Parcel or Bundle? On the Effects of Transaction Composition on Farmland Prices

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Abstract

Landowners owning several parcels need to decide whether to sell their land as a bundle or each parcel separately. While transaction, search and bargaining costs may suggest cost savings from selling a bundle, for farmers buying a bundle may appear less attractive. In thinly traded and locally specific farmland markets, distance cost for agricultural buyers can be price relevant, also their bargaining position. This makes the question for sellers a non-trivial one. We hypothesize that parcel bundles are less attractive, particularly for farmer buyers, and thus achieve lower prices. We investigate this hypothesis using a rich data set of 24,527 farmland transactions of single parcels and lot bundles in eastern Germany from 2000 to 2022. Doubly robust matching results indicate, on average, 6.7% lower prices for transactions of parcel bundles compared to similar transactions of single parcels. Landowners should carefully evaluate gains of selling parcels separately against time and transaction costs.

Keywords: *land market, farmland pricing, spatial competition, matching, hedonic model*

JEL Codes: Q15, C21

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1 Introduction

Farmland ownership is often fragmented with many owners owning multiple parcels. Particularly in post-transition economies, where restitution has led to numerous private landowners (Hartvigsen, 2014). Landowners willing to sell need to decide whether to sell their land as a bundle or each parcel separately.

The decision to sell parcels individually or as a bundle becomes pivotal when considering dynamics of thinly traded and locally specific farmland markets with related search and bargaining costs. Selling as a bundle suggests potential savings of transaction, search and bargaining costs. However, farms usually prefer land in proximity to their farmstead due to distance costs (Graubner, 2018; Pennerstorfer, 2022), potentially reducing the demand for parcel bundles of spatially separated parcels. Potential farmer buyers may thus associate higher distance costs with bundles, lowering their willingness to bid and pay. For non-farmer buyers, bundles may also incur higher transaction costs post-sale related to finding the tenant with the highest willingness to pay for the land (Humpesch *et al.*, 2022). Lastly, some buyers may be interested only in some parcels of the bundle and may therefore not enter the competition if the lands are only sold as a bundle.

In this paper, we investigate the price difference between single transactions and parcel bundles. We hypothesize that parcel bundles are less attractive, particularly for farmer buyers, and thus achieve lower prices. We investigate this hypothesis empirically for the eastern German Federal State of Brandenburg. This study region is particularly suitable as it is characterized by notable land ownership fragmentation with more than 170,000 private persons owning 52% of farmland, on average 7 parcels per owner (Jänicke, 2023). We rely on a rich dataset of 24,527 arable land transactions between 2000-2022, including information on whether the transaction consists of a single parcel or a bundle of parcels. We apply a doubly robust approach (Ho *et al.*, 2007) combining matching and regression to contrast bundle transactions with single parcels. The first-stage matching finds for each bundle transaction a control group of single parcels with similar characteristics, traded at the same time, in the same region. The second stage regression uses a flexible hedonic model to control for further imbalances and to estimate the treatment effect on sales prices. We investigate the heterogeneity of the treatment effect by transaction volume, space, and time and perform several robustness checks throughout.

To the best of our knowledge, our paper provides the first approach that explicitly discusses and quantifies the impact of parcel bundles on farmland prices. Our results show that parcel bundles achieve, on average, lower sales prices compared to similar single parcel transactions traded in the same market at the same time. From an academic perspective, our paper contributes to the literature on spatial pricing of farmland, price formation of farmland in thinly traded markets, and land fragmentation. From a policy perspective, our results enhance the understanding of the price formation process of farmland and thus contribute to farmland transparency by identifying potential biases from bundles in available price publications. The insights from this study are particularly valuable for landowners and professional sellers for the design of farmland transactions.

The paper is structured as follows: Section 2 introduces the study region and data. Section 3 outlines empirical strategy and methods. In Section 4, we present the results. Section 5 discusses the results and provides the conclusion.

2 Study Region and Data

2.1 Study region

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

As in other eastern German Federal States and other post-communist transition economies (Hartvigsen, 2014), Brandenburg’s land ownership structure and agricultural sector has been shaped by the communistic era between 1945 and 1989, followed by subsequent restitution and privatization.[1] Following World War II, farms exceeding 100 ha as well as of active Nazi members were expropriated between 1945-1949, 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, intending to increase agricultural productivity, the Socialist Party initiated the consolidation of private farms and their land into collective farms known as agricultural production cooperatives (LPGs). The collectivization process continued until the fall of the Iron Curtain in 1989, leading to a large-scale farm structure with around 580 state farms and 4,000 corporate farms and cooperatives. After Germany’s reunification, land from collectivized farms was returned to its members and former owners expropriated after 1949. The enormous amounts of state-owned land were first

[1] See Wolz (2013) and Wilson and Wilson (2001) for a detailed overview of the history of land reforms and agricultural production in eastern Germany.

managed and leased by the *Treuhandanstalt* until 1992. In 1992, the land fell under the jurisdiction of the state agency *Bodenverwertungs- und Verwaltungs GmbH* (BVVG) and should be gradually transferred to private ownership. Since 2005, the BVVG adopted a highly efficient tendering mechanism besides direct sales to privatize land at market prices (Seifert and Hüttel, 2023).

As the result of several land reforms and restitution processes, Brandenburg's farmland ownership is fragmented with more than 170,000 private persons owning 52% of the total farmland in 7 parcels (Jänicke, 2023). Despite the fragmented ownership structure, farms benefit from large field sizes of around 12 ha on average (Wesemeyer *et al.*, 2023).

In total 5,400 farms operate in Brandenburg. The average farm size of 242 ha is around four times the German average (MLUL BB, 2023). The farm structure includes both small privately-owned farms and larger agricultural holdings and cooperatives with average farm sizes of 133 ha and 704 ha, respectively. With the privatization process, the share of rented land decreased from 81,3% in 2005 to 66.6% in 2020 (EU's average ∼50%). Privately owned farms show a lower share at 55% compared to farms operated as legal entities at 70%.

Despite the farmland privatization process, the farmland market in Brandenburg is thinly traded with 1-2% of the total agricultural area traded annually in the last 20 years. Farmland prices developed, however, dynamically. Between 2005 and 2020, prices have more than tripled from around 2,585 €/ha in 2005 to 12,951 €/ha in 2020. Average rents for arable land likewise rose from 91€/ha to 184€/ha. Given Germany's rather liberal farmland market regulation (Vranken *et al.*, 2021), investigating Brandenburg's land market provides a suitable case for investigation.

2.2 Farmland transactions data

We rely on detailed transaction data for arable land between 2000 and 2022 in Brandenburg provided by the committee of land valuation experts (*Oberer Gutachterausschuss*). To track market activity and to ensure market transparency, the committee documents on behalf of the federal state all farmland transactions and publishes standard land value zones. For each transaction, we observe the sales price, key land characteristics (e.g., transaction volume and a soil quality index[2]), major transaction information (e.g., contract date and circumstances of a transaction), and location information including the geocoordinate of the upper right corner of the transaction. The data also

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

entails information on whether a transaction consists of a single parcel or whether more than one parcel was included (bundle). A bundle is thereby defined as a transaction of farmland consisting of at least two spatially separated parcels. Spatial separation requires that the parcels do not border each other and are located in different *Gemarkungen* or *Fluren*[3] as illustrated in Figure 1. We note, however, that our data does not allow identifying all parcels from bundle transactions and characteristics of the bundles relate only to the "price-determining parcel" (red labelled).

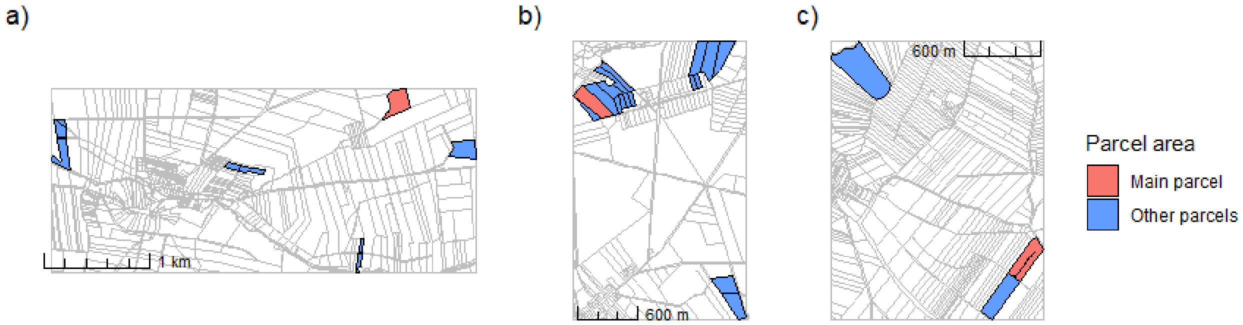

Figure 1: Examples of bundle transactions based on ALKIS cadastre data and transaction data.

Our initial data set comprises 50,959 transactions of arable land. We consider only arm's-length transactions and remove 145 transactions with prices of € 500/ha or less, and with total prices of 1€ or less as these transactions are unlikely to 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 leads to an exclusion of another 6,913 observations. Following the OGA's definition of regular land market activity, we remove 4,203 transactions of less than 0.25 ha. We drop 811 transactions located in Brandenburg's four independent cities (Brandenburg an der Havel, Cottbus, Frankfurt (Oder), and Potsdam) as we suspect an unobserved price impact of urbanization potentially correlated with the choice of selling a single parcel or a bundle of parcels. 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 bundle a large number of parcels of heterogeneous qualities in one offer (Seifert and Hüttel, 2023). We also need to exclude data from eight counties in the early years of the observation period, where parcel transactions are erroneously recorded. 3,487 observations are excluded due to missing information, mainly due to non-documented soil quality.[4] We further remove 370 transactions identified as

[3] *Gemarkung* is a cadastal unit comprising multiple *Flure*. Each *Flur* contains multiple *Flurstücke (parcels)*, for which the land owners are registered. Brandenburg has 2,364 *Gemarkungen* comprising in total 14,967 *Flure* with an average size of 198.13 ha. (LGB (2023).

[4] Soil quality data are missing in particular for transactions of farmland intended for non-agricultural use, e.g., public infrastructure investments.

outliers by the minimum covariance determinant estimator (Rousseeuw and van Driessen, 1999) to mitigate a potential bias.

The final dataset comprises 24,528 transactions with a total transaction volume of 104,624 hectares generating revenues of 671 million Euro deflated to 2015 values using the GDP deflator (Destatis, 2022). Thereof, 17,112 are transactions of single parcels of in total of 53,567 ha and 352 million Euro (deflated), and 7,416 bundle transactions of in total of 51,057 ha and 320 million Euro (deflated).

Farmland price determinants

We enhance the transaction data with information on factors affecting the expected returns from owning the land, which are likely to be reflected in the observed sales prices (Nickerson and Zhang, 2014). For each transaction, we consider the land's productivity, local farming conditions, and the local farming structure.

We capture expectations about the returns of land ownership by the transaction volume, 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 to the buyer for a bundled transaction. For very large lots, competition may however be reduced due to the financing constraints of the potential buyers. A price premium may be observed for smaller parcels (Brorsen *et al.*, 2015) as they may attract a wider range of potential buyers, including, for instance, non-agricultural buyers intending to use the land for non-agricultural activities such as horse keeping. To account for water availability, we use the long-term average annual precipitation in the 30 years before the transaction extracted from a 1km grid[5] (DWD, 2022b) at the transaction coordinate. As agricultural yields and their stability are affected by climate change (Ortiz-Bobea, 2020), we indicate a parcels' drought exposure in the three years before the transaction using the average de Martonne drought index[6] over this period derived at a 1 km grid (DWD, 2022a).

Tied to the location of a transaction, the expectation of higher returns from non-agricultural land use may influence farmland prices (e.g., Delbecq *et al.*, 2014). We account for such effects using multiple variables: a dummy variable if a transaction takes place in municipalities bordering the city-state of Berlin due to potential urban sprawl impacts. A second dummy variable accounts for

[5] For each transaction, we project its location coordinate into this raster to assign the local precipitation.

[6] The de Martonne drought index (dMI) is calculated by dMI = P/(T+10) with T=temperature in degrees Celsius and P=precipitation in mm in a 1°km grid cell.

potential conversion to building land by indicating that a transaction is adjacency to a settlement if the most distant point of the parcel is within 500m of a settlement. Additionally, we consider the distance to the next upper or middle centres[7] (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 consider the demand for land by animal husbandry, we add information on the capacity-weighted livestock density using geo-referenced 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 capitalize on land rents (e.g., Hennig and Latacz-Lohmann, 2017) and farmland values (e.g., Haan and 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 and 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.

2.3 Descriptive statistics

Table 1 shows the descriptive statistics of our sample for bundle transactions and single parcel transactions. Around 30% of all transactions are lot bundles with shares ranging from 17% to 45% in Elbe-Ester and Teltow-Fläming, respectively (see Figure 2). Over time, the share varies between 25.2% and 40.8% lower without a clear time trend. We observe only minor unconditional average markdowns for lot bundles (0.58€/m²) compared to single parcels (0.59 €/m²) with no clear patterns over the observation period (e.g., -0.057 €/m² in 2002 and -0.018 €/m² 2022).

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

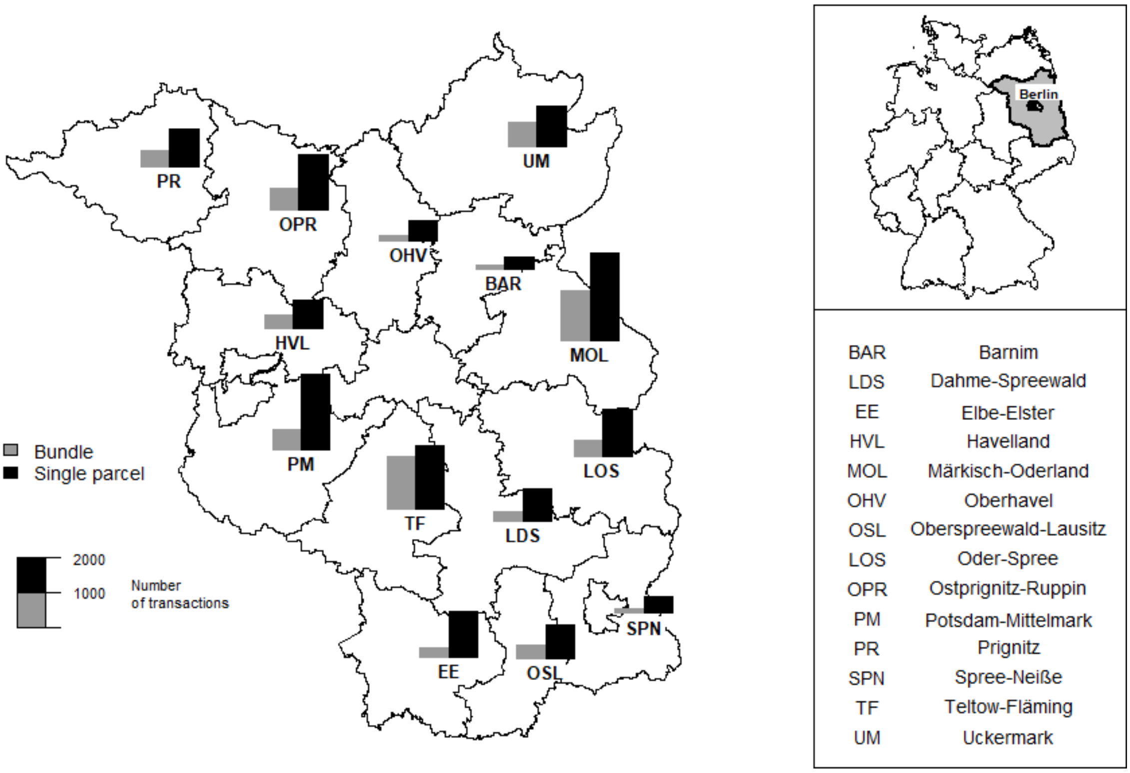

Figure 2: Number of transactions by composition in Brandenburg, Germany

Bundles and single parcels offer, on average, similar soil qualities of around 32 index points with similar ranges between 14 and 62 index points. The transaction volume, however, is 6.88 ha on average for parcel bundles, thus, twice as high as for single transactions (3.13 ha). Also for the largest transactions, the transaction volume of parcels is notably larger (29.5 ha) compared to single transactions (21.34 ha).

Location indicators suggest that transactions of single parcels are potentially more impacted by urban sprawl than bundle transactions. Approximately 28% of the single transactions are adjacent to settlements compared to around 15% for bundles. We observe a small difference regarding the distance to the nearest regional and administrative centre (38 km for lot bundles, 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%). Bundle transactions are located in regions with higher intensity of wind power and biogas installation. In summary, the descriptive statistics suggest that bundle transactions are located more in rural areas with a higher intensity of agricultural production compared to single parcel transactions.

Table 1: Descriptive statistics by treatment status

n = 24,528	Bundles n_t = 7,416				Single parcels 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 volume [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 centre [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

3 Empirical strategy

To identify the price effect of the transactions' composition on sales prices, we contrast sales prices of transactions of multiple parcels (treatment group) with transactions consisting of one single parcel (control group). We consider that whether a transaction belongs to the treatment or the control may not be random but may rather depend on the lot's characteristics and its location. For instance, sellers may prefer selling a bundle as they are notably larger and may thus attract additional potential buyers with a higher financial power. Also, in regions with excess demand and strong competition for agricultural land, buyers might be more willing to buy a bundle of heterogeneous parcels if the bundle would otherwise be sold to another buyer. This potential relationship between the effect of interest and the lot's characteristics would bias a potential price difference without further control.

To mitigate a potential bias in the identification of the price differentials from such self-selection, we compare transactions with similar land characteristics traded in the same local market and at the same time that differ otherwise only in their treatment status. We use the procedure proposed by Ho *et al.* (2007) and adopt a doubly robust two-stage approach that combines non-parametric matching with parametric post-matching regression. The first step uses matching to find a control group with similar characteristics (counterfactual) by matching on key characteristics, location and time (cf. Isenhardt *et al.*, 2023; Seifert *et al.*, 2023). In the second step, we rely on a hedonic post-matching regression to control for the remaining imbalances and other price-relevant factors not included in the matching and estimate the treatment effect of parcel bundles on sales prices. The non-parametric first stage reduces model dependence in the parametric second stage and offers robust parameter estimates if one of the two steps is correctly specified (Wooldridge, 2010, p. 930).

3.1 Matching

We adopt a non-parametric two-nearest neighbour matching to identify for each treated observation the two nearest control transactions with the most similar covariate values. The similarity between treated and control units is assessed through the Mahalanobis distance, which combines information in a unitless measure accounting for the potential correlation of these variables (Rubin, 1980). Thus, matching on Mahalanobis distance creates pairs on close covariate values (i.e., following the idea of matching a "perfect" twin), which addresses critiques on other matching approaches such as propensity score matching (King and Nielsen, 2019). The two-nearest neighbour matching based on the Mahalanobis is particularly suitable for our approach as we match on few covariates and have a sufficiently large pool of control units for matching twice, which reduces the dependence of the identified effects on single matches.

In the matching, we consider transaction volume x_s, soil quality x_q, and longitude and latitude of the transaction coordinate as covariates. Matching on transaction volume and soil quality should thereby ensure similarity in the main land productivity characteristics (Nickerson and Zhang, 2014). Matching on the coordinates should further ensure that matched treated and control units are traded in the same market environment, including similar demand and supply structures, and competition for farmland. The geographical proximity of treated and control units may further increase similarity in location-specific factors observed and unobserved by us, including weather characteristics, topographic features or the degree of urban sprawl. Matching on coordinates instead of an exact matching on administrative units further helps us to mitigate problems of defining the relevant market and allows matching across administrative borders. To ensure that treated and control transactions take place in times of similar market sentiment, and to account for the price surge in our observations period, we only match treated transactions with control transactions from the same year, or one year apart.

To avoid a potential bias from extreme control group observations, we allow the matching of a control transaction only up to three times (Stuart, 2010). This avoids an overuse of control units and a high dependence on a few control units. We access the matching quality based on the standardized difference in means and the Euclidian distance between treated and matched controls.

3.2 Post-matching regression

In the second step, we use the matched sample and run a hedonic post-matching regression to control for further imbalances and estimate the treatment effect on prices. We take the logarithm of the deflated price p in € per m² of the transaction i as the dependent variable.

For the hedonic part of the post-matching regression, we consider a flexible functional form based on a Box-Cox transformation. To allow for potential non-linear relationships (e.g., Ritter *et al.*, 2020), the main price determinants transaction volume (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}) enter the regression in linear and quadratic form. To control for location, we include dummy variables indicating the location in the metropolitan area of Berlin (d_{berlin}), and the adjacency to a settlement (d_{settle}). Distance to the next high or middle centre enters the regression in linear and squared form. We further describe the local land use by the shares of agricultural land (x_{uaa}) and settlements (x_{settle}) at the municipal level. We acknowledge demand for land for renewable energy production using wind and biogas plants as well as from animal husbandry by including the respective kernel densities. To capture unobserved temporal and spatial heterogeneity, we add fixed effects indicating the location in one of the 14 counties and for the respective year of sales. We also control for potentially higher cash flows of farms after the harvest season by a dummy variable indicating the time of transaction in the third quarter of a year (d_{Q3}). Omitting the transaction-specific subscript i, the hedonic specification denotes as

$$\begin{aligned} h(.) = \quad & \beta_1\sqrt{x_s} + \beta_2 x_s^2 + \beta_3\sqrt{x_q} + \beta_4 x_q^2 + \beta_5\left(x_s \times x_q\right) + \\ & \beta_6 z_{pre} + \beta_7 z_{pre}^2 + \beta_8 z_{dro} + \beta_9 z_{dro}^2 + \\ & \beta_{10} d_{berlin} + \beta_{11} d_{settle} + \beta_{11} x_{dist} + \beta_{11} x_{dist}^2 + \beta_{12} x_{UAA} + \beta_{13} x_{settle} + \\ & \beta_{14} x_{LSU} + \beta_{15} x_{biogas} + \beta_{16} x_{wind} \\ & \textstyle\sum_l \gamma_l^{county} d_l + \sum_t \gamma_t^{year} d_t + \gamma_1^{Q3} d_{Q3} \end{aligned} \qquad (1)$$

where $\beta's$ and $\gamma's$ are parameters to be estimated related to controls and time-spatial controls. To estimate the treatment effect of bundle parcels on sales prices, we add a treatment indicator variable d_{parcel}. This gives our baseline model M1:

$$log(p) = \alpha + h(.) + \delta^{parcel} d_{parcel} + \epsilon \qquad (2)$$

where α denotes the intercept and ϵ the error term; δ^{parcel} indicates the average log price difference of a treatment observation compared to a single parcel with identical characteristics.

We estimate the model using weighted least squares. Weights for the treated units equal one; weights for the control units reflect the matching frequency in the first step scaled to the sum of the uniquely matched controls (Ho *et al.*, 2011). Unmatched controls receive a weight of zero and are, thus, dropped from the second-stage regression.

We implement our approach using R, version 4.2. Matching is implemented using the MatchIt package v.4.5.4 (Ho *et al.*, 2011). Estimation of the second-stage regression uses the lm() function. As our observations might be non-independence within clusters (Abadie *et al.*, 2022), we draw statistical inferences on clustered standard errors. To determine the appropriate level of clustering, we implement the test by MacKinnon *et al.* (2023), which sequentially tests 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 show standard errors clustered at the municipal level. For inference of our effect estimates, we refer to the 95% confidence intervals derived from cluster-robust standard errors. As results could be sensitive to the choice of matching algorithm and defined specification of the regression, we perform several robustness checks using different matching approaches and investigate the treatment effect under different specifications.

3.3 Effect heterogeneity and robustness checks

We perform robustness checks related to our model specification. Further, we investigate heterogeneity of the treatment effect for different transaction volumes, across space, and across time.

The treatment effect may vary with transaction volume due to economies of scale and financial volume (Valtiala *et al.*, 2023; Ritter *et al.*, 2020). Moreover, the number of parcels and thus the degree of fragmentation of the offered bundle may increase with transaction volume. To test for variation of the treatment effect with transaction volume, we interact the treatment indicator d_{parcel} with dummy variables representing the deciles of transaction volume observed in our matched sample. We employ $D = 10$ dummy variables $d_{k,volume}$ that equal one if a transaction lies in the D^{th} decile of the transaction volume. This gives our second model M2:

$$log(p) = \alpha + h(.) + \sum_{D=1}^{10} \delta_{D,volume}^{parcel}(d_{parcel} \times d_{k,volume}) + \sum_{D=1}^{10} \beta_{D,volume} d_{D,volume} + \epsilon \tag{3a}$$

where $\delta_{D,volume}^{parcel}$ gives the average log price difference of the treatment observations in decile group D compared to the refence group, conditional on characteristics included in $h(.)$.

To uncover the potential effects of a spatially varying market and ownership structure (Balmann *et al.*, 2021; Jänicke, 2023), we interact the treatment indicator d_{parcel} with the dummy variables for each of the 14 respective counties $d_{l,county}$. This gives our third model M3:

$$log(p) = \alpha + h(.) + \sum_{l=1}^{14} \delta_{l,county}^{parcel}(d_{parcel} \times d_{l,county}) + \epsilon \quad (3b)$$

where $\delta_{l,county}^{parcel}$ indicates the estimated log price difference of the treatment observation in the county l compared to control observations in the county l.

Given the considerable price surge in our study region during the observation period, we also investigate the temporal heterogeneity of the treatment effect. We perform a rolling window analysis: We split our unmatched sample into consecutive and overlapping subsamples of three years each, resulting in 21 overlapping intervals (2000-2002, 2001-2003, …, 2020-2022). Within each interval, we apply the doubly robust approach with two-nearest neighbour matching in the first step, and post-matching regression based on eq. 1 in the second step. For each interval, all control observations from the same period, one year prior, and one year subsequent are considered as potential matches. This gives the average log price difference between treated and control transactions for each of the 21 intervals. In contrast to a time treatment interaction model that spans the entire period, the rolling window approach offers flexibility to other explanatory variables, providing a more comprehensive and robust basis for parameter estimation in each interval.

4 Results

4.1 Matching quality

The results of the two-nearest-neighbour matching based on the Mahalanobis distance with up to three replacements matches the 7,416 lot bundle transactions with 7,711 control transactions of single parcels; 3,436 of the control units are matched once, 1,429 units are matched twice, and 2,846 units are matched three times. Figure 3 shows the absolute standardized mean difference of the main variables for the unmatched (grey) and the matched sample (black). After matching, the standardized difference for all core characteristics is below 0.2, indicating a good matching balance (Harder *et al.*, 2010).

The average distance between the location of the treated and matched controls is 13.66 km (median 10.5 km). Overall, the matching approach provides us with a counterfactual outcome for bundle transactions with similar characteristics traded at the same time and in the same market.

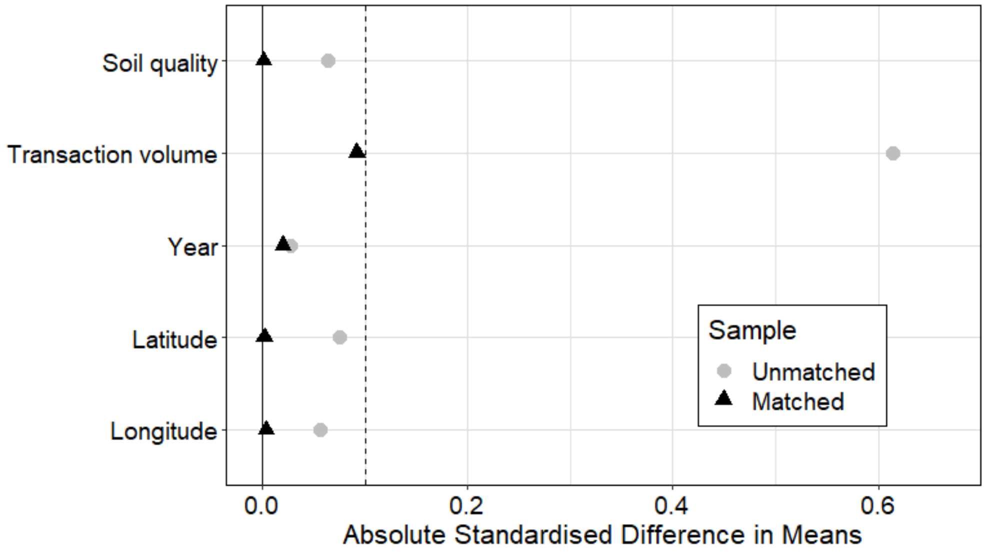

Figure 3: Matching quality

4.2 Post-matching regression

Table 2 shows the post-matching regression results for our baseline model M1. The regression shows with an R^2 of 0.708, a satisfying fit to explain the variation in prices. The model indicates a consistently increasing non-linear relationship between transaction volume and prices with a marginal effect decreasing in the transaction volume. The model also indicates positive effects of urbanization on land prices, with average markups of 23.8% 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.

Regarding our treatment effect, the model indicates that transactions of multiple parcels (bundles) yield, on average, 6.7% lower prices compared to similar transactions involving only one parcel. The 95%-CI, derived from robust standard errors clustered at the municipal level, spans from -8.0% to -5.5%, 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 model M1

	Coef.	95%-CI
Intercept	-0.655	(-1.899, 0.588)
Land characteristics		
√Transaction volume	0.112	(0.084, 0.140)
√Soil quality index	0.036	(0.021, 0.052)
Transaction volume²	-0.015	(-0.024, -0.006)
Soil quality²	-0.0001	(-0.003, 0.003)
Transaction volume · soil quality	0.002	(0.001, 0.003)
Agro-climatic conditions	0.112	(0.084, 0.140)
Precipitation	-0.047	(-0.092, -0.001)
Precipitation²	0.0004	(-0.00003, 0.001)
Drought index	-0.145	(-0.396, 0.107)
Drought index²	0.032	(-0.010, 0.073)
Location	0.200	
Metro region Berlin	0.238	(0.204, 0.272)
Adjacency to settlement	0.071	(0.055, 0.088)
Distance to next centre	0.064	(0.044, 0.084)
Distance to next centre²	-0.007	(-0.010, -0.005)
Share UAA	0.003	(0.002, 0.003)
Share settlement	0.001	(-0.00004, 0.003)
LSU density	0.001	(-0.003, 0.005)
Renewable energy intensity		
Wind density	0.014	(0.008, 0.019)
Biogas density	0.001	(0.0005, 0.002)
Treatment effect		
Bundle transaction	-0.067	(-0.080, -0.055)
Year FE	Yes	
County FE	Yes	
Weights	Yes	
Control	7,711	
Treated	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 time dummy variables are listed in the Appendix Table A1.

To illustrate the magnitude of the effect, we simulate the price differentials between transactions of single parcels and a bundle consisting of two parcels with the same transaction volume. Using the parameter estimates obtained through model M1 (Table 2) with soil quality fixed at the sample mean and all other variables set to zero, we predict prices for bundle transactions consisting of two parcels ranging from 0.25 to 17.5 ha. For single transactions, we obtain the predicted price for the same transaction volume, i.e., 0.5 to 35 ha. Figure 4 illustrates the predicted price differentials between single parcels and a bundle transaction consisting of two parcels.

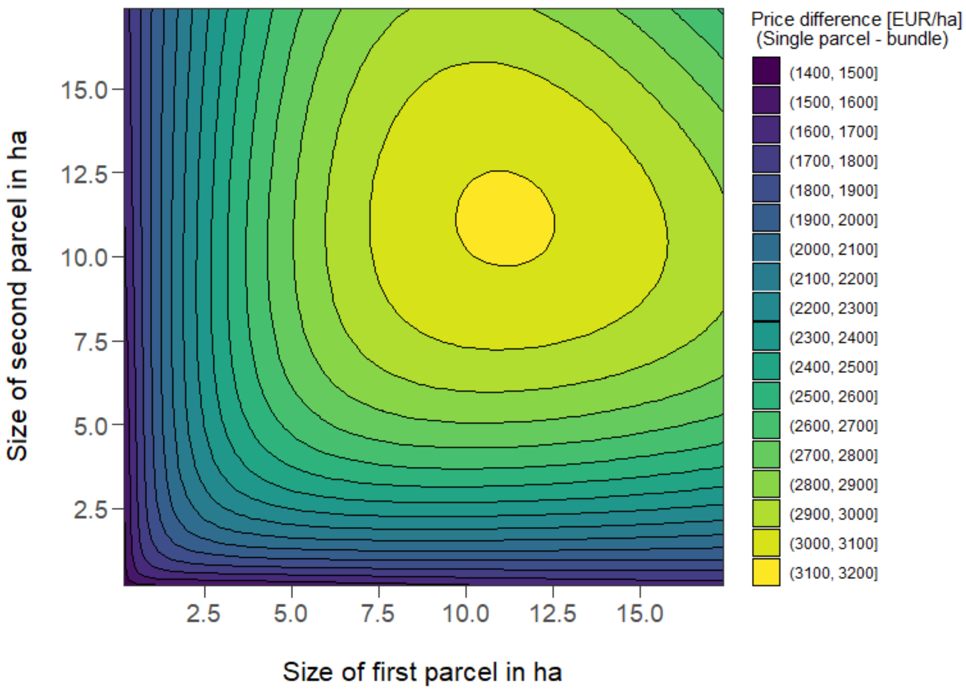

Figure 4: Predicted price difference (contours) between a single parcel and a bundle transaction consisting of two parcels of different sizes (vertical and horizontal axes) in € per ha.

Due to the flexible non-linear nature of the estimated relationship, the price differentials vary with the total transaction volume and with the proportional composition of the two combined parcels. For instance, a bundle transaction consisting of two 10-hectare parcels shows a predicted price-mark down of around 3000-3100 € per ha compared to the transaction of a single parcel of 20 ha. Price gaps of bundles to single parcels tend to be small in cases, where one parcel of the bundle is small in size (less than 2.5 ha), as indicated by blue contours. That is, price differences to single parcel transactions are less pronounced for the sale of a large parcel with a small parcel than for the sale of two medium-sized parcels of the same size.

4.3 Effect heterogeneity and robustness checks

Model specification

Despite our rich model specification, we cannot rule out bias from omitted variables in hedonic models (Abbott and Klaiber, 2011; Kuminoff *et al.*, 2010). To investigate the robustness of the estimated treatment effect, we replicate the analysis for a large set of different specifications of equation (2), and with and without matching. Results are shown in Figure 4, where the treatment effect estimates derived from our procedure (depicted in red) are contrasted against various empirical specifications.

With few exceptions, we find treatment effects slightly smaller or larger than our baseline specification. Confidence intervals generally overlap with our baseline specification. We note that our baseline specification indicates the smallest 95% CI for the treatment effect among all models. The mean price difference between the treated and control samples are statistically insignificant based on a t-test only for the unmatched sample and unconditional on any other control variables. Omitting only the matching but using the full specification of the hedonic regression (column 11) suggests a higher effect size than the baseline model, with a coefficient estimate of -7.5% (95% CI: -8.75% to -6.29%). We note that the unconditional matched price difference between the treated and matched control of -6.9% is nearly identical to the treatment effect of our baseline model. The point estimate suggests higher uncertainty, with confidence intervals ranging from -9.17% to -4.66%. This suggests that the first-stage matching controls very well for the main farmland price determinants, whereas the second stage helps to account for other price-determining factors not considered in the first stage, but potentially of minor importance. Further robustness checks based on different matching estimators and subsamples indicate that our results are not driven by sample selection or matching algorithms.[8]

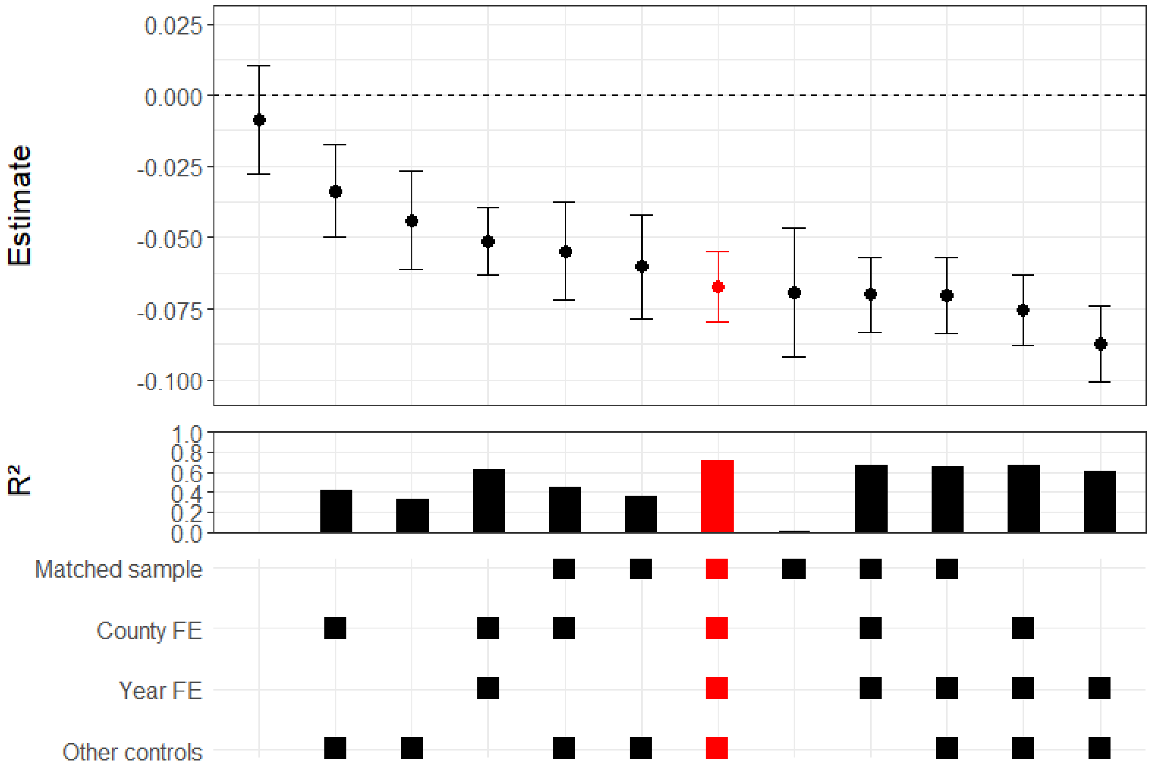

Figure 5: Specification chart with different model variants in decreasing order of the treatment estimate, red indicates the matched full model.

[8] Results of the robustness-checks are available on request.

Effect heterogeneity by transaction volume, space and time

Figure 6 summarizes the treatment effect heterogeneity over transaction volume (panel a), space (panel b), and time (panel c). For deciles of the transaction volume, treatment interaction terms range from -3.8% to -8.7% with generally overlapping 95% CIs. Pairwise t-tests do not indicate statistically distinguishable point estimates at conventional levels of statistical significance. Treatment effect estimates by county (panel b) show some spatial heterogeneity and vary between +3.8% (Barnim, BAR) to -14.0% (Oder-Spree, LOS). Except for one county, point estimates are negative with 95% CIs covering only a negative range for around half of the estimates. Results do not suggest obvious spatial patterns across our study region.

Results also indicate only minor variation over our observation period (panel c). The figure suggests a slight decrease in the treatment effect for time slices after the onset of the farmland price boom in 2007, 95% CIs are, however, overlapping across all time slices.

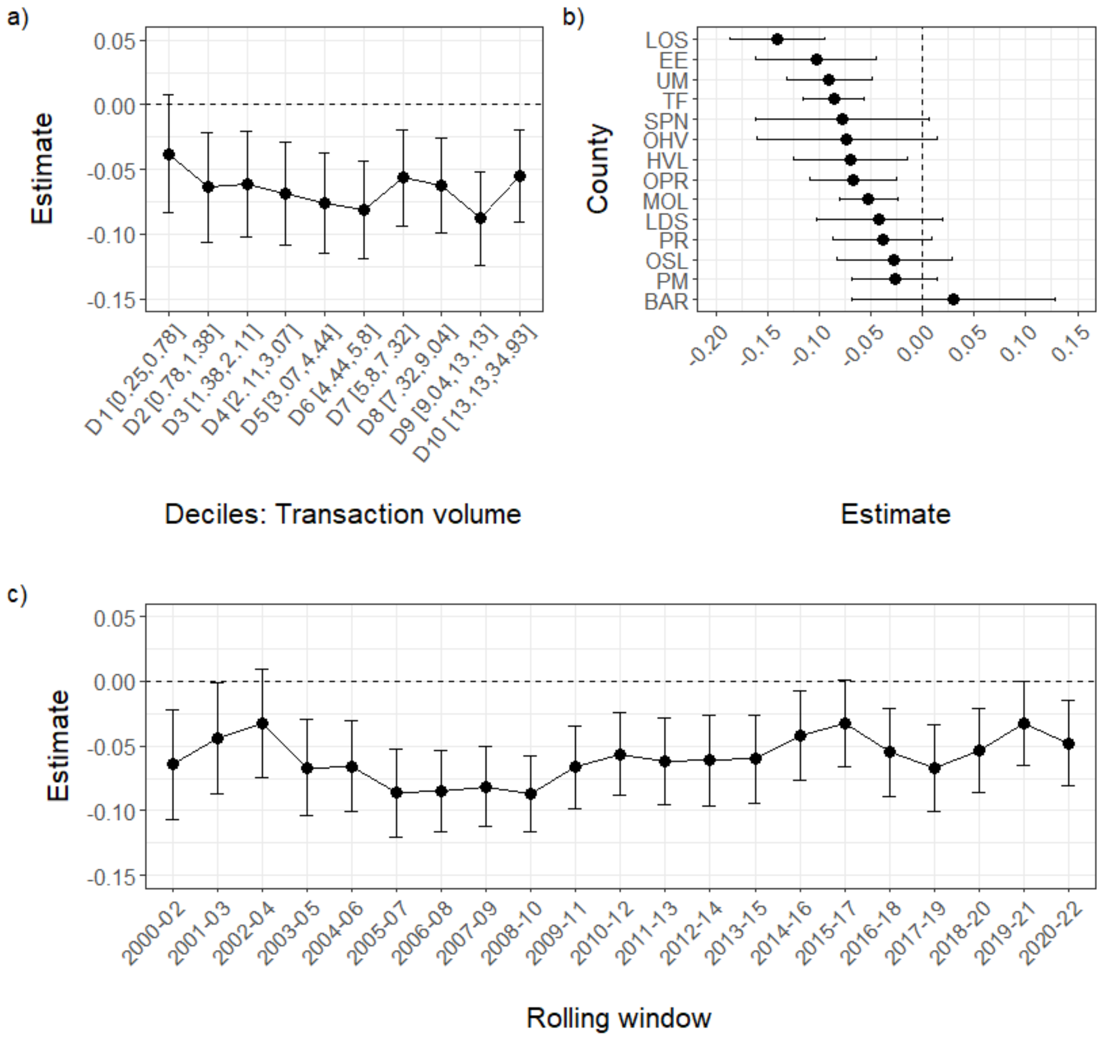

Figure 6: Treatment effect heterogeneity by a) transaction volume, b) county, and c) time via rolling window

5 Discussion and Conclusion

In this study, we investigate the impact of bundling parcels in transactions on farmland prices. We rely on a dataset of 24,528 arable land transactions in Brandenburg from 2000-2022, providing information on whether the transaction consisted of spatially separated parcel or single parcel. We rely on a treatment effect framework. We apply a doubly robust approach and contrast the transaction of bundled parcels with single parcels by combining matching with a hedonic-post-matching regression.

Consistent with prior studies on price formation on farmland (e.g., Seifert *et al.*, 2021), we find positive effects of soil quality and traded transaction volume on sales prices. Further, we observe a positive impact on land prices attributable to increasing demand for land for renewable energy production in our observation period, aligning with previous findings (e.g., Hennig and Latacz-Lohmann, 2017). We observe with markups for transactions adjacent to settlements and in the metropolitan region of Berlin suggesting positive price effects from the demand for land for non-agricultural land use (Delbecq *et al.*, 2014).

Our results indicate that bundle transactions achieve, on average, -6.7% lower sales prices compared to single parcel transactions with similar characteristics. Compared to a situation where all parcels would have been sold individually, this corresponds to 22 million € lower revenues for sellers selling bundles for our sample. This markdown (net effect) is robust against different model specifications, matching approaches, and samples. Analysis of treatment effect heterogeneity suggest that the effect is independent of the traded transaction volume. Despite the dynamic evolution of the analysed farmland market in our observation period, we find also rather stable treatment effects over the observation period. Investigating the spatial heterogeneity of the treatment effect, we find markdowns for almost all of Brandenburg's counties. The latter may point to differences in the local market and ownership structure varying across Brandenburg (Balmann *et al.*, 2021).

We offer two potential explanations for the identified negative price effect of bundles on farmland prices, in line with the theory on spatial pricing of farmland (Graubner, 2018). First, the negative price effect can be interpreted as the result of a reduced WTP of buyers for spatially separated land due to higher distance costs from farming. This is consistent with the empirical findings of Latruffe and Piet (2014), who show adverse effects of land fragmentation on farm performance in multiple dimensions (i.e., production costs, yields, revenue, profitability and efficiency). Results of Pennerstorfer (2022) on spatial competition of farmland support this interpretation, indicating the greater importance of distance costs in long-term land purchase decisions compared to short-term rentals. The buyer group of farmers may buy spatially separated farmlands at markdowns to compensate for negative effects on farm performance from higher fragmentation in the long run. Non-farmer buyers looking to acquire land for renting may factor in higher transaction costs post-purchase, anticipating additional costs for managing the portfolio related to finding the tenant with the highest willingness to pay (Humpesch *et al.*, 2022).

Second, the negative effect can be interpreted as a result of reduced competition for spatially dispersed farmland. Bundles may be of interest for a larger group of buyers as more buyers would be interested in one of the parcels. Bundles may, however, ultimately only attract those buyers that have a sufficiently high WTP across all offered parcels. This buyer group may be smaller and potentially distinct from those interested in the individual parcels. As a seller, facing a smaller and potentially different pool of buyers may lead to a weakened bargaining position in the price formation with lower prices as a result (Seifert *et al.*, 2021). This aligns with studies on farmland competition, indicating that more productive parcels attract more bidders and different bidder types including also non-agricultural investors (Isenhardt *et al.*, 2023; Piet *et al.*, 2021; Seifert and Hüttel, 2023). The observed effects are consistent with the role of market and bargaining power in farmland price formation (Cotteleer *et al.*, 2008; Balmann *et al.*, 2021). We note, however, that these two effects of a reduced WTP and reduced competition for bundle appear simultaneously and are thus observed as a net effect in our treatment effect estimate.

We illustrate the effect using a simulation approach to compare the outcomes of selling the same acreage with a single parcel or two parcels in a bundle. Results show that the effect on sales prices varies with the total volume of the transaction and with the composition of the bundle. Notably, price differentials are less pronounced if one parcel of a bundle is small in size. In contrast, selling two medium-sized to large parcels with equal proportions, price differences compared to a single parcel increase. This suggests that a bundle comprising a large and a small parcel has less effect on sales prices than selling two medium-sized parcels. In the former case, considering transaction costs including search and bargaining costs, a seller might be better off selling the two parcels jointly, despite the markdown. We note, however, that the simulation results are limited due to the underlying assumption, e.g., we consider only two parcels per bundle.

Our results enhance the understanding of spatial pricing of farmland and the price formation of farmland in thinly traded markets. For landowners and sellers, our results suggest that a careful evaluation of the gains of selling parcels separately against transaction costs is warranted. In particular, if multiple medium/large-sized plots are for sale, a separate sale should be considered weighing up potentially higher revenues against additional transaction costs. When advertising a bundle, it might be worth emphasising the option of a partial acquisition of the single parcels. Professional sellers using auction mechanisms may consider multi-tract auction systems, where interested buyers can bid on single parcels or the entire bundle. For potential buyers that are already landowners, our findings suggest that strategic purchases to consolidate parcels may allow to increase the value of their owned farmland.

From an academic perspective, research on farmland prices should consider the effect of bundle transactions to reduce omitted variable bias, especially when investigating the relationship between the size of transactions and land prices. From a policy perspective, we suggest offering this information on transaction composition in price publications and official statistics to prevent biases in the future price formation of farmland (Seifert and Hüttel, 2023).

Our study has the following limitations, which allow suggestions for future research: First, because we lack detailed information about parcels included in a bundle (e.g., size or distance to the main parcels), our results provide only the average price differential for bundle and single transactions. Second, despite our rich model specification, unobserved heterogeneity may confound the treatment effect estimate. This may concern buyer-specific information, e.g., if a single parcel was purchased by a nonfarmer for specific reasons other than farming (e.g., horse breeding). Third, we lack explicit information on the local farm structure (number of farms, their size and cultivated fields) around transacted parcels. Therefore, combining detailed transaction data on each parcel with land-use data from IACS and information on the location of the buyers (e.g., farmstead) would be an interesting approach to further differentiate between distance costs and competition effects.

References

ABADIE, A., S. ATHEY, G. W. IMBENS AND J. M. WOOLDRIDGE (2022): WHEN SHOULD YOU ADJUST STANDARD ERRORS FOR CLUSTERING? IN: THE QUARTERLY JOURNAL OF ECONOMICS.

ABBOTT, J. K. and H. A. KLAIBER (2011): An embarrassment of riches: Confronting omitted variable bias and multiscale capitalization in hedonic price models. In: The Review of Economics and Statistics 93 (4): 1331–1342.

BALMANN, A., M. GRAUBNER, D. MÜLLER, S. HÜTTEL, S. SEIFERT, M. ODENING, J. PLOGMANN and M. RITTER (2021): Market Power in Agricultural Land Markets: Concepts and Empirical Challenges. In: German Journal of Agricultural Economics 70 (4): 213–235.

BBSR (2019): Laufende Stadtbeobachtung - Raumabgrenzungen. Großstadtregionen. In: https://www.bbsr.bund.de/BBSR/DE/Raumbeobachtung/Raumabgrenzungen/deutschland/regionen/Grossstadtregionen/stadtregionen_node.html.

BNETZA (2022): Marktstammdatenregister – Öffentliche Einheitenübersicht. Bundesnetzagentur. In: https://www.marktstammdatenregister.de/MaStR/Einheit/Einheiten/OeffentlicheEinheitenuebersicht. Call: 25.2.2022.

BRORSEN, B. W., D. DOYE and K. B. NEAL (2015): Agricultural Land and the Small Parcel Size Premium Puzzle. In: Land Economics 91 (3): 572–585.

COTTELEER, G., C. GARDEBROEK and J. LUIJT (2008): Market Power in a GIS-Based Hedonic Price Model of Local Farmland Markets. In: Land Economics 84 (4): 573–592.

DELBECQ, B. A., T. H. KUETHE and A. M. BORCHERS (2014): Identifying the Extent of the Urban Fringe and Its Impact on Agricultural Land Values. In: Land Economics 90 (4): 587–600.

DESTATIS (2022): VGR des Bundes - Deflatoren: Deutschland, Jahre, Verwendung des Bruttoinlandsprodukts. Statistisches Bundesamt, Wiesbaden. In: https://www.destatis.de/DE/Methoden/Qualitaet/Qualitaetsberichte/Land-Forstwirtschaft-Fischerei/flaechenerhebung.html. Call: 12.5.2022.

DWD (2022a): Annual grids of drought index (de Martonne) over Germany. Deutscher Wetterdienst, Offenbach. In: https://opendata.dwd.de/climate_environment/CDC/grids_germany/annual/drought_index. Call: 11.11.2022.

DWD (2022b): Multi-annual grids of precipitation height over Germany 1981-2010. Deutscher Wetterdienst, Offenbach. In: https://opendata.dwd.de/climate_environment/CDC/grids_germany/multi_annual/precipitation/. Call: 7.4.2020.

GRAUBNER, M. (2018): Lost in space? The effect of direct payments on land rental prices. In: European Review of Agricultural Economics 45 (2): 143–171.

HAAN, P. and M. SIMMLER (2018): Wind electricity subsidies — A windfall for landowners? Evidence from a feed-in tariff in Germany. In: Journal of Public Economics 159: 16–32.

HARDER, V. S., E. A. STUART and J. C. ANTHONY (2010): Propensity score techniques and the assessment of measured covariate balance to test causal associations in psychological research. In: Psychological methods 15 (3): 234–249.

HART, T. and P. ZANDBERGEN (2014): Kernel density estimation and hotspot mapping. In: Policing: An International Journal of Police Strategies & Management 37 (2): 305–323.

HARTVIGSEN, M. (2014): Land Reform and Land Fragmentation in Central and Eastern Europe. In: Land Use Policy 36: 330–341.

HENNIG, S. and U. LATACZ-LOHMANN (2017): The incidence of biogas feed-in tariffs on farmland rental rates – evidence from northern Germany. In: European Review of Agricultural Economics 44 (2): 2231–2254.

HO, D. E., K. IMAI, G. KING and E. A. STUART (2007): Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference. In: Political Analysis 15 (3): 199–236.

HO, D. E., K. IMAI, G. KING and E. A. STUART (2011): MatchIt : Nonparametric preprocessing for parametric causal inference. In: Journal of Statistical Software 42 (8).

HUMPESCH, M., S. SEIFERT, A. BALMANN and S. HÜTTEL (2022): How does tenancy affect farmland prices? Effects of lease status, lease term and buyer type. In: Agricultural Finance Review 83 (2): 242–263.

ISENHARDT, L., S. SEIFERT and S. HÜTTEL (2023): Tenant Favoritism and Right of First Refusals in Farmland Auctions: Competition and Price Effects. In: Land Economics 99 (2): 302-324.

JÄNICKE, C. (2023): Farmland ownership structure in Brandenburg based on ALKIS cadastre-data.

KING, G. and R. NIELSEN (2019): Why Propensity Scores Should Not Be Used for Matching. In: Political Analysis 27 (4): 435–454.

KUMINOFF, N. V., C. F. PARMETER and J. C. POPE (2010): Which hedonic models can we trust to recover the marginal willingness to pay for environmental amenities? In: Journal of Environmental Economics and Management 60 (3): 145–160.

LATRUFFE, L. and L. PIET (2014): Does land fragmentation affect farm performance? A case study from Brittany, France. In: Agricultural Systems 129: 68–80.

LFU (2022): Tierhaltungsanlagen nach BImSchG im Land Brandenburg. In:

LGB (2023): Flurübersichtskarte. Aus den Daten des Liegenschaftskatasters. Landvermessung und Geoinformation Brandenburg.

MACKINNON, J. G., M. Ø. NIELSEN and M. D. WEBB (2023): Testing for the appropriate level of clustering in linear regression models. In: Journal of Econometrics 235 (2): 2027–2056.

MLUL BB (2023): Agrarbericht des Ministeriums für Landwirtschaft, Umwelt und Klimaschutz des Landes Brandenburg. Agrarbericht. In: https://agrarbericht.brandenburg.de. Call: 9.3.2023.

NICKERSON, C. J. and W. ZHANG (2014): Modeling the Determinants of Farmland Values in the United States. In: Duke, J. M. and J. Wu (Eds.): 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. In: American Journal of Agricultural Economics 102 (3): 934–959.

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

PIET, L., R. MELOT and S. DIOP (2021): What drives competition on the farmland market? A case study in Brittany (France). In: European Review of Agricultural Economics 48 (1): 60–96.

RITTER, M., S. HÜTTEL, M. ODENING and S. SEIFERT (2020): Revisiting the relationship between land price and parcel size in agriculture. In: Land Use Policy 97: 104771.

RUBIN, D. B. (1980): Bias Reduction Using Mahalanobis-Metric Matching. In: Biometrics 36 (2): 293.

SCHMITZ, T. and D. MÜLLER (2020): Digitale Karte der Bodenwertzahlen für Brandenburg.

SEIFERT, S. and S. HÜTTEL (2023): Is there a risk of a winner's curse in farmland auctions? In: European Review of Agricultural Economics 50 (3): 1140-1177.

SEIFERT, S., S. HÜTTEL and A. WERWATZ (2023): Organic cultivation and farmland prices: Does certification matter? httpp://doi.org/10.18452/26264

SEIFERT, S., C. KAHLE and S. HÜTTEL (2021): Price Dispersion in Farmland Markets: What Is the Role of Asymmetric Information? In: American Journal of Agricultural Economics 103 (4): 1545–1568.

STUART, E. A. (2010): Matching methods for causal inference: A review and a look forward. In: Statistical Science 25 (1): 1–21.

VALTIALA, J., O. NISKANEN, M. TORVINEN, K. RIEKKINEN and A. SUOKANNAS (2023): The relationship between agricultural land parcel size and cultivation costs. In: Land Use Policy 131: 106728.

VRANKEN, L., P. ROEBELING, E. TABEAU, P. CIAIAN and 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. In: https://op.europa.eu/en/publication-detail/-/publication/c903d5d4-482e-11ec-91ac-01aa75ed71a1/language-en.

WESEMEYER, M., J. KAMP, T. SCHMITZ, D. MÜLLER and T. LAKES (2023): Multi-objective spatial optimization to balance trade-offs between farmland bird diversity and potential agricultural net returns. In: Agriculture, Ecosystems & Environment 345: 108316.

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

WOLZ, A. (2013): The Organisation of Agricultural Production in East Germany since World War II: Historical Roots and Present Situation. In: Discussion Paper, Leibniz Institute of Agricultural Development in Central and Eastern Europe 139.

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

Appendix

Table A1: Parameter estimate for county and year fixed effects of model M1

	Coef.	95%-CI
County		
Dahme-Spreewald	-0.340	(-0.399, -0.281)
Elbe-Elster	-0.503	(-0.564, -0.442)
Havelland	-0.145	(-0.203, -0.087)
Märkisch-Oderland	-0.002	(-0.056, 0.052)
Oberhavel	-0.109	(-0.176, -0.042)
Oberspreewald-Lausitz	-0.481	(-0.542, -0.420)
Oder-Spree	-0.324	(-0.381, -0.268)
Ostprignitz-Ruppin	0.062	(0.006, 0.118)
Potsdam-Mittelmark	-0.140	(-0.197, -0.084)
Prignitz	0.065	(0.006, 0.124)
Spree-Neiße	-0.645	(-0.715, -0.575)
Teltow-Fläming	-0.249	(-0.303, -0.196)
Uckermark	0.373	(0.317, 0.429)
Time		
2001	0.020	(-0.033, 0.074)
2002	-0.035	(-0.088, 0.019)
2003	-0.047	(-0.104, 0.010)
2004	-0.135	(-0.187, -0.082)
2005	-0.107	(-0.157, -0.056)
2006	-0.111	(-0.163, -0.060)
2007	-0.027	(-0.077, 0.022)
2008	0.093	(0.044, 0.143)
2009	0.206	(0.157, 0.256)
2010	0.331	(0.279, 0.383)
2011	0.507	(0.455, 0.559)
2012	0.618	(0.565, 0.672)
2013	0.776	(0.724, 0.828)
2014	0.898	(0.847, 0.948)
2015	1.033	(0.983, 1.083)
2016	1.073	(1.019, 1.126)
2017	1.169	(1.113, 1.224)
2018	1.173	(1.120, 1.225)
2019	1.208	(1.153, 1.263)
2020	1.245	(1.189, 1.301)
2021	1.264	(1.195, 1.333)
2022	1.269	(1.211, 1.326)
Q3	0.010	(-0.004, 0.024)

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.