling window analysis: We split our unmatched sample into consecutive, overlapping subsamples of three years each, resulting in 21 overlapping intervals (2000-2002, 2001-2003, …, 2020-2022). For each interval, we apply the doubly robust approach with two-nearest neighbor matching, and post-matching regression based on Equation (1). For each interval, all single transaction observations from the same years, one year prior, and one year afterwards are considered as potential matches. This procedure gives the average log price difference between package and matched single transactions for each of the 21 intervals. In contrast to a time interaction model that spans the entire period, the rolling window approach offers flexibility regarding other explanatory variables and provides a more nuanced analysis for each interval.

3.4 Robustness Checks

We investigate the robustness of our results using additional analyses. First, we compare various empirical model specifications with and without matching, including and excluding county fixed effects, year fixed effects, and the hedonic control variables. Second, we investigate the robustness of our results under different matching estimators. We perform one- and three-nearest-neighbor matching as well as kernel matching. The kernel matching uses a Gaussian kernel; bandwidths are selected to minimize the mean integrated squared error (Wand, Jones, 1994). In all cases, the second step regression uses the specification of Equation 2. Third, we run our procedure on different samples. We consider samples based on our cleaning procedure enlarged by transactions (i) in the four independent cities of Brandenburg, (ii) including public sellers, and (iii) in counties with erroneous recordings. We also conduct a robustness check based on a sample without further filtering except for removing observations with missing values and inconsistent data.

4 Results

4.1 Matching Quality

The results of the two-nearest-neighbor matching based on the Mahalanobis distance with up to three replacements matches 7,416 package transactions with 7,711 single transactions. Of the matched single transactions, 3,461 are matched once, 1,406 are matched twice, and 2,853 units are matched three times (see Appendix Table B1 for descriptive statistics). Figure 2 shows the absolute standardized mean difference of the main variables for the unmatched (grey) and the matched sample (black). After matching, the absolute standardized difference in means is below 0.1 for all core characteristics, indicating a good matching balance (Stuart, 2010). The average mean distance between the location of the matched pairs is 13.68 km (median 10.58 km) indicating that transactions of the matched samples occurred in the same region.

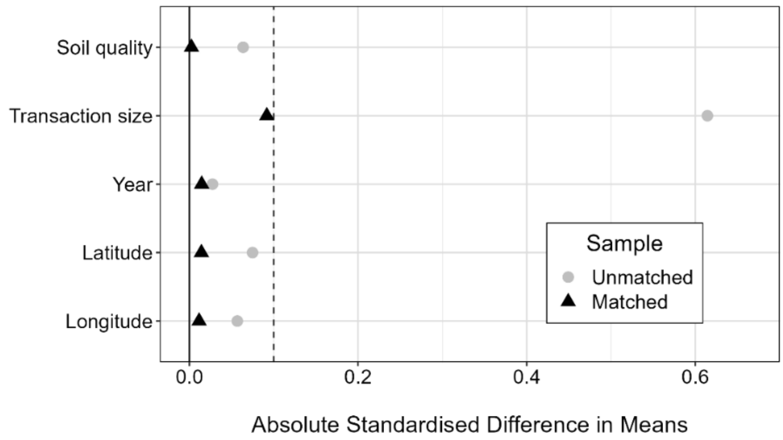

Figure 2. Matching quality

Source: own illustration based on estimates from first-stage matching

4.2 Hedonic Post-Matching Regression

Table 2 shows the post-matching regression results for our main model. The regression shows an R^2 of 0.708, indicating a satisfying fit in explaining the price variation. We interpret the coefficients as the percentage change in the dependent variable by one unit change in the independent variable by transforming the reported coefficient by $(\exp(\hat{\beta}) - 1) * 100$ (Wooldridge, 2010: 186). Coefficients smaller than 0.1 can be directly read as the proportional change.

In line with other studies (e.g., Ritter et al., 2020), we find a non-linear relationship between transaction size and prices with a decreasing marginal effect. Results also show a positive effect of urbanization on land prices, with average markups of 26.9% ($(e^{0.238} - 1) * 100$) and 7.1% for transactions located in the metropolitan region of Berlin and adjacent to settlements, respectively. An increasing intensity of renewable energy production from wind and biogas is associated with higher prices.

We find that transactions of spatially separated parcels (packages) yield, on average, 6.7% lower prices compared to similar transactions of single or contiguous parcels. The 95%-CI, derived from robust standard errors clustered at the municipal level, spans from -7.9% to -5.4%, suggesting some statistical uncertainty but robust negative effects. A t-test rejects the null hypothesis of no effect of transaction composition on farmland prices at any conventional level of statistical significance.

Table 2. Post-matching regression results of the main model

	Coef.	**95%-CI**
Intercept	-0.712	(-1.955, 0.531)
Land characteristics		
√Transaction size	0.035	(0.020, 0.051)
√Soil quality index	0.111	(0.083, 0.140)
Transaction size²	-0.0002	(-0.000, -0.000)
Soil quality²	-0.0000	(-0.000, 0.000)
Transaction size × soil quality	0.0002	(0.000, 0.000)
Agro-climatic conditions		
Precipitation	-0.045	(-0.091, 0.000)
Precipitation²	0.000	(-0.000, 0.001)
Drought index	-0.136	(-0.387, 0.116)
Drought index²	0.030	(-0.012, 0.072)
Location		
Metro region Berlin	0.238	(0.203, 0.272)
Adjacency to settlement	0.071	(0.054, 0.087)
Distance to next center	0.006	(0.004, 0.008)
Distance to next center²	-0.0001	(-0.001, -0.0005)
Share UAA	0.003	(0.002, 0.003)
Share settlement	0.001	(-0.000, 0.003)
LSU density	0.001	(-0.003, 0.005)
Renewable energy		
Wind density	0.001	(0.000, 0.002)
Biogas density	0.014	(0.008, 0.019)
Transaction composition		
Package	-0.067	(-0.079, -0.054)
Year FE	Yes	
County FE	Yes	
Weights	Yes	
Single transactions	7,720	
Package transactions	7,416	
R^2	0.708	

Notes: The dependent variable is the log price in €/m² deflated to Q4/2015 Euro values using the quarterly GDP deflator (Destatis, 2022). 95%-confidence intervals are based on heteroscedasticity-consistent standard errors clustered at the municipal level. Fixed effects for county and year dummy variables are listed in Appendix Table B2.
Source: own calculation using Equation (1)

The post matching regression results indicate price markdowns for package transactions and markups for larger transaction sizes, with a non-linear relationship between price and size. Figure 3 illustrates in panel a) the estimated relationship between transaction size and prices for single transactions and package transactions in Märkisch-Oderland for 2022 fixing all other variables at the matched sample means. Panel b) shows the results of the predicted difference in revenues between the separate sale of two parcels and the sale of as a package of the same size.

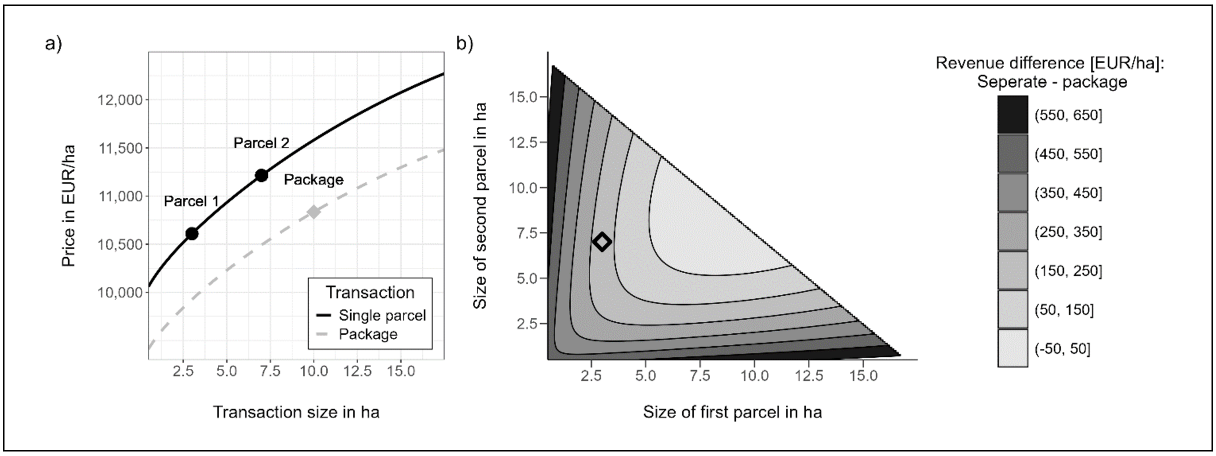

Figure 3. a) Predicted price-size relationship for single transactions and packages and b) difference in revenues between the separate sale of two parcels and their sale as a package in €/ha

Source: own illustration based on estimates from Table 2

The difference in revenues between two parcels sold either separately or together as a package varies with total transaction size and with the composition of the package. For instance, a package transaction consisting of one 3-ha parcel and a 7-ha parcel shows lower revenues of around 150–250 € per ha. For two medium-sized parcels equal in size (6–8 ha), results suggest that selling two parcels together as a package could achieve higher revenues compared to a separate sale. That is, with increasing transaction size and similar proportions of the two parcels, the difference in revenues between separate sales and sale as a package decreases.

Figure 4 contrasts the package effect estimate results from our main model (depicted in black) against effect estimates obtained through alternative specifications. We find markdowns for package sales in all specifications. Nearly all confidence intervals overlap with our main estimate. Exceptions are models that do not account for the time effect and, thus, omit the strong price increase in the observation period. We note that our main specification has the smallest 95% CI for the parcel price effect among all models. The mean price difference between the package transactions and single transactions in the unmatched sample is statistically insignificant based on a t-test; without condition on any other control variables. Regression using the full specification of the hedonic regression without matching (column 11) suggests a higher effect size than the main model, with a coefficient estimate of -7.5% (95%-CI: -8.75% to -6.29%). The unconditional matched price difference between in the matched sample (-6.3%) is nearly identical to our main model; we note a notably larger confidence, interval ranging from -8.59% to -4.08%. This underscores that the matching already accounts for the main farmland price determinants, whereas the second step helps to reduce statistical uncertainty of the estimated effect of interest by accounting for other price determinants.

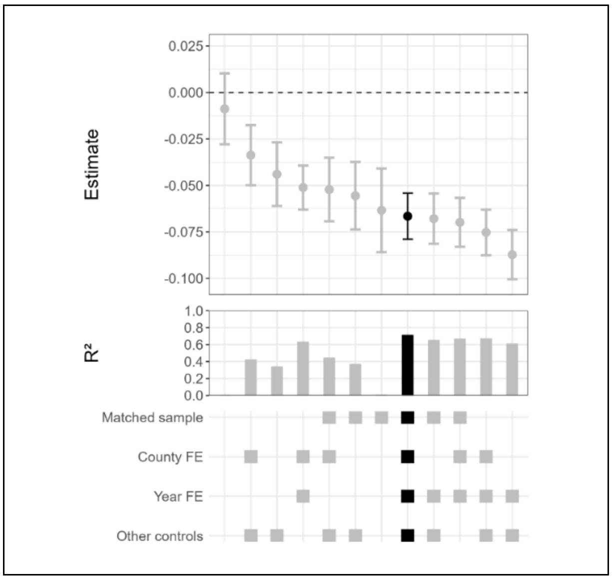

Figure 4. Specification chart with different models in decreasing order of the package estimate, black indicates the main model

Source: own illustration

Second, we investigate the robustness of our results under different matching estimators and using different sample selection criteria. Results of the robustness check, summarized in Appendix C, show markdowns for package sales with magnitudes close to our main estimate and overlapping confidence intervals. Pairwise t-tests do not reject the null hypothesis of identical effects at conventional levels of statistical significance.

4.3 Effect Heterogeneity

Figure 5 illustrate the package effects by transaction size (panel a), over space (panel b), and time (panel c). For deciles of the transaction size, the interaction terms range from -3.6% to -8.8% with generally overlapping 95% CIs. Pairwise t-tests do not indicate statistically distinguishable point estimates at conventional levels of statistical significance (see Appendix B, Table B3). The package effect estimates by county (panel b) show some spatial heterogeneity and vary between +3.5% (Barnim, BAR) and -13.7% (Oder-Spree, LOS). Except for one county, point estimates are negative; for around the half of the estimates, 95% CIs cover only negative values. Results do not suggest obvious spatial patterns across our study region. Results also indicate only minor variation over our observation period (panel c). The panel suggests a slight decrease in the price effect attributable to package transactions for time intervals after the onset of the farmland price boom in 2007; 95%-CIs are, however, overlapping across all intervals.

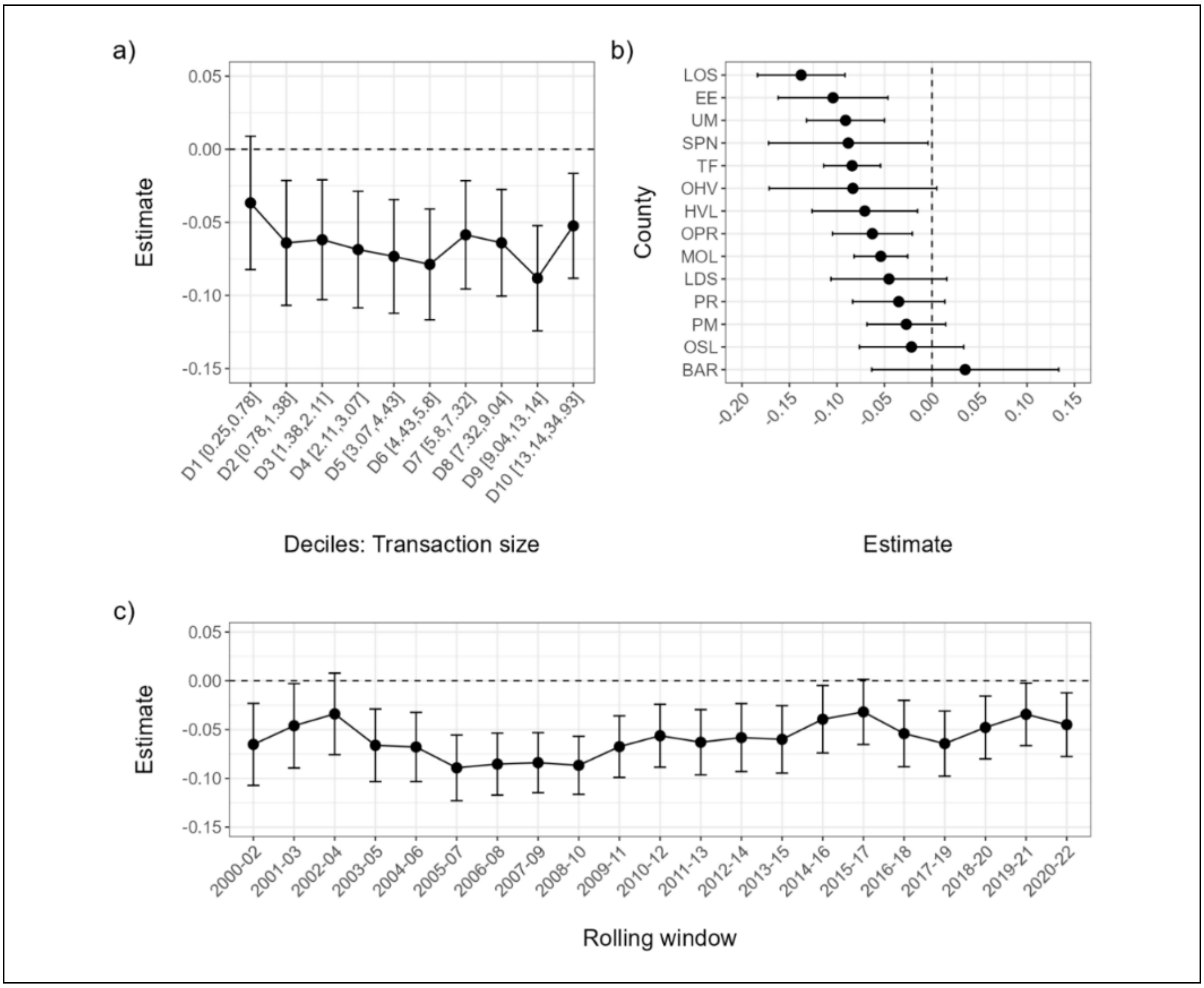

Figure 5. Package estimate by a) transaction size, b) county, and c) time

Source: own illustration

5 Discussion and Conclusion

The aim of the study was to quantify costs of farmland fragmentation based on market-based approach. Using 24,528 arable land transaction in Brandenburg between 2000-2022, we quantify price differences between packages transaction of spatially separated farmland and transaction of single contiguous parcels.

Our doubly robust approach combining matching and hedonic price regression indicate that package transactions of spatially separated parcels achieve, on average, 6.7% (95%-CI: -7.9% to -5.4%) lower prices compared to transactions of single or contiguous parcels of the same size traded at the same time in the same market. Simulation results suggest that price differences between package and single transaction vary with the composition of the packages with lower markdowns for packages containing lots of rather equal sizes. For our sample, this corresponds to 20.5 million € lower revenues, relative to a hypothetical case in which all parcels were consolidated. We qualify this markdown for spatially separated parcels as buyers' and sellers' costs of land fragmentation, i.e., the reduced valuation for farmland associated with fragmentation. In turn, the increase in land values if parcels were consolidated could also be interpreted as the positive valuation for land consolidation (Veršinskas et al., 2021).[5] The markdown for spatially separated farmland remains robust across various model specifications,

[5] We thank the anonymous reviewer for offering this interpretation.

matching approaches, and sample selections (see Appendix C). The heterogeneity analysis indicates that the package effect exhibits some spatial variation across the study region.

We offer two explanations of the markdown for fragmented farmland, consisting with spatial theory for farmland markets (Graubner, 2018): First, buyers may associate fragmented farmland with higher management and operation costs, reducing their willingness to pay. For farmer buyers, increased distances between parcels raise transportation costs and limit benefits from economies of scale of larger field sizes (Ptacek et al., 2024; Valtiala et al., 2023), reducing the expected returns from farming. This aligns with Latruffe, Piet (2014), who show that land fragmentation has adverse effects on farm performance in various dimensions (i.e., production costs, yields, revenue, profitability and efficiency). Non-farmer buyers aiming to acquire land for renting out may factor in higher transaction costs post-sale including anticipated additional costs for managing the portfolio related to the search of the tenant with the highest willingness to pay (Humpesch et al., 2023). The markdown may also reflect the reduced development potential associated with fragmented farmland, i.e., fragmentation hinders implementation of infrastructure projects or investment in renewable energy (e.g., Winikoff, Parker, 2023).

Second, the markdown can also be interpreted as the result from reduced demand for fragmented land and altered bargaining position of sellers and buyers in the price formation. Packages of spatially-fragmented parcels may draw interest of buyers willing to acquire all parcels in the package. This buyer group is likely smaller and potentially distinct from those interested in the individual parcels as more productive parcels tend to attract more bidders and different bidder types including also non-agricultural investors (Isenhardt et al., 2023; Piet et al., 2021; Seifert, Hüttel, 2023). This interpretation is supported by Pennerstorfer (2022) and Michels et al. (2024), who find that farms are more likely to opt for short-term rentals rather than purchasing land as distance costs increase. Sellers facing a smaller pool of potential buyers may have a weakened bargaining position in the price formation process (Balmann et al., 2021). Interested buyers may benefit from reduced competition and may have an improved bargaining position in the price formation, with lower prices as a result (Curtiss et al., 2021; Balmann et al., 2021). We note, however, that we cannot differentiate these two effects of a reduced valuation and reduced competition for packages. These effects are likely to appear simultaneously and are thus observed as net effect in our markdown for packages of fragmented farmland.

The observed markdown for fragmented farmland raises concerns of allocation efficiency and the potential of foregone revenues for sellers in a land market with high search and information gathering costs. Ideally, farmland should be allocated to most productive land-user with the highest valuation (Seifert, Hüttel, 2023). An ex-ante design of the package, however, may create an entry barrier by deterring some buyers type that are interest only in some parcels of the package.

Multi tract auctions offer a potential mechanism to improve the allocative efficiency in the presence of farmland fragmentation (Cramton et al., 2010; Milgrom, 2012). In contrast to standard auctions formats with bidders bidding on packages predefined by the auctioneer, multi-tract auctions allow bidders to place offers on individual tracts, combinations of tracts, or the entire package. The auctioneer awards the land to the bidder(s) offering the revenue-maximizing allocation. This mechanism can attract a broader range of buyers (Milgrom, 2012), ranging from a non-agricultural buyer interest in one specific parcel up to an agricultural investor valuing the entire package. Attracting broader range of bidders and allowing for a more nuanced expression of bids can result in higher revenues for the auctioneer and a more efficient allocation of the farmland (e.g., Milgrom, 2012; Levin, Skrzypacz, 2016).

For landowners and buyers, our findings indicate that strategic land consolidation may increase the overall value of farmland. Even if not all parcels in a package are ideally aligned in terms of location or suitability, purchasing the package may be still attractive for farmers and may offer the potential for growth (Appel, Balmann, 2023). Distant parcels may later be exchanged with neighboring farms to improve spatial efficiency (Rönnqvist et al., 2023), or used to meet EU CAP requirements for non-productive landscape features such as set-aside areas (Cuadros-Casanova et al., 2023).

From a policy perspective, our results highlight the costs associated with farmland fragmentation in use and ownership and emphasize the benefit of land consolidation programs to address these inefficiencies. Land consolidation programs restructure ownership and parcels, thereby increase parcel size and reducing the number of parcel per owner (Veršinskas et al., 2021; Veršinskas et al., 2020). A central element in this process is land valuation commonly following the *"least as well-off"* principle. Ideally, this means that a landowner receives an equivalent area of land within the same cadastral unit, at a similar distance to the settlement, and with comparable characteristics but as one parcel. Our approach adds to market-based valuation used in voluntary land consolidations programs that relies on comparable sales transaction to determine land value at market price. By combining matching and hedonic regression, we provide a tractable framework that can inform policymakers and practitioners in land consolidation procedures, offering a transparent, market-based benchmark for valuation in thinly traded land markets. Beyond land consolidation, the approach can also be helpful in other contexts where equitable land valuation is required, for instance, compensation for land loss or increased fragmentation resulting from infrastructure projects. Moreover, for land markets, our results also highlight that information about the transactions' composition should recorded in price publications and official statistics to prevent biases in the future price formation of farmland (Seifert, Hüttel, 2023).

We note the following limitations of our study, which also provide opportunities for future research: First, we lack detailed information on the degree of fragmentation within a package, such as the number of parcels, their individual sizes, and distances from the main parcel. Consequently, we are unable to uncover in detail how the degree of fragmentation influences farmland valuation. Second, despite our rich model specification, unobserved heterogeneity may confound the effect estimate. This may concern buyer-specific information, for instance, if a single parcel was purchased by a nonfarmer for non-agricultural purposes. Third, we lack explicit information on buyers' locations (e.g., farmstead or residence), which determine distance costs and thereby influence willingness to pay and bid behavior. Fourth, the applied approach of combining matching and regression provides a well-established and interpretable framework. However, a misspecification of the functional form in the hedonic regression could bias the estimated effect attributed to package transactions. Although the matching step reduces model dependence by improving comparability between transactions, it does not fully resolve concerns about functional form assumptions. Alternative approaches, such as causal forests (Athey, Imbens, 2016) or double/debiased machine learning (Chernozhukov et al., 2018) offer greater flexibility by allowing the data to determine the functional relationships. Such methods are particularly suited to high-dimensional settings and to uncover effect heterogeneity with a trade-off regarding interpretability. Given our focus on farmland price formation - where domain knowledge informs model specifications - our chosen approach balances robustness, transparency, and practical applicability. Nevertheless, future research could benefit from using more advanced approaches such as causal forest (e.g., Schmidt et al., 2024) with geo-referenced transaction data and detailed land-use information, and buyer location data.

Data Availability Statement

The data underlying this article cannot be shared publicly due to data privacy restrictions on the farmland transaction data. Remote access to the data may be provided upon reasonable request to the corresponding author.

Underlying and Related Material

The code of used of the analysis and a synthetic dataset for testing purposes are available at https://doi.org/10.15456/gjae.2025168.0821751054

Author Contributions

Lars Isenhardt: Conceptualization, Methodology, Formal analysis, Data curation, Visualization, Writing – original draft, Writing - Review & Editing. **Stefan Seifert**: Conceptualization, Methodology, Writing – original draft, Funding acquisition, Writing - Review & Editing. **Theelke Wiltfang**: Formal analysis, Data curation, Writing – original draft. **Silke Hüttel**: Conceptualization, Resources, Writing - Review & Editing, Funding acquisition.

Competing Interests

The authors declare no competing interests.

Funding

The authors gratefully acknowledge financial support from the German Research Foundation (DFG) through Research Unit 2569 "Agricultural Land Markets: Efficiency and Regulation" (Grant number: 317374551).

Acknowledgement

We thank the Committee of Land Valuation Experts of Brandenburg for providing the data. We also thank the two anonymous referees and the participants of the AES Conference and GeWiSoLa 2024 for their valuable comments and suggestions.

Declaration of AI

The authors acknowledge the use of Artificial Intelligence, specifically the large language model chatGPT v.4, for consistency checks in programming tasks and proofreading of the manuscript.

References

Abadie, A., Athey, S., Imbens, G.W., Wooldridge, J.M. (2023): When Should You Adjust Standard Errors for Clustering? The Quarterly Journal of Economics 138 (1): 1-35. https://doi.org/10.1093/qje/qjac038.

Appel, F., Balmann, A. (2023): Predator or prey? Effects of farm growth on neighbouring farms. Journal of Agricultural Economics 74 (1): 214-236. https://doi.org/10.1111/1477-9552.12503.

Athey, S., Imbens, G.W. (2016): Recursive partitioning for heterogeneous causal effects. PNAS 113 (27): 7353-7360. https://doi.org/10.1073/pnas.1510489113.

Balmann, A., Graubner, M., Müller, D., Hüttel, S., Seifert, S., Odening, M. et al. (2021): Market Power in Agricultural Land Markets: Concepts and Empirical Challenges. German Journal of Agricultural Economics 70 (4): 213-235. https://doi.org/10.30430/gjae.2021.0117.

BBSR (Bundesinstitut für Bau-, Stadt-, und Raumforschung) (2019): Laufende Stadtbeobachtung - Raumabgrenzungen (Urban Monitoring - Spatial Denomination of Metropolitan Areas). Hg. v. Federal Institute for Research on Building, Urban Affairs and Spatial Development, Bonn. https://www.bbsr.bund.de/.

BNetzA (Bundesnetzagentur) (2022): Marktstammdatenregister – Öffentliche Einheitenübersicht (Core energy market data register of the Bundesnetzagentur). Bonn. http:/www.marktstammdatenregister.de.

Brorsen, B. W., Doye, D., Neal, K.B. (2015): Agricultural Land and the Small Parcel Size Premium Puzzle. Land Economics 91 (3): 572-585. https://doi.org/10.3368/le.91.3.572.

Buchanan, J.M., Yoon, Yong, J. (2000): Symmetric Tragedies: Commons and Anticommons. The Journal of Law and Economics 43 (1): 1-14. https://doi.org/10.1086/467445.

BVVG (Bodenverwertungs- und verwaltungs GmbH) (2023): Zahlen und Fakten 2023 (Facts and figures 2023). https://www.bvvg.de/wp-content/uploads/2024/06/Zahlen_und_Fakten_2023.pdf.

Chernozhukov, V., Chetverikov, D., Demirer, M., Duflo, E., Hansen, C., Newey, W., Robins, J. (2018): Double/debiased machine learning for treatment and structural parameters. The Econometrics Journal 21 (1): C1-C68. https://doi.org/10.1111/ectj.12097.

Cramton, P.C., Shoham, Y., Steinberg, R. (2010): Combinatorial auctions. 1st MIT Press paperback ed. MIT Press, Cambridge, Mass., London.

Cuadros-Casanova, I., Cristiano, A., Biancolini, D., Cimatti, M., Sessa, A.A., Mendez Angarita, V.Y. et al. (2023): Opportunities and challenges for Common Agricultural Policy reform to support the European Green Deal. Conservation biology: the journal of the Society for Conservation Biology 37 (3): e14052. https://doi.org/10.1111/cobi.14052.

Curtiss, J., Jelínek, L., Medonos, T., Hruška, M., Hüttel, S. (2021): Investors’ impact on Czech farmland prices: a microstructural analysis. European Review of Agricultural Economics 48 (1): 97-157. https://doi.org/10.1093/erae/jbaa029.

Delbecq, B.A., Kuethe, T.H., Borchers, A.M. (2014): Identifying the Extent of the Urban Fringe and Its Impact on Agricultural Land Values. Land Economics 90 (4): 587-600. https://doi.org/10.3368/le.90.4.587.

Destatis (Statistisches Bundesamt) (2022): VGR des Bundes - Deflatoren: Deutschland, Jahre, Verwendung des Bruttoinlandsprodukts. Wiesbaden. http://www.destatis.de.

DWD (Deutscher Wetterdienst) (2022a): Annual grids of drought index (de Martonne) over Germany. Offenbach, https://dwd-geoportal.de/products/GRD_DEU_P1M_DI-M/, accessed 11.11.2022.

DWD (2022b): Multi-annual grids of precipitation height over Germany 1981-2022. Offenbach.

Eurostat (2024): Agriculture, fisheries, and forestry: Agriculture - Farm tenure. European Union. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Farm_tenure#Data_sources.

Gatterer, M., Leonhardt, H., Salhofer, K., Morawetz, U. (2024): The legacy of partible inheritance on farmland fragmentation: Evidence from Austria. Land Use Policy 140: 107110. https://doi.org/10.1016/j.landusepol.2024.107110.

Graubner, M. (2018): Lost in space? The effect of direct payments on land rental prices. European Review of Agricultural Economics 45 (2): 143-171. https://doi.org/10.1093/erae/jbx027.

Graubner, M., Hüttel, S. (2024): Rental and sale prices of agricultural lands under spatial competition. Letters in Spatial and Resource Science 17 (32): 1-12. https://doi.org/10.1007/s12076-024-00396-6.

Haan, P., Simmler, M. (2018): Wind electricity subsidies - A windfall for landowners? Evidence from a feed-in tariff in Germany. Journal of Public Economics 159: 16-32. https://doi.org/10.1016/j.jpubeco.2018.01.011.

Hainbach, T., Hüttel, S., Werwatz, A. (2024): What Moves Farmland Markets: Decomposing the Price Surge in Eastern Germany. European Review of Agricultural Economics 51 (4): 967-1011. https://doi.org/10.1093/erae/jbae029.

Hart, T., Zandbergen, P. (2014): Kernel density estimation and hotspot mapping. Policing: An International Journal of Police Strategies & Management 37 (2): 305-323. https://doi.org/10.1108/PIJPSM-04-2013-0039.

Hartvigsen, M. (2014): Land Reform and Land Fragmentation in Central and Eastern Europe. Land Use Policy 36: 330-341. https://doi.org/10.1016/j.landusepol.2013.08.016.

Hennig, S., Latacz-Lohmann, U. (2017): The incidence of biogas feed-in tariffs on farmland rental rates - evidence from northern Germany. European Review of Agricultural Economics 44 (2): 2231-2254. https://doi.org/10.1093/erae/jbw023.

Ho, D.E., Imai, K., King, G., Stuart, E.A. (2007): Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference. Political Analysis 15 (3): 199-236. https://doi.org/10.1093/pan/mpl013.

Ho, D.E., Imai, K., King, G., Stuart, E.A. (2011): MatchIt: Nonparametric preprocessing for parametric causal inference. Journal of Statistical Software 42 (8): 1-28. https://doi.org/10.18637/jss.v042.i08.

Humpesch, M., Seifert, S., Balmann, A., Hüttel, S. (2023): How does tenancy affect farmland prices? Effects of lease status, lease term and buyer type. Agricultural Finance Review 83 (2): 242-263. https://doi.org/10.1108/AFR-03-2022-0038.

Isenhardt, L., Seifert, S., Hüttel, S. (2023): Tenant Favoritism and Right of First Refusals in Farmland Auctions: Competition and Price Effects. Land Economics 99 (2): 302-324. https://doi.org/10.3368/le.080721-0091R1.

Jänicke, C., Müller, D. (2025): Revealing agricultural land ownership concentration with cadastral and company network data. Agriculture and Human Values 42: 159-175. https://doi.org/10.1007/s10460-024-10590-3.

King, G., Nielsen, R. (2019): Why Propensity Scores Should Not Be Used for Matching. Political Analysis 27 (4): 435-454. https://doi.org/10.1017/pan.2019.11.

Latruffe, L., Piet, L. (2014): Does land fragmentation affect farm performance? A case study from Brittany, France. Agricultural Systems 129: 68-80. https://doi.org/10.1016/j.agsy.2014.05.005.

Levin, J., Skrzypacz, A. (2016): Properties of the Combinatorial Clock Auction. The American Economic Review 106 (9): 2528-2551. https://doi.org/10.1257/aer.20141212.

LfU (Landesamt für Umwelt Brandenburg) (2022): Tierhaltungsanlagen nach BImSchG im Land Brandenburg. https://registry.gdi-de.org/id/de.bb.metadata/5b98270b-4280-48e3-bf93-744a07a263b0, accessed at 25.07.2022.

MacKinnon, J.G.; Nielsen, M.Ø., Webb, M.D. (2023): Testing for the appropriate level of clustering in linear regression models. Journal of Econometrics 235 (2): 2027-2056. https://doi.org/10.1016/j.jeconom.2023.03.005.

Michels, M., Hobe, C.-F. von, Merk, M.S., Kneib, T., Musshoff, O. (2024): Analyzing individual rent price ratios in eastern German agricultural land markets: A GAMLSS approach. Agribusiness, Artikel agr.21976. https://doi.org/10.1002/agr.21976.

Milgrom, P. (Hg.) (2012): Putting Auction Theory to Work. Cambridge University Press, Cambridge, UK.

MLUL BB (Ministerium für Landwirtschaft, Umwelt und Klimaschutz des Landes Brandenburg) (2023): Agrarbericht des Ministeriums für Landwirtschaft, Umwelt und Klimaschutz des Landes Brandenburg. Brandenburg Ministry for Rural Development, Environment and Agriculture. Potsdam. https://agrarbericht.brandenburg.de, accessed at 09.03.2023.

Nickerson, C.J., Zhang, W. (2014): Modeling the Determinants of Farmland Values in the United States. In: Duke, J.M., Wu, J. (Hg.): The Oxford Handbook of Land Economics. Oxford University Press, New York: 111-138.

Ortiz-Bobea, A. (2020): The Role of Nonfarm Influences in Ricardian Estimates of Climate Change Impacts on US Agriculture. American Journal of Agricultural Economics 102 (3): 934-959. https://doi.org/10.1093/ajae/aaz047.

Pennerstorfer, D. (2022): Farm exits and competition on the land market: Evidence from spatially explicit data. Economics working papers, 2022-09. Department of Economics (Ed.), Johannes Kepler University Linz.

Piet, L., Melot, R., Diop, S. (2021): What drives competition on the farmland market? A case study in Brittany (France). European Review of Agricultural Economics 48 (1): 60-96. https://doi.org/10.1093/erae/jbaa019.

Ptacek, M., Frick, F., Pahl, H., Stetter, C., Wimmer, S., Sauer, J. (2024): 'ShapeCostTUM': A calculation tool for field geometry dependent cultivation and transport costs. Computers and Electronics in Agriculture 225: 109254. https://doi.org/10.1016/j.compag.2024.109254.

Ritter, M., Hüttel, S., Odening, M., Seifert, S. (2020): Revisiting the relationship between land price and parcel size in agriculture. Land Use Policy 97: 104771. https://doi.org/10.1016/j.landusepol.2020.104771.

Rönnqvist, M., Frisk, M., Flisberg, P., Casimir, J., Engström, J., Hansson, E., Kihlstedt, A. (2023): Collaboration and optimization in farmland exchanges. International Transactions in Operational Research 30 (4): 1591-1616. https://doi.org/10.1111/itor.13145.

Rosen, S. (1974): Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition. Journal of Political Economy 82 (1): 34-55. http://www.jstor.org/stable/1830899.

Rousseeuw, P.J., van Driessen, K. (1999): A fast algorithm for the minimum covariance determinant estimator. Technometrics 41 (3): 212-223. https://doi.org/10.2307/1270566.

Rubin, D.B. (1980): Bias Reduction Using Mahalanobis-Metric Matching. Biometrics 36 (2): 293-298. https://doi.org/10.2307/2529981.

Schaak, H., Meissner, L., Musshoff, O. (2023): New insights on regional differences of the farmland price structure: An extended replication study on the parcel size-price relationship. Applied Economic Perspectives and Policy 45 (3): 1255-1775. https://doi.org/10.1002/aepp.13366.

Schmidt, L., Odening, M., Ritter, M. (2024): Do non-farmers pay more for land than farmers? European Review of Agricultural Economics 51 (4): 1094-1128. https://doi.org/10.1093/erae/jbae023.

Schmitz, T., Müller, D. (2020): Digitale Karte der Bodenwertzahlen für Brandenburg. FORLand Technical Paper Series 01. https://doi.org/10.22004/ag.econ.308812.

Seifert, S., Hüttel, S. (2023): Is there a risk of a winner's curse in farmland auctions? European Review of Agricultural Economics 50 (3): 1140-1177. https://doi.org/10.1093/erae/jbad002.

Seifert, S., Hüttel, S., Werwatz, A. (2025): Organic cultivation and farmland prices: Does certification matter? European Review of Agricultural Economics, Artikel jbaf026. https://doi.org/10.1093/erae/jbaf026.

Seifert, S., Kahle, C., Hüttel, S. (2021): Price Dispersion in Farmland Markets: What Is the Role of Asymmetric Information? American Journal of Agricultural Economics 103 (4): 1545-1568. https://doi.org/10.1111/ajae.12153.

Sklenicka, P. (2016): Classification of farmland ownership fragmentation as a cause of land degradation: A review on typology, consequences, and remedies. Land Use Policy 57: 694-701. https://doi.org/10.1016/j.landusepol.2016.06.032.

Sklenicka, P., Janovska, V., Salek, M., Vlasak, J., Molnarova, K. (2014): The Farmland Rental Paradox: Extreme land ownership fragmentation as a new form of land degradation. Land Use Policy 38: 587-593. https://doi.org/10.1016/j.landusepol.2014.01.006.

Stuart, E.A. (2010): Matching methods for causal inference: A review and a look forward. Statistical Science 25 (1): 1-21. https://doi.org/10.1214/09-STS313.

Valtiala, J., Niskanen, O., Torvinen, M., Riekkinen, K., Suokannas, A. (2023): The relationship between agricultural land parcel size and cultivation costs. Land Use Policy 131: 106728. https://doi.org/10.1016/j.landusepol.2023.106728.

Veršinskas, T., Vidar, M., Hartvigsen, M., Mitic Arsova, K., van Holst, F., Gorgan, M. (2020): Legal guide on land consolidation: Based on regulatory practices in Europe. (FAO Legal

Guide, 3). https://openknowledge.fao.org/server/api/core/bitstreams/6af8f082-7482-4c1c-b6c4-f21ba0d735dd/content.

Veršinskas, T., Vidar, M., Hartvigsen, M., Mitic-Arsova, K., van Holst, F., Gorgan, M. (2021): Land consolidation. FAO (Legal Brief, 1.). https://openknowledge.fao.org/items/3f5b5edf-b7d9-4ac1-90ba-754fe8301a44.

Vranken, L., Roebeling, P., Tabeau, E., Ciaian, P. with contributions from country experts (2021): Agricultural land market regulations in the EU Member States. (EUR 30838 EN) Publications Office of the European Union, Luxembourg.

Wand, M.P., Jones, M.C. (1994): Multivariate plug-in bandwidth selection. Computational Statistics 9 (97-116).

Wesemeyer, M., Kamp, J., Schmitz, T., Müller, D., Lakes, T. (2023): Multi-objective spatial optimization to balance trade-offs between farmland bird diversity and potential agricultural net returns. Agriculture, Ecosystems & Environment 345: 108316. https://doi.org/10.1016/j.agee.2022.108316.

Wilson, G.A., Wilson, O.J. (2001): German Agriculture in Transition. Society, Policies and Environment in a Changing Europe. Palgrave Macmillan, UK, London.

Winikoff, J.B., Parker, D.P. (2023): Farm size, spatial externalities, and wind energy development. American Journal of Agricultural Economics 106 (4): 1518-1543. https://doi.org/10.1111/ajae.12438.

Wolz, A. (2013): The Organisation of Agricultural Production in East Germany since World War II: Historical Roots and Present Situation. Discussion Paper. Leibniz Institute of Agricultural Development in Central and Eastern Europe 139. http://hdl.handle.net/10419/83981.

Wooldridge, J.M. (2010): Econometric analysis of cross section and panel data. 2. ed. MIT Press, Cambridge, Mass.

Zheng, Y., Long, H., Chen, K. (2022): Spatio-temporal patterns and driving mechanism of farmland fragmentation in the Huang-Huai-Hai Plain. Journal of Geographical Sciences 32 (6): 1020-1038. https://doi.org/10.1007/s11442-022-1983-8.

Appendix

Appendix A: Data

Table A1. Data profile

Data set	Information	Publicly accessible	Source
Farmland transaction	• Price • Soil quality • Transaction size • Packages • Adjacency to settlement • Location of transaction • Date of transaction	No	Oberer Gutachterausschuss Brandenburg (OGA-BB)
Cadastral data	• Shapefiles of *Flur*	Yes	Landesvermessung und Geobasisinforma-tion Brandenburg (LGB) https://geobroker.geobasis-bb.de
Weather data	• de Martonne drought index • Precipitation	Yes	Deutscher Wetterdienst (DWD) https://dwd-geoportal.de
Land cover	• Settlement area at munici-pality • Utilized agricultural area at municipality	Yes	Statistisches Bundesamt (DESTATIS) https://www.destatis.de
Stables in Brandenburg	• Location of stables • Type of animals • Stable size	Yes	Landesamt für Umwelt Brandenburg (LFU) https://www.metaver.de
Deflator	• Quarterly BIP deflator	Yes	Statistisches Bundesamt (DESTATIS) https://www.destatis.de
Administrative borders	• Shapefiles of administrative units	Yes	Landesvermessung und Geobasisinforma-tion Brandenburg (LGB) https://geobroker.geobasis-bb.de
Marktstamm-datenregister	• Location of wind and biogas plant • Year of installation • Installed electric capacity	Yes	Bundesnetzagentur (BNetzA) https://www.marktstammdatenregister.de

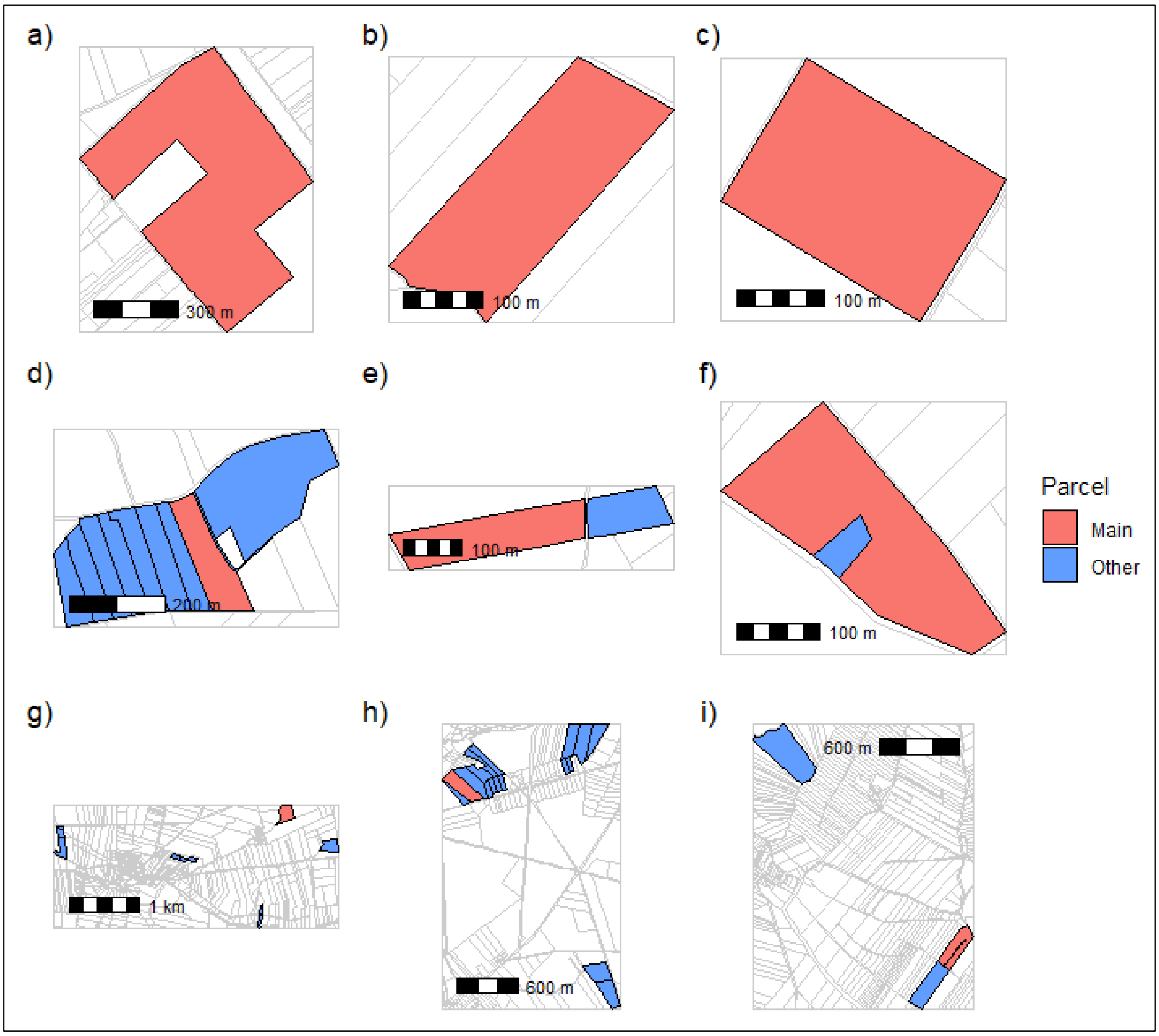

Figure A1. Examples of identified package transactions in the transaction data using ALKIS cadastral data. (not available for all transactions)

Caption: Panels (a-c) depict transactions involving a single parcel. Panels (d-f) represent transactions involving contiguous parcels. Panels (g-i) illustrate transactions where additional parcels are affected and are spatially separated. The main parcel in each transaction is shown in red, while additional affected parcels are shown in blue. Source: own illustration based on data from the Committee of Land Valuation Experts in Brandenburg

A1 Filtering of erroneously documentation by county

We label transactions from counties as erroneous if time-series of the shares of package transactions suggest no package transaction in some time period. Based on the observed shares of package transactions by observation year, we exclude all transactions from counties where no package transactions are observed in a specific year, suggesting that this attribute was not correctly recorded.

We exclude 708 transactions in Barnim for 2000-2014 as package transactions seem not to be recorded. In Dahme-Spreewald, 336 transactions are removed (2000-2005), 218 in Elbe-Elster (2000-2002), 440 in Havelland (2000-2007), 276 in Oberhavel (2000-2004), 296 in Potsdam-Mittelmark (2000-2001), 343 in Prignitz (2000-2003), and 852 in Spree-Neiße (2000-2014). Figure A2 presents the share of package transactions at a county by year after the filtering step.

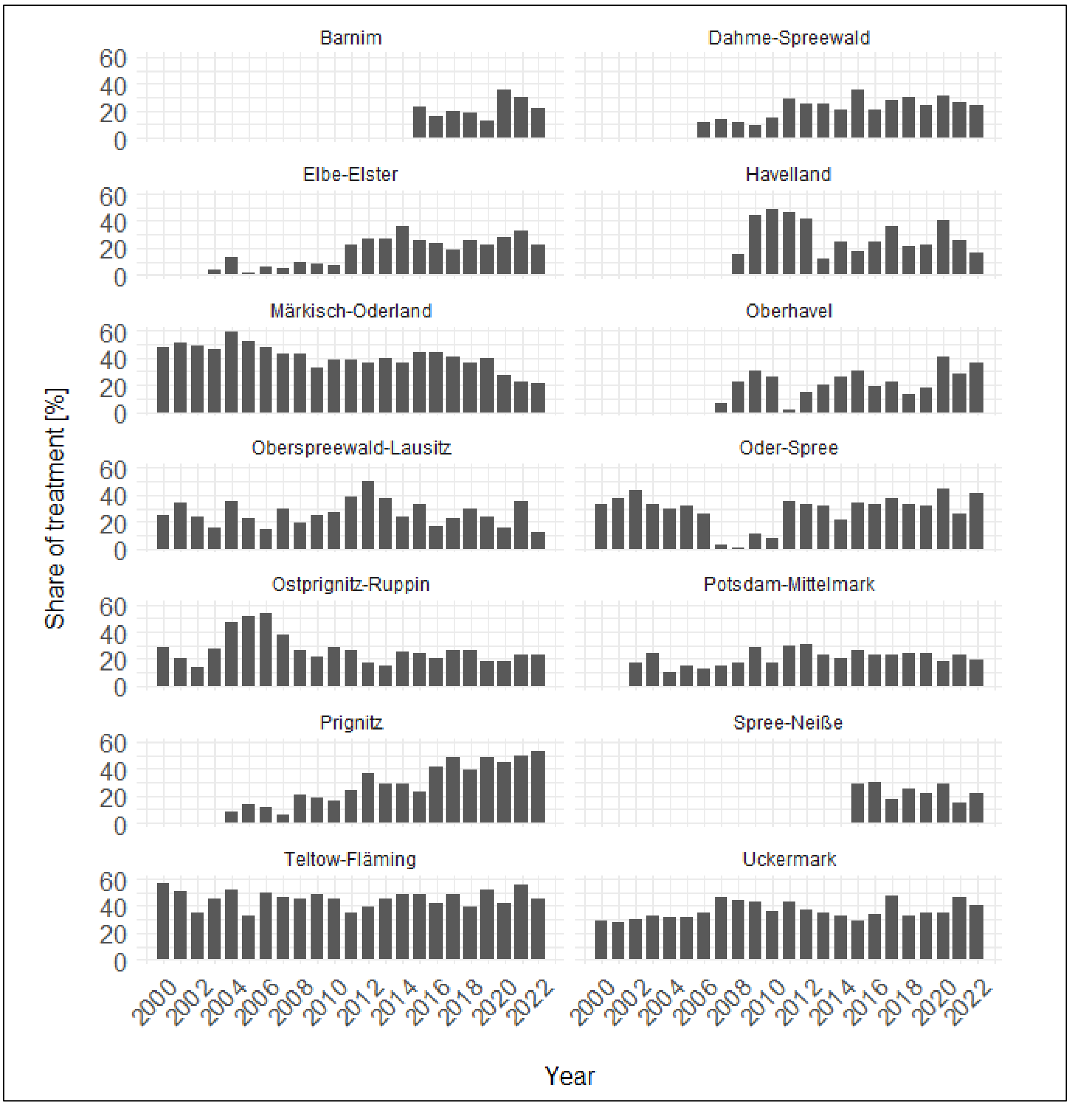

Figure A2. Share of package transactions by county and year

Source: own illustration based on data from the Committee of Land Valuation Experts in Brandenburg

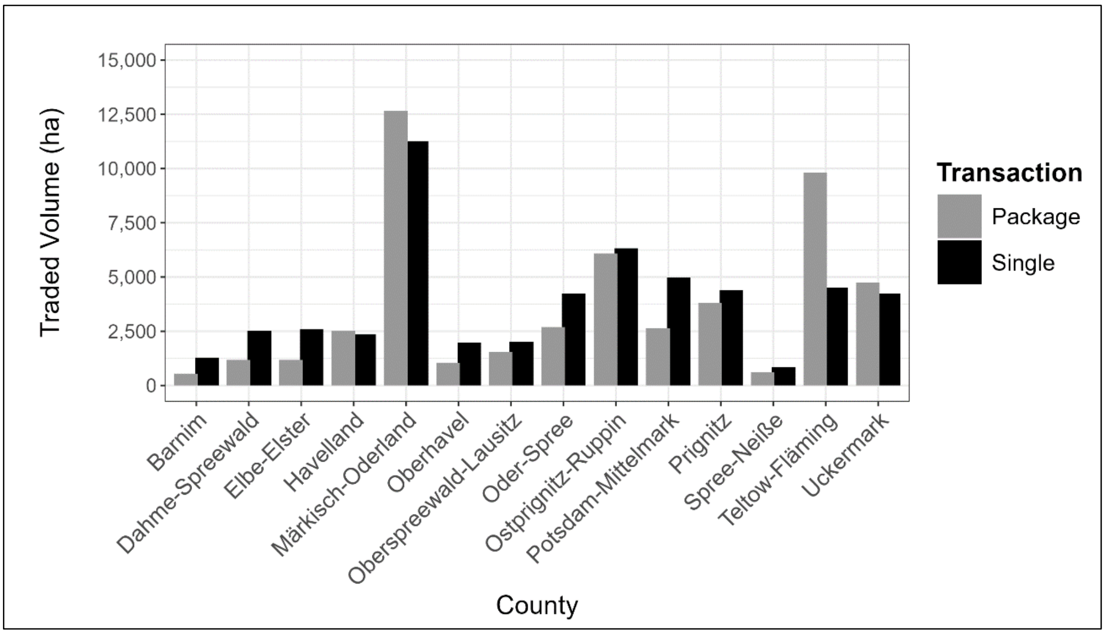

Figure A3. Traded volume by transaction composition and county, 2000-2022

Source: own illustration based on data from the Committee of Land Valuation Experts in Brandenburg

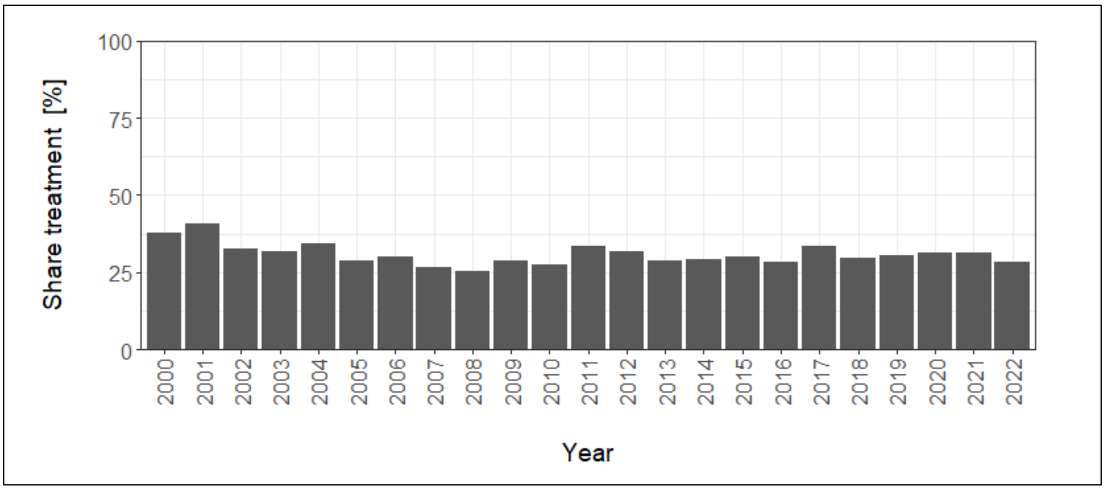

Figure A4. Share of package transactions by year

Source: own illustration based on data from the Committee of Land Valuation Experts in Brandenburg

Table A2. Average transaction size by composition and county, 2000-2022

County	Mean size: Package	Mean size: Single	Ratio Package/single
Barnim	5.79	3.88	1.49
Dahme-Spreewald	4.63	2.81	1.65
Elbe-Elster	4.15	1.94	2.14
Havelland	6.63	2.89	2.29
Märkisch-Oderland	8.92	4.49	1.99
Oberhavel	8.22	3.44	2.39
Oberspreewald-Lausitz	4.25	2.09	2.03
Oder-Spree	5.45	3.07	1.78
Ostprignitz-Ruppin	9.66	4.02	2.40
Potsdam-Mittelmark	4.59	2.28	2.01
Prignitz	8.10	3.98	2.04
Spree-Neiße	4.08	1.82	2.24
Teltow-Fläming	6.56	2.49	2.63
All	**6.88**	**3.13**	**2.19**

Source: calculations based on data from the Committee of Land Valuation Experts in Brandenburg

Appendix B. Results

Table B1. Descriptive of matched sample based on two-nearest neighbor matching

	Packages n_t **= 7,416**				**Matched single** n_c**= 7,711**			
	Mean	SD	Q1	Q99	Mean	SD	Q1	Q99
Dependent variable								
Deflated price [€/m²]	0.58	0.43	0.11	2.01	0.63	0.46	0.10	2.07
Price [€/m²]	0.59	0.46	0.10	2.10	0.63	0.5	0.09	2.23
Land characteristics								
Transaction size [ha]	6.88	6.11	0.39	29.5	6.32	5.77	0.30	26.95
Soil quality [index]	32.95	9.87	16.00	61.00	32.93	9.81	16.00	60.00
Agro-climatic conditions								
Precipitation [cm]	56.38	3.67	47.75	65.12	56.62	3.61	47.93	65.14
Drought index [count]	2.87	0.37	2.02	3.74	2.88	0.37	2.03	3.72
Location								
Metro region [0/1]	0.04	0.20	0.00	1.00	0.05	0.22	0.00	1.00
Adjacency to settlement [0/1]	0.15	0.36	0.00	1.00	0.24	0.43	0.00	1.00
Distance to next center [km]	38.63	15.08	10.21	81.47	37.95	14.95	9.89	80.88
Share UAA [%]	55.8	19.25	18.41	89.8	55.45	19.19	16.72	89.05
Share settlement [%]	5.86	5.32	1.61	29.83	6.27	5.74	1.58	31.59
LSU density [LSU/cell]	3.47	2.10	0.12	9.17	3.51	2.22	0.11	9.93
Renewable energy								
Wind density [MW_{el}/cell]	4.92	11.24	0.00	51.57	5.11	11.15	0.00	56.76
Biogas density [MW_{el}/cell]	1.01	1.40	0.00	6.88	0.95	1.32	0.00	6.48

Notes: descriptive for matched single parcels are calculated using weights from matching procedure.
Source: own calculation

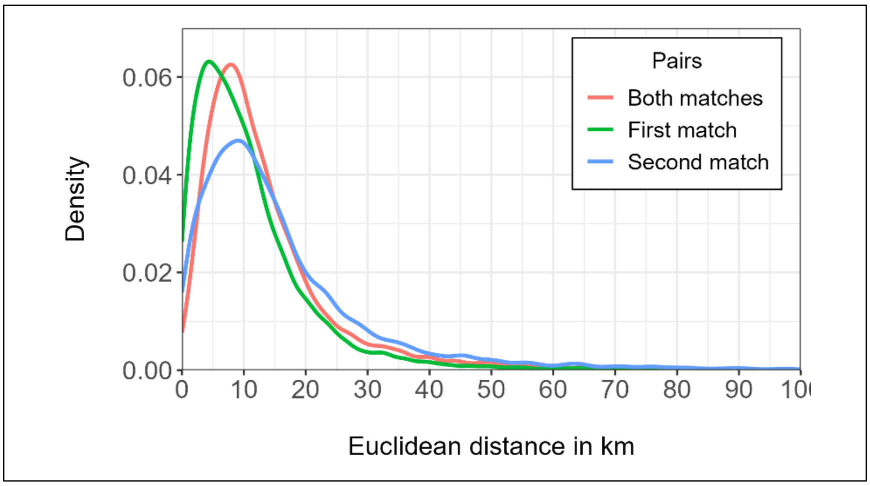

Figure B1. Distance between matched pairs

Source: own calculation

Table B2. Parameter estimate for county and year fixed effects of the main model

	Coef.	95%-CI
County		
Dahme-Spreewald	-0.335	(-0.3945, -0.2764)
Elbe-Elster	-0.500	(-0.5610, -0.4388)
Havelland	-0.142	(-0.2006, -0.0839)
Märkisch-Oderland	0.002	(-0.05257, 0.05607)
Oberhavel	-0.100	(-0.1667, -0.0324)
Oberspreewald-Lausitz	-0.480	(-0.541, -0.419)
Oder-Spree	-0.322	(-0.3787, -0.2653)
Ostprignitz-Ruppin	0.063	(0.00684, 0.11877)
Potsdam-Mittelmark	-0.137	(-0.1934, -0.0810)
Prignitz	0.067	(0.00776, 0.12538)
Spree-Neiße	-0.635	(-0.7051, -0.5652)
Teltow-Fläming	-0.247	(-0.3008, -0.1939)
Uckermark	0.374	(0.3181, 0.4303)
Time		
2001	0.018	(-0.0355, 0.0719)
2002	-0.036	(-0.0895, 0.0177)
2003	-0.044	(-0.1010, 0.0125)
2004	-0.135	(-0.1868, -0.0824)
2005	-0.109	(-0.1603, -0.0586)
2006	-0.112	(-0.1635, -0.0604)
2007	-0.028	(-0.0779, 0.0220)
2008	0.095	(0.0456, 0.1442)
2009	0.208	(0.1583, 0.2571)
2010	0.331	(0.2792, 0.3832)
2011	0.507	(0.4550, 0.5586)
2012	0.620	(0.5664, 0.6732)
2013	0.774	(0.7221, 0.8260)
2014	0.893	(0.8430, 0.9440)
2015	1.031	(0.9812, 1.0811)
2016	1.070	(1.0172, 1.1237)
2017	1.167	(1.1116, 1.2230)
2018	1.173	(1.1205, 1.2252)
2019	1.208	(1.153, 1.263)
2020	1.244	(1.1880, 1.2998)
2021	1.260	(1.1906, 1.3286)
2022	1.265	(1.2077, 1.3226)
Q3	0.012	(-0.00258, 0.02590)

Notes: dependent variable is the log price in €/m² deflated to Q4/2015 Euro values using the quarterly GDP deflator (Destatis, 2022). 95%-confidence intervals are based on heteroscedasticity-consistent standard errors clustered at the municipal level.
Source: own calculation

Table B3. Two-side t-test: $\widehat{\delta_{D,size}^{package}} = \widehat{\delta_{K,size}^{package}}$ based on model 2 in Equation (3-1)

D \ K	1	2	3	4	5	6	7	8	9
2	-0.825 (0.41)	-							
3	-0.798 (0.425)	0.073 (0.942)	-						
4	-0.979 (0.328)	-0.145 (0.884)	-0.229 (0.819)	-					
5	-1.117 (0.264)	-0.294 (0.769)	-0.385 (0.7)	-0.152 (0.879)	-				
6	-1.363 (0.173)	-0.500 (0.617)	-0.614 (0.539)	-0.353 (0.724)	-0.189 (0.85)	-			
7	-0.707 (0.479)	0.189 (0.85)	0.122 (0.903)	0.352 (0.725)	0.512 (0.609)	0.758 (0.448)	-		
8	-0.846 (0.397)	0.002 (0.998)	-0.073 (0.942)	0.153 (0.879)	0.306 (0.76)	0.521 (0.602)	-0.194 (0.846)	-	
9	-1.627 (0.104)	-0.798 (0.425)	-0.926 (0.354)	-0.662 (0.508)	-0.500 (0.617)	-0.341 (0.733)	-1.074 (0.283)	-0.829 (0.407)	-
10	-0.493 (0.622)	0.383 (0.702)	0.331 (0.741)	0.544 (0.587)	0.696 (0.486)	0.945 (0.345)	0.219 (0.827)	0.394 (0.694)	1.244 (0.214)

Note: value of t-statistic reported with the p-values in parentheses below.
T-test is based on cluster-robust standard errors.
Source: own calculation

Appendix C. Robustness Checks

We perform two types of robustness-checks: First, we use different matching algorithm to test the sensitivity our results to the chosen matching approach. Second, we run the two-stage procedure on different subsamples to test for sensitivity of our results with respect to our selection procedure.

Robustness-checks: Matching algorithm

We perform one and three nearest matching as well as Kernel matching as robustness checks. The model specification is based on Equation 2. The kernel matching follows Cameron and Trivedi (2008) and we rely on a Gauss-Kernel with bandwidth selection following Wand and Jones (1994). Figure C1 presents the matching quality based on the standardized difference in means and Table C1 presents the post-matching regression.

Robustness-checks: Sample selection

We run the doubly robust approach outlined in Section 3 on different samples. We create five subsamples using following selection procedures:

S1. No filtering: only missing values and inconsistent data were removed
S2. Cleaned sample including transactions in the four independent cities of Brandenburg
S3. Cleaned sample including transactions by public sellers
S4. Cleaned sample without excluding transactions in counties with erroneously recordings
S5. Cleaned sample without an outlier detection.

Results of the doubly robust approach based on samples S1 to S5 are presented in Table C2.

References

Cameron, A.C., Trivedi, P.K. (2008): Microeconometrics: Methods and applications. 7. print. Cambridge University Press, Cambridge.

Wand, M.P., Jones, M. (1994): Multivariate plug-in bandwidth selection. Computational Statistics 9 (97-116).

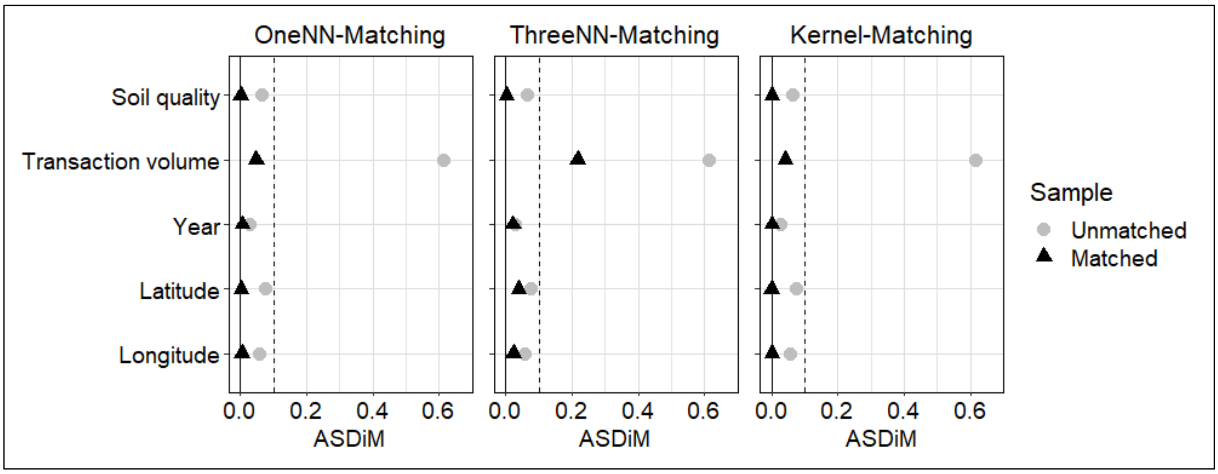

Figure C1. Matching quality of One-NN, Three-NN, and Gauss-Kernel matching

Source: own illustration

Table C1. Post-matching regression based One-NN, Three-NN, and Gauss-Kernel matching

	One-NN	Three-NN	Kernel matching
Intercept	-0.654 (-2.011, 0.703)	-1.060 (-2.237, 0.118)	-1.659 (-2.751, -0.567)
Land characteristics			
√Transaction size	0.036 (0.018, 0.053)	0.034 (0.019, 0.049)	0.004 (-0.009, 0.017)
√Soil quality index	0.114 (0.082, 0.145)	0.100 (0.074, 0.126)	0.066 (0.046, 0.086)
Transaction size²	-0.0001 (-0.0002, -0.00005)	-0.0002 (-0.0003, -0.0001)	-0.0002 (-0.0003, -0.0001)
Soil quality²	-0.00001 (-0.00004, 0.00003)	0.00001 (-0.00002, 0.00004)	0.00003 (0.00001, 0.0001)
Transaction size × SQ	0.0002 (0.0001, 0.0003)	0.0002 (0.0001, 0.0003)	0.0004 (0.0003, 0.0005)
Agro-climatic conditions			
Precipitation	-0.047 (-0.097, 0.003)	-0.029 (-0.072, 0.014)	-0.012 (-0.051, 0.027)
Precipitation²	0.0004 (-0.0001, 0.001)	0.0002 (-0.0002, 0.001)	0.0001 (-0.0003, 0.0004)
Drought index	-0.166 (-0.440, 0.109)	-0.133 (-0.370, 0.104)	0.158 (-0.059, 0.375)
Drought index²	0.036 (-0.010, 0.081)	0.029 (-0.011, 0.068)	-0.021 (-0.057, 0.015)
Location			
Metro region Berlin	0.236 (0.198, 0.274)	0.232 (0.200, 0.264)	0.217 (0.189, 0.245)
Adjacency to settlement	0.071 (0.053, 0.090)	0.071 (0.055, 0.086)	0.086 (0.073, 0.099)
Distance to next center	0.075 (0.053, 0.098)	0.051 (0.032, 0.070)	0.020 (0.003, 0.037)
Distance to next center²	-0.009 (-0.011, -0.006)	-0.006 (-0.008, -0.004)	-0.003 (-0.005, -0.001)
Share UAA	0.002 (0.002, 0.003)	0.002 (0.002, 0.003)	0.002 (0.002, 0.002)
Share settlement	0.001 (-0.0004, 0.003)	0.002 (0.0003, 0.003)	0.003 (0.001, 0.004)
LSU density	0.001 (-0.003, 0.005)	0.002 (-0.002, 0.005)	0.0003 (-0.003, 0.003)
Renewable energy intensity			
Wind density	0.001 (0.0003, 0.002)	0.001 (0.0005, 0.002)	0.001 (0.001, 0.002)
Biogas density	0.015 (0.010, 0.021)	0.012 (0.007, 0.017)	0.012 (0.007, 0.017)
Transaction composition			
Package	-0.063 (-0.077, -0.049)	-0.069 (-0.081, -0.058)	-0.075 (-0.088, -0.063)
Weights	Yes	Yes	Yes
Time and County FE	Yes	Yes	Yes
Package transaction	7,416	7,416	7,416
Single transaction	4,812	9,949	17,112
Adjusted R²	0.715	0.703	0.666

Note: the parentheses report the 95%-CI based on robust standard errors clustered at the municipality level. Parameter estimates for county and year FE are available on request.
Source: own calculation

Table C2. Post-matching regression based on different sample selection

	S1	S2	S3	S4	S5
Intercept	-2.064 (-3.290, -0.837)	-0.914 (-2.157, 0.330)	-1.938 (-3.162, -0.714)	-1.019 (-2.256, 0.217)	-0.702 (-1.954, 0.549)
Land characteristics					
√Transaction size	0.054 (0.047, 0.062)	0.030 (0.015, 0.046)	0.041 (0.027, 0.055)	0.039 (0.023, 0.054)	0.053 (0.043, 0.063)
√Soil quality index	0.077 (0.050, 0.104)	0.107 (0.079, 0.136)	0.078 (0.051, 0.106)	0.114 (0.086, 0.143)	0.111 (0.082, 0.139)
Transaction size²	-0.000 (-0.000, -0.000)	-0.000 (-0.000, -0.000)	-0.000 (-0.000, -0.000)	-0.000 (-0.000, -0.000)	-0.000 (-0.000, -0.000)
Soil quality²	0.000 (0.000, 0.000)	-0.000 (-0.000, 0.000)	0.000 (0.000, 0.000)	-0.000 (-0.000, 0.000)	0.000 (-0.000, 0.000)
Transaction size × SQ	0.000 (0.000, 0.000)	0.000 (0.000, 0.000)	0.000 (0.000, 0.000)	0.000 (0.000, 0.000)	0.000 (-0.000, 0.000)
Agro-climatic conditions					
Precipitation	0.006 (-0.038, 0.051)	-0.037 (-0.082, 0.009)	-0.006 (-0.051, 0.039)	-0.031 (-0.077, 0.014)	-0.045 (-0.091, 0.000)
Precipitation²	-0.000 (-0.000, 0.000)	0.000 (-0.000, 0.001)	0.000 (-0.000, 0.000)	0.000 (-0.000, 0.001)	0.000 (-0.000, 0.001)
Drought index	-0.125 (-0.368, 0.118)	-0.118 (-0.366, 0.130)	0.019 (-0.226, 0.265)	-0.205 (-0.455, 0.045)	-0.151 (-0.405, 0.103)
Drought index²	0.028 (-0.012, 0.068)	0.029 (-0.012, 0.070)	0.008 (-0.033, 0.049)	0.039 (-0.003, 0.080)	0.033 (-0.009, 0.075)
Location					
Metro region Berlin	0.207 (0.174, 0.239)	0.239 (0.205, 0.274)	0.224 (0.191, 0.258)	0.230 (0.197, 0.263)	0.228 (0.193, 0.263)
Adjacency to settlement	0.073 (0.058, 0.089)	0.068 (0.052, 0.084)	0.073 (0.057, 0.089)	0.072 (0.056, 0.088)	0.071 (0.055, 0.087)
Distance to next center	0.057 (0.038, 0.077)	0.060 (0.039, 0.080)	0.051 (0.031, 0.071)	0.055 (0.035, 0.076)	0.069 (0.048, 0.090)
Distance to next center²	-0.007 (-0.009, -0.005)	-0.007 (-0.009, -0.005)	-0.006 (-0.008, -0.004)	-0.006 (-0.009, -0.004)	-0.008 (-0.011, -0.006)
Share UAA	0.003 (0.002, 0.003)	0.003 (0.002, 0.003)	0.003 (0.002, 0.003)	0.002 (0.002, 0.003)	0.003 (0.002, 0.003)
Share settlement	0.001 (0.000, 0.003)	0.001 (0.000, 0.003)	0.002 (0.000, 0.003)	0.001 (-0.000, 0.002)	0.001 (-0.000, 0.002)
LSU density	0.001 (-0.002, 0.005)	0.000 (-0.004, 0.004)	0.002 (-0.002, 0.006)	0.002 (-0.002, 0.006)	0.001 (-0.003, 0.005)
Renewable energy					
Wind density	0.001 (0.001, 0.002)	0.001 (0.000, 0.002)	0.001 (0.001, 0.002)	0.001 (0.001, 0.002)	0.001 (0.000, 0.002)
Biogas density	0.015 (0.010, 0.020)	0.014 (0.008, 0.019)	0.014 (0.009, 0.020)	0.015 (0.010, 0.020)	0.012 (0.007, 0.017)
Transaction composition					
Package	-0.069 (-0.081, -0.057)	-0.067 (-0.080, -0.055)	-0.065 (-0.077, -0.053)	-0.068 (-0.080, -0.055)	-0.070 (-0.083, -0.058)
Weights	Yes	Yes	Yes	Yes	Yes
Time and County FE	Yes	Yes	Yes	Yes	Yes
Raw sample	40,764	25,094	30,089	27,043	24,898
Package transactions	9,921	7,540	8,895	7,493	7,631
Single transactions	11,292	7,872	9,476	8,022	8,106
Adjusted R²	0.661	0.702	0.688	0.705	0.699

Note: the parentheses report the 95%-CI based on robust standard errors clustered at the municipality level. Parameter estimates for county and year FE are available on request.

Source: own calculation