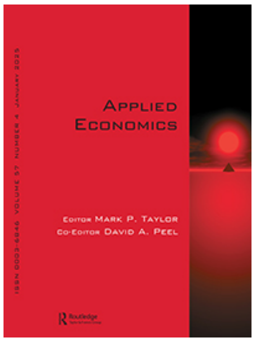

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Municipality-level estimates of agricultural land prices in Germany: applying the small area estimation method

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ABSTRACT

Agricultural land prices in Germany exhibit considerable regional heterogeneity, yet publicly accessible data are typically aggregated at the state level, obscuring small-scale geographic variations. Obtaining reliable estimates at a small-scale geographic level is challenging due to market illiquidity, resulting in limited availability of transaction records for specific areas within the year of interest. This study aims to address this knowledge gap by employing the Small Area Estimation (SAE) method for the first time to estimate agricultural land prices at the municipality level. Using transaction data from the German federal state of Brandenburg in 2021, the study incorporates auxiliary variables informed by hedonic price models to re-estimate prices for municipalities with at least two transactions (in-sample municipalities) and generate estimates for municipalities not covered in the sample (out-of-sample municipalities). The model produces reliable price estimates for 412 municipalities. Our findings demonstrate the effectiveness of the SAE approach in generating localized price estimates as a quantitative complement to standard land values, while also confirming its validity and generalizability. These estimates enhance market transparency and inform policy-making, while the SAE approach is broadly applicable to regions and countries with comparable data needs.

KEYWORDS

Agricultural land prices; municipality-level estimates; small area estimation; hedonic price model

JEL CLASSIFICATION

Q24; Q15

1. Introduction

Agricultural land serves as a crucial input in agricultural production, attracting substantial interest from various stakeholders in the agricultural land market, particularly regarding land prices (Hüttel et al. 2013; Schaak and Musshoff 2022). Over the last decade, agricultural land prices in the European Union have grown extensively (Eurostat 2022). This is especially the case in Western Europe, which is exemplified by Germany where the average purchase price for agricultural land soared by 126%, from 11,854 €/ha in 2010 to 26,777 €/ha in 2020 (Federal Statistical Office of Germany 2011, 2021). The increase has also been accompanied by considerable price disparities among regions within Germany (Kirschke, Häger, and Schmid 2021). In 2010, the federal state of Brandenburg recorded the lowest agricultural land price in Germany at 6,334 €/ha, while Nordrhein-Westfalen's had the highest at 28,051 €/ha. By 2020, the gap widened, with Saarland's prices at 10,678 €/ha being the lowest and Bayern's the highest at 63,986 €/ha, indicating a sixfold disparity in regional prices (Federal Statistical Office of Germany 2011, 2021). This heterogeneity of agricultural land prices is observed not only at the federal state level, but also at lower geographical units, such as at the municipality level. Yang, Ritter, and Odening (2017, 2019) show that, within the German state of Lower Saxony, agricultural land prices exhibit variability across regions and, additionally, that these prices experience divergent growth rates. This pattern of heterogenous agricultural land prices within a state is evident across many states and persisting over time (Hüttel, Jetzinger, and Odening 2014; Seifert, Kahle, and Hüttel 2021).

Most publicly accessible databases, such as the statistics on average purchase prices of agricultural land published annually by the German Federal Statistical Office, rely on actual sales transactions aggregated at broader geographic levels, typically at

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the county or federal-state level (Federal Statistical Office of Germany 2021). As a result, these statistics offer only coarse geographical insights into agricultural land prices, masking the price variations at small-scale geographic levels. The publicly available small-scale price estimates are the standard land values (Bodenrichtwerte), published annually by Local Committees of Land Valuation Experts (Gutachterausschüsse für Grundstückswerte) for almost all municipalities. However, these price estimates are the result of qualitative expert discussions and are not based on standardized statistical approaches. There is a strong demand in research for transparent and empirically derived estimates of agricultural land prices at a more detailed geographic level to accurately depict the price development. Similarly, agricultural stakeholders seek detailed market insights to support practical decision-making.

However, due to the market illiquidity and the resulting low number of transactions, reliable aggregated estimates of agricultural land prices often reach only up to the county level. Many municipalities may have few or even no transactions, making it challenging to directly estimate average agricultural land prices at the municipality level, especially on an annual basis. Even when estimates are feasible, they often come with large standard errors. To overcome the limitation of large standard errors when applying direct estimation, 'indirect' estimations can be employed, which utilize models linking related areas and/or time periods to increase the effective sample size and reduce mean squared errors (MSE) (Rao and Molina 2015). Small Area Estimation (SAE), an explicit linking model with random area-specific effects accounting for the between-area variation that cannot be explained by auxiliary covariate information, offers several advantages in providing more reliable estimates at the small-scale geographic level. Although widely used by statistical offices to estimate indicators such as poverty and unemployment at the small-scale geographic level (Hastings et al. 2003; Office for National Statistics 2017), SAE technique has not yet been applied to the agricultural land market.

The objective of this study is to provide reliable and almost complete estimates of agricultural land prices at the municipality level. We apply the SAE technique to the land transaction data from the German federal state of Brandenburg as an illustrative example, marking the first use of this method to estimate agricultural land prices. Within the framework of SAE, reliable price estimates can be generated not only for municipalities with available agricultural land transactions but also for those without transactions or with an insufficient number of transactions. Brandenburg provides a suitable context for this study, given its available transaction records and auxiliary variables, diverse natural and economic conditions (Hüttel, Jetzinger, and Odening 2014), and geographic and economic relevance for agricultural production as a state surrounding Berlin.

This study makes an important applied contribution by being the first to apply the SAE method for estimating agricultural land prices at the municipality level. The results show that SAE can produce precise and reliable estimates using existing transaction and auxiliary data, providing a practical and cost-effective approach that reduces the need for additional data collection. Model validation confirms the robustness and generalizability of the approach across different years, indicating its potential for consistent application over time. The findings have important policy implications, as the localized price estimates generated through SAE enhance market transparency, inform decision-making, and support more effective land management strategies. While this study demonstrates the effectiveness of the SAE approach for estimating agricultural land prices using Brandenburg as an example, this approach can be applied to other regions with similar data needs.

The remainder of the paper is structured as follows: Section II provides a literature overview and Section III explains the estimation methodology. Subsequently, Section IV describes the data and presents the results, followed by a discussion in Section V. Finally, Section VI offers concluding remarks.

II. Literature review

SAE methodology and its applications

SAE is a technique for obtaining precise estimates for a specific measure in areas where the sample size is small or even zero. The method focuses on regionalization, where aggregated data from larger regions are 'downscaled' into finer geographic units (Ghosh and Rao 1994). By incorporating information from coarser spatial levels as well as information from similar areas, SAE facilitates enhanced precision in estimates, effectively addressing the challenges posed by areas with only small or even no values (Rao 2010). In comparison to the direct estimation, which generally has large variances and estimates are unreliable when the sample sizes are small, the SAE method minimizes the mean squared error (MSE) of the resulting estimates by 'borrowing strength' from auxiliary information in each area (Rao and Molina 2015). Furthermore, compared with indirect estimation based on implicit models, the SAE method can handle complex data structures and allow for specific area variation through complex error structures in the regression. Model validity can be assessed using the sample data (Rao and Molina 2015). For a more detailed explanation of SAE methods, see Jiang and Lahiri (2006), Pfeffermann (2002, 2013), and Rao (2008, 2015).

SAE methods are extensively used by national statistical offices and in research, enhancing the precision of small area estimates across various sectors. The Office for National Statistics in the UK, for instance, has utilized SAE since the 1990s to generate detailed small-area statistics within resource and sample size limitations (Silva and Clarke 2008). The SAE technique leverages existing datasets, such as administrative records and census data, to enhance the accuracy of estimates for poverty, unemployment, and other socioeconomic indicators for small geographic areas (Hastings et al. 2003; Office for National Statistics 2017). Such refined estimates have supported local economic planning, resource allocation, and policy making through more granular statistical outputs. Additionally, its application in the UK Census has improved population estimates by adjusting for social exclusion (Ambler et al. 2001). These applications illustrate SAE's critical role in producing reliable, policy-relevant statistics despite challenges like data scarcity.

One of the standout advantages of the SAE technique lies in its resource efficiency, minimizing the need for considerable additional resources, budgets, or extensive data collection. This benefit is particularly valuable in fields, where generating detailed small area estimates traditionally demands substantial effort and financial investment. Combining publicly available survey and census data, Mutai (2022) and Yu et al. (2007) estimate health insurance coverage in small geographic areas in Kenya and the US, respectively. Researchers also utilize SAE to enhance data quality for disaggregated Sustainable Development Goals (SDGs) indicators, such as poverty rates, child mortality, and educational achievements across various nations (Chandra, Aditya, and Sud 2018; Christiaensen et al. 2012; Dwyer-Lindgren et al. 2018; Mercer et al. 2015; Molina and Rao 2010; Pratesi et al. 2021). The application of SAE method extends beyond these areas, facilitating research in predicting building-level municipal solid waste generation (Kontokosta et al. 2018), estimating smoking prevalence rates (Li et al. 2009), calculating labour force indicators (López-Vizcaíno, Lombardía, and Morales 2015), or assessing the welfare of environmental activities (Gibson 2018; Prisley et al. 2021). Regarding agronomic research, studies have applied the SAE to generate reliable small-area information on crop statistics, given that crop yields usually vary considerably within small areas (Militino, Ugarte, and Goicoa 2007; Rao 2010). Despite its broad applicability, this method has yet to be applied to agricultural land markets.

Determinants of agricultural land prices

As agricultural land is not a homogeneous good and its quality varies spatially, it is important for empirical estimations to use models that account for potential price-influencing factors when valuing agricultural land. The hedonic pricing theory (Griliches 1971), which suggests that the price of a good is determined by a combination of its internal and external quality characteristics, is frequently used to estimate constant quality price indexes for owner occupied housing. In such models, the property's sale price is regressed on various price-determining characteristics (Diewert, Haan, and Hendriks 2015). Hedonic regression models are also widely applied in agricultural land price research. Studies demonstrate that both agricultural attributes, such as farm size and structure, livestock density and production, and agricultural gross values, as well as non-agricultural attributes, such as population density, distance to the nearest market, and urban sprawl, influence agricultural land prices in different countries (Livanis et al. 2006; Sklenicka et al. 2013; Wang 2018; Zhang and Nickerson 2015). In Germany, Lehn and Bahrs (2018) show that urban sprawl and livestock production are the main price drivers in the federal state of North Rhine-Westphalia. Similarly, urban pressure and regional land market structure are found to be a substantial influence on land productivity and thus land prices in the federal state of Bavaria (Feichtinger and Salhofer 2013). In countries like Germany, where population density is high and land markets are well regulated, land development policy and government support payments can have a considerable effect on land prices (Drescher, Henderson, and McNamara 2001; Feichtinger and Salhofer 2013). Agricultural land prices are also affected by the rapid development of renewable energy in Germany. Myrna, Odening, and Ritter (2019) find that a higher cumulative capacity of wind turbines in communities can lead to higher agricultural land prices. All these characteristics may vary at a small-scale spatial level. Moreover, Menzel et al. (2017) find that differences in agricultural land prices are higher within, relative to between Germany and Italy. Similarly, Yang, Odening, and Ritter (2019) find that the German land price is more differentiated at the regional level than at the aggregated level. These findings suggest the importance of having precise agricultural land price estimates at small-scale spatial levels.

III. Empirical strategy

SAE models are generally classified as unit-level models and area-level models. Since auxiliary information is available at the municipality level in this study, an area-level model based on the procedure explained by Rao and Molina (2015) is employed. The basic area-level model comprises two components. In the first stage, a sampling model is defined as:

$$\widehat{\theta}_i = \theta_i + e_i \tag{1}$$

where $\widehat{\theta}_i$ is the direct sample estimator of the mean θ_i for area (municipality) $i = 1, \ldots, I$. e_i stands for independent and normally distributed sampling errors with means zero and known variances $\sigma^2_{e_i}$ $\left(N\left(0, \sigma^2_{e_i}\right)\right)$. We calculate θ_i as the unweighted average agricultural land price in each sampled municipality i, formally:

$$\theta_i = \frac{1}{N_i}\sum_{j=1}^{N_i} y_{ij}, \tag{2}$$

where $j = 1, \ldots, N_i$. J refers to the agricultural land transaction and N_i is the number of land transactions in municipality i. y_{ij} denotes the agricultural land price of the j-th transaction in municipality i.

In the second stage, the target indicator θ_i is linked to the municipality-level auxiliary covariates x_i^T through a linear regression model:

$$\theta_i = x_i^T\beta + u_i \tag{3}$$

where β denotes an unknown fixed-effect parameter and u_i, the random effects, are assumed to be independent and normally distributed with $N\left(0, \sigma^2_u\right)$.

Combining the Equations (1) and (3), a special linear mixed model is obtained:

$$\widehat{\theta}_i = x_i^T\beta + u_i + e_i \tag{4}$$

This is the basic municipality-level model, which is obtained as a special case of the general linear mixed model.

The best linear unbiased prediction (BLUP) estimators of interest θ_i can be achieved under the classical frequentist framework. While the BLUP estimators do not require the normality assumption on the error terms u_i and e_i, they depend on variance components, i.e. the variances (and covariances) of random effects (Rao and Molina 2015). The empirical BLUP (EBLUP) estimator can be obtained by substituting the estimated variance components into the BLUP estimator, which is also known as the Fay-Herriot (FH) model (Fay and Herriot 1979). For known sampling variance, $\sigma^2_{e_i}$, the EBLUP of θ_i is in the form of a composite estimate:

$$\hat{\theta}_i^{FH} = \hat{\gamma}_i\hat{\theta}_i^{Dir} + \left(1 - \hat{\gamma}_i\right)x_i^T\hat{\beta} \tag{5}$$

where $\hat{\gamma}_i = \hat{\sigma}_u^2 / \left(\hat{\sigma}_u^2 + \sigma_{e_i}^2\right)$ is a tuning (shrinkage) coefficient that assigns more weight to the direct estimator $\hat{\theta}_i^{Dir}$ when the sampling variance, $\sigma_{e_i}^2$, is small relative to the model variance, σ_u^2, while assigning more weight to the synthetic estimator, $x_i^T\hat{\beta}$, when $\sigma_{e_i}^2$ is large (Rao 2015). For areas without direct estimate (out-of-sample areas), the EBLUP is reduced to the regression synthetic component $\hat{\theta}_i^{FH} = x_i^T\hat{\beta}$, which is estimated based on the available auxiliary covariates associated with the non-sampled areas (Rao and Molina 2015). The estimator of the variance of the random area-specific effects, σ_u^2, is performed with the Residual Maximum Likelihood (REML) method.

To assess the precision of the SAE model, the Mean Squared Error (MSE) is used and calculated as:

$$MSE\left(\hat{\theta}_i^{FH}\right) = E\left(\hat{\theta}_i^{FH} - \theta_i\right)^2 = \gamma_i \sigma_{e_i}^2 \qquad (6)$$

This indicates that the SAE estimate is more efficient than the direct estimate when γ_i is small, i.e. when the model variance, σ_u^2, is small relative to the sampling variance, $\sigma_{e_i}^2$ (Rao 2015). Therefore, the success of the SAE model depends heavily on the selection of good auxiliary variables. Drawing on empirical evidence from hedonic pricing models on factors influencing agricultural land prices (see Section II), we initially considered two main categories of indicators as auxiliary covariates at the municipality level: (i) socio-economic indicators, including population density, employment density, tax revenue per capita, distance to Berlin (in kilometres), transportation area per inhabitant, and residential area per inhabitant; and (ii) environmental and agriculture-specific indicators, including soil quality index, the proportion of agricultural area, the proportion of electricity generated from renewable energy sources, and the number of sewage treatment plants. Subsequently, we conducted a stepwise variable selection procedure based on the information criteria studied by Marhuenda, Morales, and Del Carmen Pardo (2014). Their simulation experiments show that if minimizing the probability of choosing an incorrect model is the goal, the Kullback Information Criterion (KIC) with bootstrap and a bias correction, KICb2, should be the best selection criteria for FH models. The lowest KICb2 is achieved when agricultural area (share), distance to Berlin (in km), and soil quality index are included in the regression. Therefore, only these three auxiliary variables will be used in the following analysis.

One concern is the potential spatial autocorrelation, as agricultural land prices in neighbouring municipalities may exhibit similar price patterns. Empirical studies show that ignoring spatial lag dependence leads to biased estimating of agricultural land prices (Feichtinger and Salhofer 2013; Patton and McErlean 2003). To identify spatial structures, we conducted Moran's I and Geary's C tests. The test statistics of 0.4343 for Moran's I test (a p-value of 0.0000) and 0.5418 for Geary's C test (a p-value of 0.0000) indicate a moderate positive spatial autocorrelation. Therefore, we incorporate the spatial pattern into random effects in the FH model. A proximity matrix is calculated, assigning a weight of one if an area shares a boundary with another area and zero if the respective areas are not neighbours, and included in the model.

IV. Data and results

Data

To perform the SAE analysis, multiple datasets are utilized. The agricultural land price data used in this study are provided by the Committee of Land Valuation Upper Experts in Brandenburg (Oberer Gutachterausschuss für Grundstückswerte im Land Brandenburg) and contains all agricultural land transactions in Brandenburg for the years of interest. The dataset provides detailed information on each transaction, including contract date, location, land type and size, transaction price, soil quality, and anonymized seller and buyer types. Following the methodology of the German Federal Statistical Office for the statistics on average purchase values of agricultural land (Federal Statistical Office of Germany 2021), agricultural land in this context refers to arable land and grassland.[1] Exemplarily, we use data from arable land and grassland transactions in 2021. To ensure statistical soundness, we exclude 17 observations

[1]The purchase prices for arable land and grassland can differ considerably (in our case, a p-value of 0.0000 based on the Wilcoxon rank sum test). To account for price heterogeneity, we run the SAE model separately for arable land and grassland data and the results are reported in Appendix B and C, respectively.

with an unrealistic purchase price below 1,000 €/ha or above 100,000 €/ha. A total of 2,554 transactions for agricultural land from 346 out of 417 Brandenburg municipalities are used for the analysis, consisting of 1,703 transactions for arable land and 851 for grassland. In addition, to demonstrate the generalizability of the SAE method, we perform the same analysis with data from 2020, with the results shown in Appendix D.

We enrich the agricultural land price data with municipality-level auxiliary variables from various data sources.[2] Population density, employment density, and tax revenue per capita are obtained from the Berlin-Brandenburg Statistical Office (Amt für Statistik Berlin-Brandenburg). The soil quality index is generated from the value determination framework of the Soil Utilization and Management Company GmbH (Boden Verwertungs- und Verwaltungsgesellschaft GmbH). The State Survey and Geoinformation Brandenburg (Landesvermessung und Geobasisinformation Brandenburg) provides data on the proportion of agricultural area, the proportion of nature conservation area, as well as the number of sewage treatment plants. The proportion of electricity generated from renewable energy sources, the proportion of transportation area, and the proportion of residential area are retrieved from the Energy Portal Brandenburg (Energieportal Brandenburg). Finally, the distance to Berlin (in kilometres), located geographically in the middle of the state of Brandenburg, is retrieved from Google Maps. All of these auxiliary variables are available for 412 municipalities in Brandenburg.

Under the framework of the FH model, municipalities with more than one agricultural land transaction are considered in-sample areas and all other municipalities with one or no transaction are considered out-of-sample areas, noting that there must be auxiliary covariates for both in- and out-of-sample regions. The final dataset for the following analysis consists of 288 in-sample and 124 out-of-sample municipalities. The FH estimation is performed using the R package *emdi* (Kreutzmann et al. 2019).

Results

The direct estimation in the first stage is based on 288 in-sample municipalities, without considering auxiliary variables. There were on average 8 transactions in each of these in-sample areas, with a maximum of 53 transactions. In 2021, the average agricultural land price in Brandenburg was 11,442 €/ha, with a standard deviation of 5,090 €/ha. The lowest average purchase price at the municipality was 3,268 €/ha, while the highest was 29,859 €/ha, more than nine times higher. Direct estimates of average agricultural land prices at the municipality level are visualized on the left side of Figure 1. The average purchase price in the northern regions of Brandenburg is higher than that in the southern regions. A similar pattern of price distribution is found by other studies in Brandenburg for other years (Hüttel, Jetzinger, and Odening 2014). In addition, notable regional heterogeneity in agricultural land prices is observable within the state of Brandenburg.

In the second stage, a model-based estimation uses the direct estimator of mean and variance, along with auxiliary variables, to re-estimate the agricultural land prices for the in-sample municipalities and generate estimates for the out-of-sample municipalities. The results are presented in Table 1. The share of agricultural area, soil quality, and the proximity to Berlin exhibit a positive correlation with the prices of agricultural land. All these auxiliary variables have a statistically significant effect on agricultural land prices and their explanatory power is high with an adjusted R^2 of 0.6586 for the FH model.

The model-based estimates of agricultural land prices are visible in the middle in Figure 1. This approach offers two improvements over the direct estimation: First, average agricultural land prices in 288 in-sample municipalities have been re-estimated by considering auxiliary covariates. This is especially useful in areas where the number of observations is restricted, resulting in increased sensitivity in outliers and high variability. Second, agricultural land prices for 124 out-of-sample municipalities can be estimated by incorporating the

[2]See Table A.1 in the Appendix A for the definition and source of each auxiliary variable.

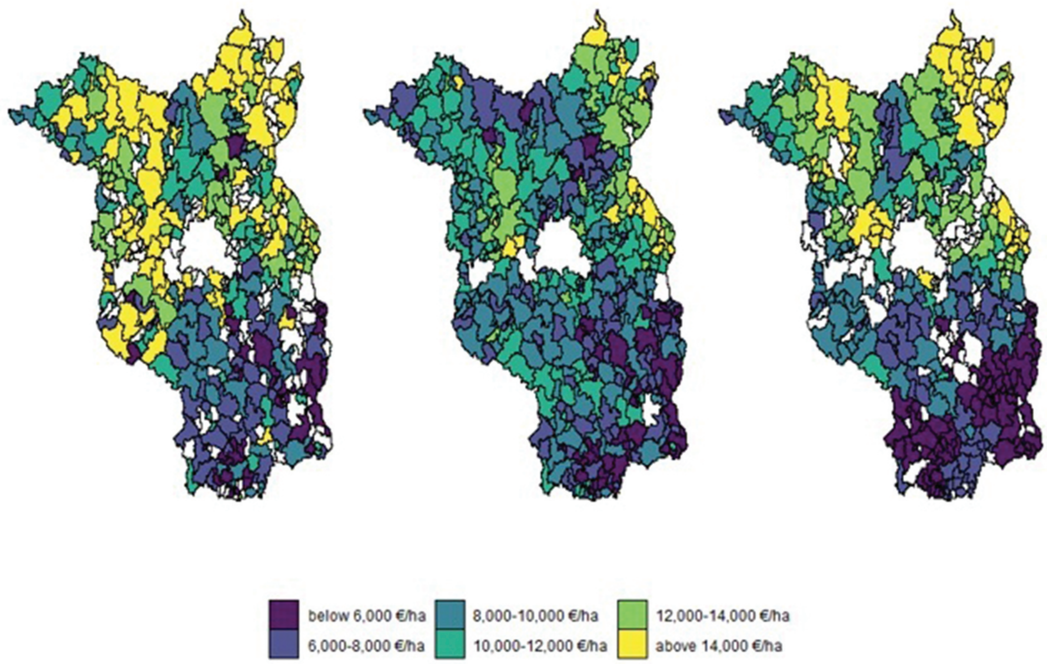

Figure 1. Estimates of agricultural land prices at the municipality level in Brandenburg in 2021. Notes: Direct estimates for 288 municipalities are shown on the left side; SAE model-based estimation for 412 municipalities (288 in-sample and 124 out-of-sample municipalities) are shown in the middle, and the standard land values for 319 municipalities are shown on the right side.

Table 1. Results of the stepwise variable selection procedure based on the information criteria (KICb2) for SAE model-based estimates of agricultural land prices in Brandenburg in 2021.

Variable	Coefficient	Standard error
Agricultural area (share)	6,180.7144***	1,337.3059
Distance to Berlin (in km)	−32.3046***	5.6617
Soil quality index	311.7451***	65.8646
Intercept	−530.4427	1,851.6237
Adjusted R^2	0.1838	
Adjusted R^2 for the FH model	0.6586	

288 in-sample municipalities and 124 out-of-sample municipalities. The spatial correlation is incorporated in the model. The number of bootstrap iterations is set to 50. *, **, and *** indicate statistical significance at the 0.05, 0.01, and 0.001 level, respectively.

auxiliary variables. Nonetheless, the agricultural land price structure of the federal state Brandenburg with relatively high prices in the north and lower prices in the south is reflected.

In addition, we illustrate the standard land values on the right-hand side of Figure 1. A P-value of 0.5765 from the Wilcoxon rank sum test indicates that there are no statistically significant differences in average agricultural land price patterns at the municipal level between the estimates based on the SAE model and the standard land values determined by expert discussions.

Model validation

Inferences from model-based (FH) estimates rely on the distributions implied by the assumed model, therefore, model validation is critical in model-based estimation (Rao and Molina 2015). A good model-based estimate should be consistent with the direct estimates, and additionally, the direct estimates should be more precise by using auxiliary variables (Harmening et al. 2023). To validate the estimates, we use the MSEs. Figure 2 illustrates the direct and model-based (FH) point estimates. The MSEs for all areas are shown in decreasing order of the MSE of the direct estimates. The line plots of direct and model-based estimates do not differ considerably from each other for a large proportion of areas. In particular, for areas with a large sample size, i.e. small MSE of the direct estimates, the FH estimates can better track the direct estimates. Moreover, a Brown test with a p-value of 0.9999 suggests that the null hypothesis that SAE model-based estimates do not differ statistically significantly from the direct estimates is not rejected, indicating that a good model fit can be achieved.

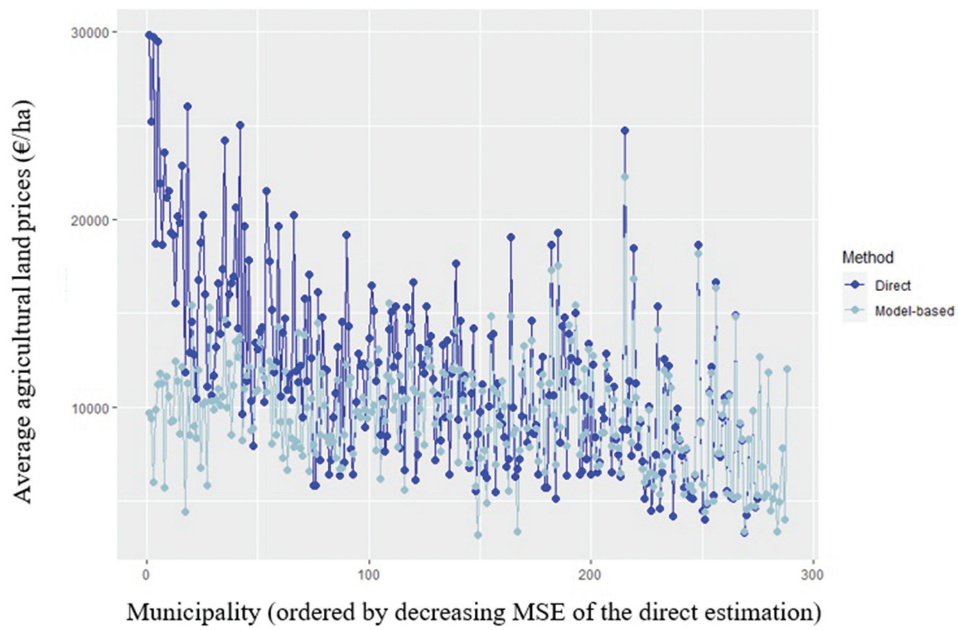

Figure 2. Comparison of the coefficient of variation estimates of the direct and model-based (FH) estimates. Notes: The plots are only created for 288 in-sample municipalities, as all comparisons need a direct estimator.

V. Discussion

Agricultural land prices in Germany exhibit considerable regional heterogeneity. However, publicly accessible data are typically aggregated at the state level, which masks small-scale geographic variations. Meanwhile, standard land values at small geographical levels are often based on expert discussions rather than statistical techniques. The objective of this study is to provide precise estimates of average agricultural land prices at a small-scale spatial level. Direct estimation in this context is challenged by the illiquid market and the resulting small number of observations in some municipalities, leading to large standard errors. Therefore, SAE is introduced and applied for the first time to estimate agricultural land prices at the municipality level.

For this purpose, we employed a standard FH model at the area level, utilizing agricultural land transaction data from the German federal state Brandenburg in 2021. Based on the previous literature and model selection criteria, our analysis incorporated three auxiliary variables: agricultural area (share), distance to Berlin (in kilometres), and soil quality index in each municipality. This approach facilitated the generation of agricultural land price estimates for 412 municipalities, including 288 municipalities with more than two transactions and 124 municipalities with one or no transactions. The estimates for in-sample areas are validated by the MSE. Additionally, the estimates generated by the SAE method show no notable differences from the standard land values, which are determined through expert discussions and are published by the Committee of Land Valuation Upper Experts.

The SAE approach provides reliable estimates for both in-sample areas (with direct estimates) and out-of-sample areas (without direct estimates) when auxiliary variables are completely available. Regarding agricultural land price estimates, the application of SAE methods is feasible with existing data sources, leveraging transaction data from Committees of Land Valuation Experts and other readily available auxiliary information. This approach eliminates the need for additional data collection, thereby minimizing resources and budget. However, the SAE approach relies on the availability of suitable auxiliary variables, which are essential for achieving accurate small-area estimations but may not always be accessible. Furthermore, the results of SAE represent statistical estimates rather than direct observations, a distinction that should be maintained to ensure transparency in published results. Additionally, the SAE method may be less responsive to short-term price shocks, which could impact its precision in rapidly fluctuating markets.

VI. Conclusion

This study presents a novel application of the SAE method to address the need for small-scale agricultural land price estimates. In Germany, where aggregated price estimates often obscure regional variations, the SAE is especially useful to obtain a more complete picture of agricultural land prices. The results from the SAE method offer a statistical complement to the standard land values established by Local Committees of Land Valuation Experts, which primarily emerge from qualitative expert discussions. This suggests that SAE could serve as an additional tool, enriching the current understanding and assessment of agricultural land prices with its quantitative approach.

The localized price estimates generated by SAE offer valuable data points for research, enabling more nuanced analyses of price dynamics and enhancing our understanding of land market mechanisms. These detailed land price data can inform land use planning and conservation efforts, allowing policymakers to act more effectively when interventions in the land market are desirable. In addition, the land price estimates at the municipal level from SAE can support in the valuation of agricultural land for taxation purposes. The results are also relevant for all stakeholders in the agricultural land market. For farmers, agricultural consultants and potential investors, access to the finer breakdown of the land price estimates supports more informed decision-making processes concerning the purchase, sale, and rental of agricultural lands. Agricultural appraisers can also benefit from more accurate comparative prices for valuation purposes, while landowners may be more motivated to adopt sustainable land management practices if they better understand the value of their land.

While this study illustrates the use of SAE with data from Brandenburg, the methodology is generalizable to other German states and internationally to improve small-scale agricultural land price assessments. National and regional statistical offices should consider SAE as a reliable approach when data are missing, and/or when variations exist that auxiliary information in commonly used models cannot fully explain. Future research could extend the application of SAE beyond Germany to international contexts, offering insights into agricultural land prices worldwide. In addition, incorporating temporal analysis in the standard FH model to account for the effects of the time factors could provide more nuanced insights into the land prices.

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Disclosure statement

No potential competing interest was reported by the author(s).

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