Price dispersion in thin farmland markets: What is the role of asymmetric information?

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Abstract This paper investigates the role of information and search cost in the price formation in thin farmland markets. We adopt a hedonic pricing model under incomplete information to analyze a comprehensive data set with more than 10,000 transactions between 2014–2017 in the Eastern German state Saxony-Anhalt. Estimation employs a two-tiered stochastic frontier to capture deviations from the efficient price due to search costs asymmetrically distributed between buyers and sellers. Relating these costs to the degree of professionalism, we find institutional sellers relying on public tenders to achieve the lowest losses from being information deficient. For buyers, we find informational advantages in particular for farmers that are also tenants, while non-tenant farmers have only advantages for large transactions.

Keywords: thin farmland markets, information deficiency, two-tier frontier, Germany
JEL Codes: D82, D83, Q15, Q24

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1 Introduction

A small number of buyers and/or sellers, low liquidity, and few transactions characterize thin markets. Farmland markets share these characteristics: land is generally limited and its immobility causes markets to be local and, thus, narrow in supply. Farms, as main users, typically operate at a local scale contributing to thinness. Capital, however, is in fact mobile, but despite a recently observed increasing demand for land by investors with the intention to store wealth or hedge against inflation (cf. Magnan and Sunley, 2017), the trading volume remains low. For instance, in Germany, since the 1990s, the annual market volume was less than one percent of the total available farmland (Destatis, 2017). Besides the overall limited or even decreasing potential supply of land, this lack of liquidity can be related to asymmetric information acquisition, search and transaction costs in farmland markets. Under such asymmetries, the maximum willingness to pay may exceed the minimum willingness to accept and expectations on surpluses emerge over which agents can bargain (Harding et al., 2003a). As a result, a single agent may influence the farmland price and, besides market power such bargaining frictions may add to illiquid markets. Prices for observed transactions may thus vary for the same fundamental value and neither send appropriate market information nor help efficient price discovery.

Sellers' and buyers' price impacts are often traced back to different expectations on potential future returns of the farmland by new owners captured by different valuations (e.g., Brorsen et al., 2015; Croonenbroeck et al., 2018). Labelled as locational value, urban land prices have been shown to vary systematically with proximity to attractive surroundings and infrastructure including cultural offers (e.g., Kolbe et al., 2015). In this regard, an optional value induced by expected future land development, in particular in urban proximity, has been discussed (e.g., Capozza and Helsley, 1989; Plantinga and Miller, 2001). Likewise, for rural land markets, expectation on future zoning regulation may impact prices in the peri-urban market (e.g., Livanis et al., 2006; Eagle et al., 2014; Turner et al., 2014).[1]

Further attempts to explain price variation for the same fundamental value comprise the locally differing relevance of policy-induced impacts (e.g., Graubner, 2017; Breustedt and Habermann, 2011), highly subsidized renewable energy production such as locally different agglomeration of biomass (e.g., Hennig and Latacz-Lohmann, 2016) or wind power stations (e.g., Ritter et al., 2015). Also local farming conditions such as regional farm and ownership concentration have been discussed (e.g., Back et al., 2018; Margarian, 2010). These authors, however, conclude that the

[1] We refer to Nickerson and Zhang (2014) for an excellent overview on farmland price determinants.

local farming conditions as well as the market micro structure in terms of supply, demand and ownership remain hard to measure, which challenges identification of price impacts. The majority of farmland price studies acknowledges such effects implicitly by means of spatial effects, where spatio-temporal dependencies of prices have been suggested at the local scale (e.g., Maddison, 2009) and also at a greater scale (e.g., Grau et al., 2018). However, these approaches remain in reduced form and interpretation of effects to be caused by market thinness is challenging.

Thus far, to our knowledge, only few studies exploit the impact of farmland market thinness explicitly; for instance, prices are shown to be sensitive to seller and buyer types (e.g., Cotteleer et al., 2008; Hüttel et al., 2016), and to bargaining power (Kuethe and Bigelow, 2018). While studies for the real estate market highlight the role of information costs along with market power in the price schedule (Kumbhakar and Parmeter, 2010), to our knowledge, the impact of search and information costs in farmland price formation are thus far rarely analysed. One notable exception is the paper by Curtiss et al. (2013) who consider differences in bargaining positions as a price determinant in the Czech farmland markets. They argue that informational deficiencies persisted due to weak land market institutions in the post-transition period. These results, however, lack external validity with respect to farmland markets with higher degrees of professionalism, stronger institutions, monitoring and regulation experience. Moreover, the authors concentrate on average effects of buyer and seller types, while the opportunity to retrieve evidence on the asymmetry of the information in the market remains unexploited.

In this paper, we aim at closing this gap and investigate how buyer and seller types can be related to informational asymmetries, and how asymmetric search cost among buyers and sellers affect the price schedule. We base our analysis on a hedonic pricing model under incomplete information (Polachek and Yoon, 1987; Harding et al., 2003b). In this framework, asymmetric information and search cost induce either losses to the sellers or additional cost to the buyers, which can be observed as price deficiencies if a transaction takes place. Observed prices will thus vary with agents' levels of information and search cost as well as their market positions. Following the idea that these costs are related to the degree of professionalism of sellers and buyers, we proxy search costs by categorizing agents, for example, professional real estate agents on the seller side, or tenants and farmers on the buyer side. To measure the impact on prices, we expand a hedonic price function by two one-sided error terms specified as functions of observed characteristics of buyers and sellers. This results in a two-tier stochastic frontier model in the spirit of Kumbhakar and Parmeter (2010), where these error terms represent different levels of informational costs for buyer and seller types given the expected surplus due to market thinness.

Our empirical analysis uses a comprehensive data set with more than 10,000 farmland transactions between 2014–2017 in one of the eastern Federal States in Germany, Saxony-Anhalt. Due to the history of economic transition, this region offers an ideal setting to contrast different degrees of professionalism and hence search cost in particular on the seller side. We can identify sales by the major land privatizing agency in eastern Germany (*Bodenverwertungs- und -verwaltungs GmbH*, BVVG) as well as other public sellers, and professional sellers such as real estate agents. We hypothesize that professional sellers benefit from lower search cost. Regarding the buyer side, we differentiate whether the former tenant buys with or without remaining rental term, or whether a farmer or a non-farmer buys. We hypothesize that farmers and former tenants have lower informational costs and better information about the plot and the local market.

We specify a two-tier model consisting of a hedonic part with main lot characteristic and enhanced by local peculiarities such as renewable energy production with wind and biomass. Modelling the hedonic price function within a stochastic frontier framework combined with spatial effects will further help to mitigate the omitted variable bias usually prevalent in such models, typically due to data limitations (Carriazo et al., 2013). Finally, we contrast the findings of a two-tier model based on the theory of thin markets to a simplified reduced from model, where seller and buyer characteristics linearly add to the price schedule. Our results give evidence on price mark-ups achieved by professional sellers. The categorization by farmer versus non-farmers and by tenancy status, however, cannot contribute to identify systematic price differences on the buyer side. The contribution of our paper aims at informing the discussion about policy measures to improve market efficiency and design effective regulation.

The remainder of the paper is organized as follows: section 2 presents the theoretical and econometric framework. Section 3 outlines the empirical strategy, the data, and the hypotheses. Results are presented and discussed in section 4, and section 5 concludes.

2 Modeling and estimation

2.1 A hedonic pricing model with incomplete information

To identify the effects of differential search costs on prices, we employ a search model with bargaining. We assume that buyers and sellers enter the market with a set of beliefs about the price distribution given the heterogeneity of the land, where both parties employ different sets of information. Finding a lot offer or a buyer is costly, and gathering information will improve an agents' bargaining position. Therefore, both agents are assumed to search optimally but the buyer faces a trade-off between incurring additional search costs for continued information gathering and finding a seller with a lower willingness to accept (WTA). Likewise, sellers may search for the highest paying buyer until costs outweigh the benefits of identifying a buyer with a higher willingness to pay (WTP). Search costs may differ between different buyer and seller groups. For instance, a local farmer may gather information more easily than a non-local buyer. Similarly, an experienced professional seller may have lower search costs than a private vendor. Hence, agents with higher search costs may stop information gathering earlier resulting in higher prices for buyers with high search costs, and lower prices for sellers with high search costs.

To model information asymmetries and search costs, we use a hedonic pricing model with incomplete information following Kumbhakar and Parmeter (2010). A two-tier frontier framework as proposed by Polachek and Yoon (1987) is used to model incomplete information. Further, heterogeneity among buyers and sellers is incorporated by expanding the hedonic function by two one-sided error terms that acknowledge buyer and seller characteristics. Starting at the standard hedonic pricing model in the spirit of Rosen (1974) under full information we model the price as:

$$P_h = h(X) + v \tag{1}$$

where P_h is the hedonic price, X denotes a vector of lot characteristics (e.g., lot size and soil quality), $h(.)$ the hedonic price function, and v denotes measurement errors and noise.

To account for information deficiencies, buyers and sellers are modeled separately using the two-tier approach. Following Polachek and Yoon (1987), the market price is modelled using an upper and a lower bound given by the maximum WTP and the minimum WTA, respectively. A seller receives:

$$P_m^s = P_b - u \tag{2}$$

where P_b refers to the highest WTP by a potential buyer in the market. Symbol $u, u > 0$ denotes the loss to a seller from information deficiency, i.e., a loss due to not identifying the buyer with the highest WTP. Likewise, from a buyer's perspective, the price paid, P_m^b, is given by

$$P_m^b = P_s + \omega \tag{3}$$

where P_s is the lowest WTA in the market, and $\omega, \omega > 0$ denotes the mark-up for being information deficient, i.e., due to not identifying the lowest WTA.

For any transaction to take place, the price paid by the buyer equals the price received by the seller, forming the market price $P_m = P_b - u = P_s + \omega$. Rearranging gives:

$$P_m + u - \omega = P_b - \omega = P_s + u, \tag{4}$$

where $P_s + u$ and $P_b - \omega$ are the hedonic prices for sellers and buyers but adjusted for their information. However, P_s, P_b, u, and ω remain unobserved and identification of effects requires further assumptions (see Kumbhakar and Parmeter, 2010). Following Kumbhakar and Parmeter (2010), who argue that $P_m + u - \omega$ corresponds to the price under full information, i.e., the hedonic price of the good, taking equations (4) and (1) gives the base for estimation as

$$P_m = h(x) + v + \omega - u = h(x) + \varepsilon. \tag{5}$$

Equation (5) states that the observed market price of a lot consists of the implied characteristics of the lot $h(x)$, unobserved noise v, and the costs of information deficiency of buyers (ω) and sellers (u). ε is a composite error term that collects noise and costs of information deficiency.

Two aspects should be noted: First, this model collapses to the standard hedonic pricing model if either no information deficiencies exists ($u = \omega = 0$) or deficiencies on buyer and seller side are identical ($u = \omega$). Second, in the current setting, information deficiencies u and ω are identical for all buyers and sellers, respectively. To address the latter, we consider information deficiencies as functions of buyers' and sellers' heterogeneity. Thus, we model costs of being information deficient for the buyer, ω, as a function of buyer characteristics z_ω, and the costs of information deficiency for a seller are expressed as a function of seller characteristics z_u. The resulting hedonic pricing model with incomplete information and buyer- and seller-specific costs of information deficiency is given by

$$P_m = h(x) + v + \omega(z_\omega) - u(z_u) = h(x) + \varepsilon. \tag{6}$$

2.2 Estimation

To estimate equation (6), we employ a two-tier stochastic frontier approach with scaling property as proposed by Parmeter (2018). For this purpose, we define the respective costs of being information deficient in land transaction i ($i = 1, ..., N$) as $u_i = u(z_{u,i}, \delta_u)$ and $\omega_i = \omega(z_{\omega,i}, \delta_\omega)$. The two random variables u_i and ω_i possess the scaling property if $u_i = u(z_{u,i}, \delta_u) = g_u(z_{u,i}, \delta_u)u_i^*$ and $\omega_i = \omega(z_{\omega,i}, \delta_\omega) = g_\omega(z_{\omega,i}, \delta_\omega)\omega_i^*$, where $g_u() \geq 0$, $g_\omega() \geq 0$, and both u_i^* and ω_i^* are independent from z. The functions $g_u()$ and $g_\omega()$ are the scaling functions, and the distributions of u_i^* and

ω_i^* are the basic distributions (cf. Wang and Schmidt, 2002). To impose the non-negativity restrictions from the theoretical model with respect to u and ω, we model the conditional means of u and ω using exponential functions: $g_u(z_{u,i}, \delta_u) = e^{z'_{u,i}\delta_u}$ and $g_\omega(z_{\omega,i}, \delta_\omega) = e^{z'_{\omega,i}\delta_\omega}$.
Imposing the scaling property implies that characteristics z_u and z_ω affect the scale of the functions $u(z_{u,i}, \delta_u)$ and $\omega(z_{\omega,i}, \delta_\omega)$, respectively, but not their shape. That is in economic terms, u_i^* and ω_i^* define the baseline costs of information deficiency, also termed baseline inefficiencies. The actual costs of information deficiency then depend on buyer and seller characteristics that scale this baseline inefficiency via the functions $g_u()$ and $g_\omega()$.
Further specifying $\mu_u^* = E[u_i]$ and $\mu_\omega^* = E[\omega_i]$ delivers a model that incorporates hedonic pricing as well as the features of a two-tier stochastic frontier that account for information deficiencies based on the scaling property. Estimation uses non-linear least squares as

$$(\hat{\beta}, \hat{\delta_u}, \hat{\delta_\omega}, \hat{\mu_u^*}, \hat{\mu_\omega^*}) = \underset{(\beta,\delta_u,\delta_\omega,\mu_u^*,\mu_\omega^*)}{min} \frac{1}{n} \sum_{i=1}^{N} \left[y_i - h(x_i, \beta) + \mu_u^* e^{z'_{u,i}\delta_u} - \mu_\omega^* e^{z'_{\omega,i}\delta_\omega} \right]^2 \qquad (7)$$

Solving this minimization gives the parameters of interest: the β coefficients represent the implicit values of lot characteristics x, the scale parameters of the costs of information deficiency μ_u^* and μ_ω^*, and δ_u and δ_ω capture the impact of buyer and seller characteristics z_u and z_ω. An equivalent model specification can incorporate the scale parameters into the exponential functions as intercepts to be estimated. Identification of the parameters for δ_u and δ_ω requires $\mu_\omega^* e^{z'_{\omega,i}\delta_\omega}$ to be different from $\mu_u^* e^{z'_{u,i}\delta_u}$. Valid inference for the parameter estimates needs to account for heteroscedasticity in the composite error term, where procedures for robust standard errors in NLS frameworks will be used (Parmeter, 2018).
Applying an estimation procedure based on the scaling property offers several advantages. First, although further assumptions on $\omega(z_\omega)$ and $u(z_u)$ are required, no distributional assumptions for those terms are necessary, which allows using NLS. On the contrary, a more efficient Maximum Likelihood procedure would require precise distributional assumptions for both inefficiency terms, but no closed form solution for the likelihood function may exist. Second, contrary to estimation of u and ω by deconvolution of a composite error term based on unobservables as proposed by Kumbhakar and Parmeter (2009, 2010), the approach allows to recover estimates of u and ω from observables z_ω and z_u.

3 Empirical strategy

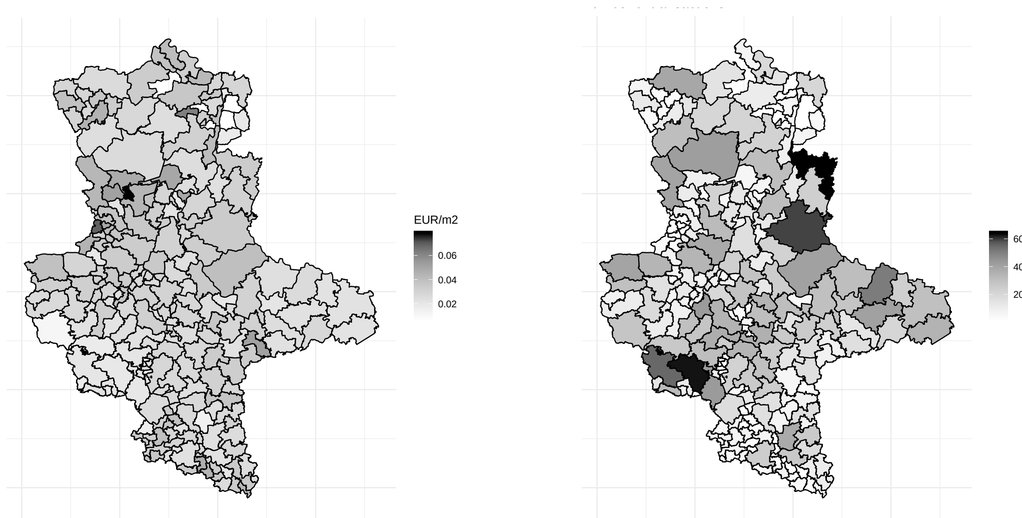
3.1 Background and hypotheses

In our empirical application, we analyze informational asymmetries in farmland transactions in the eastern German Federal State Saxony-Anhalt. Saxony-Anhalt's agricultural structure and land market has been influenced by the the eastern German history of expropriation, land collectivization and socialistic policy between 1945 and 1989. Farms operate at 280 hectares on average, are, thus, larger than western German farms, rely less on the family workforce and operate at a high land lease share of around 72 percent (State Office of Statistics, 2018). As a side effect of the economic transition, land ownership is fragmented (Hartvigsen, 2014) and in 2018, around 40 percent of the total agricultural area is operated by 280, that is, 7 percent of all farms, with more than 1,000 ha, in particular cooperatives.

The land market in Saxony-Anhalt experienced a strong price increase starting in 2007, and average prices more than tripled from 5,055 €/ha in 2007 to 17,903 €/ha in 2017, which is highest among all eastern states, but below the German average of about 24,064 €/ha (Destatis, 2017). In 2017, farmland transactions of around 8,400 ha took place, i.e., less than one percent of the total agricultural area was transacted. Further, the liquidity of land markets varies considerably across regions. For 2017, the right part of Figure 1 shows the number of transactions at municipal level and underlines this variation in market liquidity: although in total more than 3,000 transactions are registered, at a local level the number of transactions can be rather low and for half of the municipalities less than 10 transactions are observed pointing to market thinness. Further, considerable price dispersion is prevalent: As shown in the left part of Figure 1, average prices per square meter weighted with a soil quality index[2] vary considerably, do not indicate obvious spatial patterns, and do not show a strong correlation with the number of transactions.

Today's land ownership fragmentation in Saxony-Anhalt results in heterogeneous buyers and sellers. The different agents face individual search and informational costs in the market with asymmetric distributions depending on the level of professionalism and experience. To identify how such asymmetric cost affect the price schedule, we assume that the level of search and information costs is directly related to a buyer or seller type. Therefore, we group sellers and buyers according to their relative level of professionalism (search costs) and derive testable hypotheses regarding the effect

[2]The soil quality index is an official index for Germany to unify pedologic, scientific, and (agro-) economic considerations including water availability within one measure for arable land ('Ackerzahl') and grassland ('Grünlandzahl'). Low (high) numbers indicate low (high) productivity (BMJV, 2007).



(a) Average price €/m^2 per soil quality index point

(b) Number of land transactions

Figure 1: Saxony-Anhalt farmland market 2017 at municipal level

of buyer/seller identity on the market outcome.

On the seller side, the major player is the state-owned BVVG (*Bodenverwertungs- und - Verwaltungs GmbH*). Founded in 1992 as a direct successor of the German privatization agency (*Treuhandanstalt*), the BVVG has the mandate to privatize, on behalf of the Federal Ministry of Finance, the formerly state-owned agricultural and forest land in eastern Germany until 2030. As a consequence, the BVVG is the largest single agent in the eastern German land market with around 20 percent market share on average, and up to 60 percent in some regions. In the early years, the BVVG leased out land with long term contracts. However, since 2007 public tendering procedures according to the German privatization principles and in line with European law are used. These tenders are published on the BVVG website. Additionally, detailed information about the tenders are published in local newspapers and farmers' magazines in a professional layout. Auction rules and bidder requirements are clearly communicated. This eases access to information for potential buyers and may therefore facilitate the search process of the BVVG. Further, as a notable seller, the agency may not only signal professionalism but also reliability. Potential buyers may perceive lower risks concerning transaction failure, which again contributes to finding potential buyers. We therefore hypothesize that the BVVG incurs lower losses of information deficiency than other sellers.

Further, we acknowledge that BVVG regularly publishes auction results on their website making prices, location, time and core plot characteristics accessible for all potential market players. Such transparency may thus decrease information costs in regions with many BVVG transactions but for buyers and sellers. We will test for such effects by adding BVVG's share on the total number of transactions in the respective municipality.

A second seller category are professional private sellers, such as real estate agents. Such sellers use, for example, procedures comparable to public tenders, and advertize and target potential buyers efficiently. Due to this professionalism, we expect lower price deficiencies for professional sellers, in particularly compared to private persons without experience in land transactions. As a third seller group, we consider public authorities such as municipalities or local governments as they usually exhibit a high degree of experience and professionalism. However, this advantage may be off-set by costs caused by a potential principal agent problem: public sellers' goal may not primarily be selling at profit maximizing prices, and lower prices might be accepted due to time limitations and missing incentives to invest in search. Thus, we hypothesize price deficiencies for public sellers to be lower than for private sellers, but higher than for professional private sellers and BVVG.

For a buyer, we consider asymmetries regarding knowledge about potential returns from land-use and knowledge about the local market. Therefore, we suspect informational advantages for farmers and / or tenants as they have such knowledge compared to non-farmers and non-tenants. First, we hypothesize that farmers and tenants are better informed about potential returns from the land-use resulting in lower costs for information acquisition. Further, this allows to better form expectations about the returns reducing in return the likelihood of overpaying (e.g., winners' curse). Second, we hypothesize that local buyers are better informed about local market conditions including potential alternative and future offers. Thus, we expect lower search and informational costs for tenants and local farmers compared to other buyers.

Third, we hypothesize that informational advantages of farmers and tenants increase with the transaction volume. As shown by Croonenbroeck et al. (2018), non-agricultural and usually non-local investors are particularly interested in larger lots. Thus, the group of non-farmer buyers is less heterogeneous for larger plots allowing better identification of the effects of informational advantages. Second, we expect that larger transactions are less heterogeneous and do not reasonably allow alternative land use apart from farm operation. Thus, valuation is mainly based on the conventional and observable determinants of farmland prices, which in turn allows tenants and farmers to better use their knowledge about the expected returns.

Another specificity arises from leased land and we differentiate whether a tenant buys within the current lease rate, or after the lease term is finished. If the land is sold at the end of the rental term, the tenant should be prepared without time cost to make an offer as potential buyer. This would result in lower informational costs for tenants. If the land is sold within the current lease term, the tenant may face additional transaction cost for instance to finance the purchase and may not be prepared. Moreover, finding alternative land may not be possible in a short time to secure production capacity. This implies higher costs of information deficiency on the tenants side compared to non-tenants. A transaction within the lease term, however, indicates that the seller preferred the purchasing price over a constant revenue stream from the lease. This discounting could indicate that the seller was not willing or able to wait, that is, accepting at lower prices. This might offset the informational costs of the tenant and the overall effect is unclear.

3.2 Data

For the empirical analysis, we dispose of a unique and rich data set provided by the Committee of Land Valuation Experts (*Gutachterausschuss für Grundstückswerte in Sachsen-Anhalt*, LVermGeo, 2018a). The data contains all land market transactions in this state in the period 2014–2017 with comprehensive information on each transaction, including transaction details (e.g., contract date and price), lot characteristics (e.g., location, size, and soil quality), as well as anonymous buyer and seller information. The initial data set contains 12,134 transactions of arable land. A first data treatment selects only arm's-length transactions and removes observations with missing or inconsistent values. Additional outlier detection based on the minimum covariance determinant estimator (Rousseeuw and Driessen, 1999) leads to the final sample with 10,778 observations.

To grasp price variation for the same fundamental value, we consider lot characteristics as factors in the hedonic function, and variables explaining the environment in which a transaction takes place. Since many studies have shown the price impact of subsidized renewable energy sources on land market prices (e.g., Kostov, 2009; Patton and McErlean, 2003; Haan and Simmler, 2018), we use information provided by the State Office for Survey and Geoinformation (LVermGeo, 2018b) and the Federal Network Agency (BNetzA, 2018) and add the density of wind power and biomass capacity in a municipality, measured as the number of turbines and the electric capacity per hectare, respectively. Further, we indicate if a lot is in a wind energy area, which allows building a wind engine and thus captures high potential future earnings from this alternative land use.

Table 1 shows the descriptive statistics for our dataset. Due to data privacy reasons, we cannot report minima and maxima of the data, but list the first and the 99 percent quantile (Q1 and Q99). The average price over all transactions is about 1.63 €/m^2, but varies between around 0.30 and more than 4 €/m^2. The transacted lots have an average size of about 3 ha, but the distribution is wide ranging from less than

N = 10,778		Mean	Median	SD	Q1	Q99
Dependent variable						
Price (€/m^2)	P	1.63	1.50	0.86	0.35	4.08
Lot Characteristics						
Lot size (ha)	x_S	3.08	1.02	6.40	0.03	26.93
Soil quality (Index)	x_Q	64.11	66.00	22.65	21.00	100.00
Lot independence (1/0)	x_I	0.86	1	0.35	0	1
Lot is leased (1/0)	x_L	0.73	1	0.45	0	1
Wind energy area (1/0)	x_W	0.01	0	0.08	0	1
Lease term if leased (years)	x_{LT}	5.11	4.00	5.47	0.00	24.00
Controls at municipal level						
Wind power stations per ha	m_W	0.002	0.001	0.003	0	0.02
Biomass capacity kW per ha	m_B	0.33	0.1	2.44	0	2.58
Transaction share of BVVG	m_{BVVG}	0.12	0.09	0.10	0.00	0.48
Seller Characteristics						
BVVG (1/0)	$sBVVG$	0.08	0	0.28	0	1
Professional seller (1/0)	$sProf$	0.02	0	0.13	0	1
Public seller (1/0)	$sPub$	0.02	0	0.15	0	1
Buyer Characteristics						
Farmer (1/0)	bF	0.74	1	0.44	0	1
Tenant (1/0)	bT	0.49	0	0.50	0	1
Farmer and tenant (1/0)	bFT	0.49	0	0.49	0	1
Farmer and non-tenant (1/0)	$bFNT$	0.26	0	0.44	0	1

Table 1: Descriptive statistics for dataset T = 2014–2017

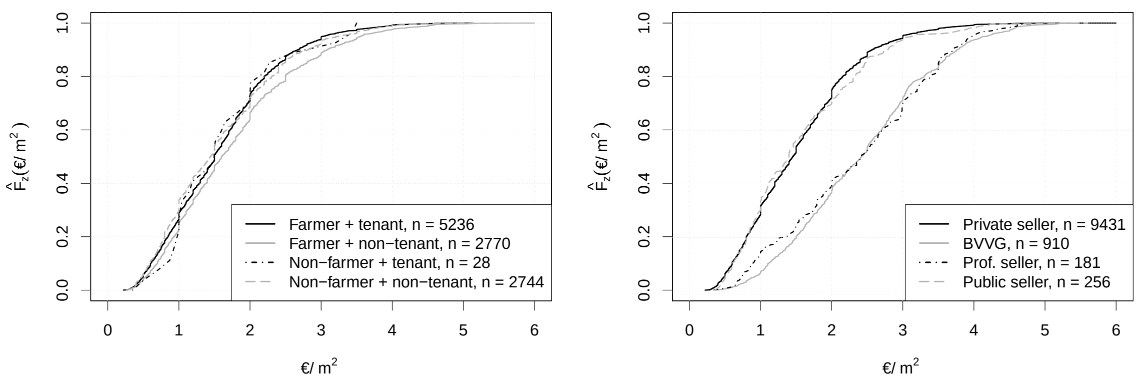
0.03 ha to more than 100 ha. 86 percent of of the lots can be operated independently (e.g., no further right of way is necessary), and one percent of the transactions lie in a region eligible for wind energy use. 73 percent of the transacted lots are leased out and, conditional on being leased out, the remaining lease duration is on average 5.11 years.

On the seller side, the BVVG is the major player and carries out about 8 percent of all transactions in the dataset (910 obs.). Public and professional sellers are responsible for about 2 percent each (256 and 181 obs.). Farmers are involved in 74 percent of all transactions (8,006 observations). In 49 percent of the cases, the buyer is the former tenant(5,264 obs.). Buyers are both farmer and tenant in nearly half of the cases (5,236 obs.), i.e. only few buyers are tenants but not farmers.

Separating transactions by buyer and seller types shows some heterogeneity.[3] On the seller side, BVVG and professional sellers are offering on average larger lots;

[3]Table 5 in the appendix shows detailed descriptive statistics for the different buyer and seller types.

Figure 2: Prices paid by buyer types (left) and seller types (right)



professional sellers offer additionally an on average higher soil quality that allow more often an independent operation. On the contrary, for public sellers, soil quality is on average lower and the lots are less often leased out. On the buyer side, heterogeneity is less pronounced and differences are small when comparing transactions of farmer and tenants to the sample mean as well as when comparing farmers and non-farmers or tenants and non-tenants.

Lastly, Figure 2 shows the cumulative distributions of the raw prices separated for the different buyer and seller types. For the different buyer types, differences for the four potential combinations of farmer and tenant types are small and only for non-tenant farmers, one might suspect slightly higher prices compared to the other groups. On the contrary, differences on the seller side are pronounced and both the BVVG and professional sellers achieve on average considerably higher sales prices per square meter than public or private sellers. However, as outlined above, the two groups also offer on average larger plots - a factor for which this unconditional distributions do not account.

3.3 Model specification

The regression equations to test our hypotheses consists of a hedonic part $h(x)$ and the combined error term ε_i that collects noise and the costs of information deficiency for buyers and sellers. To specify the functional form of the hedonic part of the regression equation, we refer to a Box-Cox transformation for the continuous variables lot size, soil quality and the price. To stabilize the variance estimate, we regress the log per hectare price on the square root of size and soil quality, and their interaction. Other hedonic parameters as well as factors controlling for the impact of renewable energy sources enter the regression function linearly. To further control for spatial and temporal effects, we add dummies LC_k for twelve location classes based on information provided by the Committee of Land Valuation Experts

(LVermGeo, 2018a). Each of the twelve classes represents a geographically compact area with similar characteristics and shall capture regional heterogeneity and other unobserved factors, such as, e.g., connection to infrastructure.[4] Second, to control for intertemporal effects, we use a linear-quadratic trend captured by τ and τ^2, where τ equals one in 2014, two in 2015, and so on. To account for spatio-temporal particularities, we interact the time trend with the location classes ($\tau \cdot LC$). The regression equation is

$$\begin{aligned} log(P) = {} & \beta_S \sqrt{x}_S + \beta_Q \sqrt{x}_Q + \beta_{SQ}(x_S \cdot x_Q) + \beta_I x_I + \beta_L x_L + \beta_W x_W \\ & + \gamma_W m_W + \gamma_B m_B + \gamma_{BVVG} m_{BVVG} + \gamma_\tau \tau + \gamma_{\tau^2} \tau^2 \\ & + \sum_{k=1}^{12} \gamma_{LC,k} LC_k + \sum_{k=1}^{12} \gamma_{LC,\tau,k}(LC_k \cdot \tau) + \varepsilon_i \end{aligned} \tag{8}$$

where the β's are hedonic parameters to be estimated and γ's are parameters for control variables at municipal level and time- and spatial effects. To test our hypotheses concerning the effect of buyer and seller characteristics on the price, we estimate four different specifications of the error term ε_i. Table 2 gives an overview of the different specifications where δ's are parameters for the impact of buyer and seller characteristics, μ_B and μ_S denote the baseline inefficiency for buyers and sellers, and v_i is a noise term. The symbol $\mathbb{1}$ denotes the indicator function that equals one if the corresponding condition is fulfilled, and zero otherwise. μ_B and μ_S are specified as intercepts of the exponential functions, which ensures the sign of the effect of information deficiency consistent to theory.

We consider three models $TT1$ to $TT3$ using the two-tier stochastic frontier approach. The three models use an identical specification of the seller side and include dummy variables for the BVVG, professional sellers, and public sellers. On the buyer side, the specifications vary across models. $TT1$ tests for information asymmetries between farmers and non-farmers as well as tenants and non-tenants. A dummy for farmers captures the former effect. For the latter, we interact a dummy for tenants with the remaining lease term if positive, and a tenant dummy if no lease term remains.[5] The second model, $TT2$, assesses if information asymmetries for tenant and non-tenant farmers compared to the group of non-farmers exist, and if such effects vary with the transaction volume. Therefore, we include dummies for tenant farmers and non-tenant farmers interacted with lot size. Third, $TT3$ tests if information asymmetry is particularly pronounced for the larger plot and we extend the specification of $TT2$

[4] A map of the location classes is provided in Appendix 6.1.

[5] We also considered a simpler model with only farmer and tenant dummies. Such model suffers convergence problems, likely caused by the high overlap of the two dummy variables.

Model	$\varepsilon_i = \omega(z_{\omega,i}, \delta_\omega) - u(z_{u,i}, \delta_u) + v_i$
$TT1$	$exp[\mu_S + \delta_{sBVVG} sBVVG + \delta_{sPub} sPub + \delta_{sProf} sProf]$
	- $exp[\mu_B + \delta_{bF} bF + \delta_{bT\|x_{LT}=0}(bT \cdot \mathbb{1}_{x_{LT}=0}) + \delta_{bT\|x_{LT}>0}(bT \cdot x_{LT})] + v_i$
$TT2$	$exp[\mu_S + \delta_{sBVVG} sBVVG + \delta_{sPub} sPub + \delta_{sProf} sProf]$
	- $exp[\mu_B + \delta_{bFT,x_S}(bFT \cdot x_S) + \delta_{bFNT,x_S}(bFNT \cdot x_S)] + v_i$
$TT3$	$exp[\mu_S + \delta_{sBVVG} sBVVG + \delta_{sPub} sPub + \delta_{sProf} sProf]$
	- $exp[\mu_B + \delta_{bFT,x_S}(bFT \cdot x_S) + \delta_{bFNT,x_S}(bFNT \cdot x_S)$
	$+ \delta_{bFT,x_S^2}(bFT \cdot x_S^2) + \delta_{bFNT,x_S^2}(bFNT \cdot x_S^2)] + v_i$
LIN	$\alpha + \delta_{sBVVG} sBVVG + \delta_{sPub} sPub + \delta_{sProf} sProf$
	$+\delta_{bF} bF + \delta_{bT\|x_{LT}=0}(bT \cdot \mathbb{1}_{x_{LT}=0}) + \delta_{bT\|x_{LT}>0}(bT \cdot x_{LT} \cdot \mathbb{1}_{x_{LT}>0}) + v_i$

Table 2: Specifications of the error term ε_i

with additional interactions with the squared lot sizes. Lastly, for comparison, we estimate a reduced form linear model LIN in which seller and buyer terms enter the regression equation linearly additive with a specification as in $TT1$. Additionally, LIN includes an intercept α, which needs to be omitted in the two-tier models for identification of the baseline inefficiency terms.

Estimation of the two-tier models uses non-linear least squares, LIN is estimated using ordinary least squares. To account for heteroskedasticity induced by the composed error term, we refer to clustered standard errors with clusters corresponding to combinations of thirty quantiles of lot size and the squared soil quality. To ensure convergence, estimations for the non-linear models are performed 5000 times with random starting values.[6]

4 Results

Table 3 present parameter estimates for variables of the hedonic part and buyer and seller characteristics for the the two-tier model specifications $TT1$, $TT2$ and $TT3$ and the linear model LIN. Parameter estimates for the spatial control variables and time trends are provided in the Appendix 6.3. The squared correlation coefficient for observed and fitted values of the dependent variable is 0.676 in all model specifications indicating a similar goodness of fit for the different specifications. From a technical perspective, it should be noted that the OLS intercept in LIN corresponds

[6]All calculations are performed with R. NLS estimation uses the nls function from the stats package. Estimation of robust standard errors uses the sandwich package. Corresponding R codes are available upon request.

to the sum of the baseline inefficiencies in the model with the identical specification $TT1$ ($-2.155 \approx e^{-3.034} - e^{0.789}$). Kumbhakar and Parmeter (2010) argue that an OLS intercept might be biased if $E(\omega - u) \neq 0$ which does not seem to be the case in our application.

Comparing the estimates of the hedonic parameters in the four models shows that non-linear and linear specifications deliver generally very similar estimates. In all models, the core hedonic variables soil quality and lot size show the expected positive significant effects, which is in line with many studies (e.g., Lehn and Bahrs, 2018), though in a non-linear manner (e.g., Maddison, 2000). Parameter estimates are also similar for the different specifications in terms of magnitude, although the effect of lot size increases slightly if the variable is additionally included in the buyer characteristics ($TT2$ and $TT3$). Interacting lot size and soil quality reveals a negative coefficient indicating that prices decrease for the larger plots at high soil qualities. As discussed by Brorsen et al. (2015), this may point to capital and borrowing constraints resulting in a lower number of competitors for such lots. Interestingly, whether a lot can be independently used or not is not relevant for the price vector. Likewise, the tenancy status of a lot does not influence the price significantly.

Among the control variables at municipal level, the positive and significant estimate of the average share of BVVG-sales within a region is noteworthy: while the magnitude of the effect is small in monetary terms, the estimate points towards the considerable role of this institution in these land markets and its contribution to overall market transparency. In this regard, the supply management of this agency over space and time may also be relevant in terms of market power.

Our results do not indicate an impact of renewable energy sources on farmland prices. For wind energy, coefficients for both variables, location in a wind energy area and the number of wind turbines within a municipality, are statistically insignificant. This is not in line with Haan and Simmler (2018) and Ritter et al. (2015). These studies, however, analyze data from the boom-phase of wind power under fixed feed-in tariffs, whereas our data already includes transactions under variable tariffs that started in 2017. As for wind energy, our results indicate no effect of biomass on farmland prices and the coefficient for the installed regional capacity in biomass for energy production is small and statistically insignificant, although with p-values close to 10%. Previous studies rather report significant effects of biomass on rental prices in the boom years (Hennig and Latacz-Lohmann, 2016), but not on purchase prices (Habermann and Breustedt, 2011). Our results indicating minor effects might be due to a lagged effect on purchase prices in a sense of a long-term effect of land-intense biomass-based production. Further, the actual effect of biomass might be stronger but could be absorbed by the spatial control variables.

N = 10,778	*LIN*		*TT1*		*TT2*		*TT3*	
Lot characteristics								
Intercept	−2.155***	(0.053)						
$\sqrt{\text{Lot size}}$	0.118***	(0.010)	0.117***	(0.010)	0.133***	(0.010)	0.106***	(0.010)
$\sqrt{\text{Soil quality}}$	0.203***	(0.006)	0.203***	(0.006)	0.203***	(0.006)	0.200***	(0.005)
Soil quality · lot size · 10^{-1}	−0.001***	(0.000)	−0.001***	(0.000)	−0.001***	(0.000)	−0.0002	(0.000)
Lot independence	−0.003	(0.011)	−0.003	(0.011)	−0.008	(0.011)	−0.005	(0.010)
Wind energy area	−0.004	(0.046)	−0.005	(0.047)	−0.006	(0.047)	−0.001	(0.046)
Lot is leased	0.011	(0.011)	0.013	(0.011)	0.008	(0.010)	0.010	(0.010)
Wind power stations	−0.556	(0.965)	−0.600	(0.953)	−0.428	(0.981)	−0.319	(0.971)
Biomass capacity	0.002	(0.001)	0.002	(0.001)	0.002	(0.001)	0.002	(0.001)
BVVG share	0.158***	(0.056)	0.156***	(0.057)	0.160***	(0.056)	0.159***	(0.055)
Seller characteristics								
Baseline inefficiency			0.789***	(0.026)	0.926***	(0.053)	0.911***	(0.062)
BVVG	0.388***	(0.016)	−0.193***	(0.012)	−0.168***	(0.009)	−0.169***	(0.011)
Public seller	0.066*	(0.036)	−0.030*	(0.017)	−0.030**	(0.015)	−0.029*	(0.015)
Professional seller	0.189***	(0.024)	−0.089***	(0.012)	−0.078***	(0.012)	−0.076***	(0.010)
Buyer characteristics								
Baseline inefficiency			−3.034***	(0.654)	−1.003***	(0.374)	−1.029**	(0.457)
Farmer	0.021***	(0.008)	0.416	(0.298)				
Tenant (no lease term)	−0.052***	(0.008)	−1.467	(1.564)				
Tenant · lease term	−0.004***	(0.001)	−0.154	(0.155)				
Farmer · tenant · lot size					−0.029**	(0.012)	−0.009***	(0.002)
Farmer · non-tenant · lot size					−0.001	(0.003)	0.040**	(0.017)
Farmer · tenant · lot size^2							−0.001***	(0.0002)
Farmer · non-tenant · lot size^2							−0.002***	(0.0005)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 3: Parameter estimates for hedonic variables and buyer and seller characteristics (standard errors in parentheses)

Concerning other control variables, (see Appendix 6.3), the trend variables indicate a positive price development for the observation period, but the negative sign for the squared trends suggest a slowdown. Spatial control variables are mostly statistically significant relative to the base category (Wittenberg). Regional time trends, modeled as interactions of the regional dummies with the trend variable point in some cases to local particularities, which might include economic and infrastructure effects not captured by other control variables.

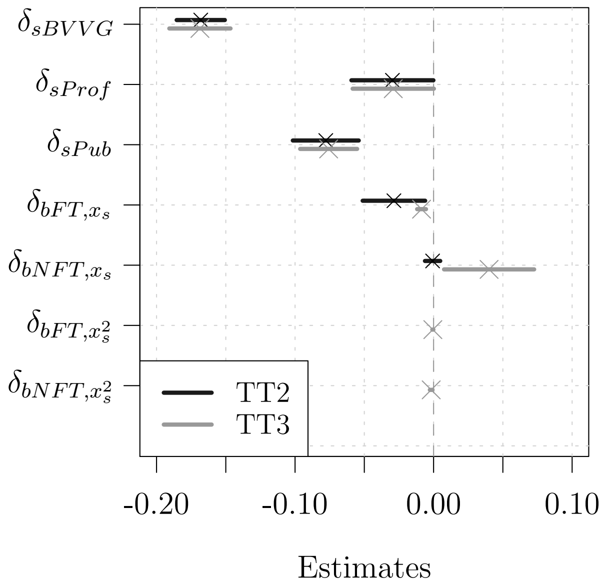
Next, we turn to the variables describing information deficiency. For the two-tier models, buyer-side effects vary considerably across the different specifications.[7] For $TT1$, coefficients indicate that information deficiencies for farmers are higher compared to non-farmers, and lower for tenants compared to non-tenents. However, coefficients are statistically insignificant which may stem from the binary coding of the variables and their strong overlap, which challenges identification and increases standard errors. On the contrary, for the similarly specified linear model effects have the same direction but are highly statistically significant.

The models $TT2$ and $TT3$ address the identification issue and interact the farmer and tenancy status and provide further variation by interaction with the lot size. Coefficient estimates for the two models are summarized in Figure 3. For $TT2$, results indicate statistically significant lower price deficiency for farmers that are also tenants, while no effect is found for non-tenants. This is in line with the hypothesis that tenants have an informational advantage and possess both knowledge about the local market as well as the sector knowledge. For the non-tenant farmers, we speculate that the identified effect might be diluted as it is not clear whether they are local or not.

Model $TT3$ tests the hypothesis of stronger informational advantages for farmers and tenants especially for larger lots. Because non-agricultural and non-local investors are particularly interested in large transactions (Croonenbroeck et al., 2018), we include the squared lot size to emphasize such transactions. Results indicate, with high statistical significance, lower price deficiency for tenants that further decreases with lot size. Further, contrary to $TT2$ results also indicate significant effects for farmers, however, with different signs. Because price deficiency increases with linear lot size, but decreases with the quadratic term, results suggest that farmers pay a mark-up that increases until 10ha, but decreases afterwards. In total, results for $TT3$ underlining again the informational advantages of tenants due to being familiar with local market conditions. On the other hand, results support the hypothesis of informational advantages for farmers for large lots compared to non-farmers and

[7] Coefficients of the two-tier models are interpreted as follows: positive coefficients indicate increasing deficiency, while negative signs decrease deficiency. Thus, a positive parameter on the buyer type indicates a higher price, but a positive parameter for sellers indicates a lower price.

Figure 3: Coefficient estimates for buyer and seller side variables



potentially non-agricultural investors.

On the seller side, in all models we differentiate the BVVG, professional sellers, and public sellers using dummy variables. Contrary to the buyer groups, the seller types are mutually exclusive, which may ease identification. Results of all two-tier models show statistically significant negative parameter estimates for the three seller types, i.e., these groups achieve on average higher sales prices than other sellers. The significant, positive estimates in the linear model LIN support this finding. Further, all estimates indicate the strongest effect for the BVVG, followed by professional sellers, and public sellers. Overall, the results support our hypotheses: we find experienced, professional sellers to be able to obtain a mark-up compared to private and other non-specialized sellers. Further, the order of the effects suggests that price deficiency further decreases with specialization. The sellers are able to reduce search costs by, e.g., advertising and efficient targeting of potential buyers. Further, these results can be traced back to the use of auctions with public tenders, where prices compared to those from negotiated sales have be shown to be higher (e.g., Bulow and Klemperer, 1996; Chow et al., 2015).

To quantify the effects and to facilitate interpretation, Table 4 shows the marginal effects of buyer and seller types on sales prices for a lot with hedonic characteristics identical to the sample mean (see Table 1). On the seller side, the parameter estimates correspond to a mark-up of 0.71 €/m^2 for the BVVG, and around 0.30 and 0.11 €/m^2 for professional and public sellers, respectively.[8] Thus, the BVVG

[8]Parameter estimates for BVVG and professional sellers drop slightly if lot size is included on the

	TT2		TT3	
	€/m^2	%	€/m^2	%
Seller				
BVVG	0.70	47.79	0.70	47.79
Prof. seller	0.31	20.81	0.30	20.81
Public seller	0.11	7.67	0.11	7.67
Buyer				
Tenancy effect	-0.05	-2.97	-0.04	-2.56
Tenant farmer effect	-0.05	-3.05	-0.05	-3.21
Farmer effect	-0.001	-0.08	-0.01	-0.67

Tenant effect: compares tenant and nontenant farmer. Tenant farmer effect: compares tenant farmer and a non-farmer. Farmer effect: compares nontenant farmer and non-farmer

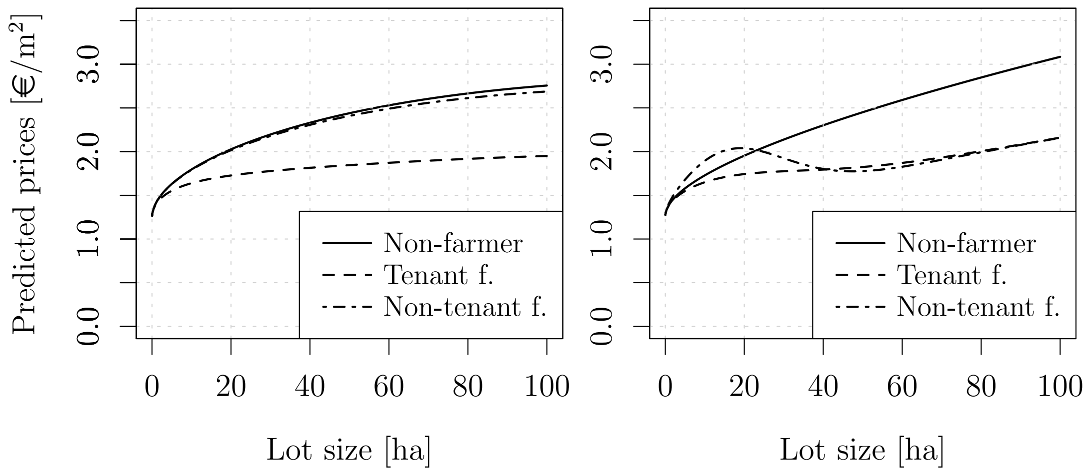
Table 4: Marginal effects of seller and buyer types evaluated at the mean

achieves a mark-up of around 47 percent, and professional and public sellers obtain 21 and 8 percent higher prices. This underlines the weak market position of non-professional private sellers. On the buyer side, the differences are much less pronounced. The marginal effect of tenancy, calculated as the difference between a tenant and a nontenant farmer, amounts to 0.03 to 0.05 €/m^2, i.e., prices are about 300 to 500 €/ha^2 lower due to being tenant (or 900 to 1500 €for the average lot of around 3 hectare). On the contrary, the effect of being tenant and farmer compared to a non-farmer is of nearly identical magnitude as the marginal effect of being a farmer is rather negligible.

However, due to the non-linear nature of the two-tier models, marginal effects provide only limited information. To provide a more comprehensive picture, Figure 4 shows for different buyer types the predicted prices as a function of the lot size with other parameters fixed at the sample mean. In the left figure, results for $TT2$ indicate an increasing gap between tenant farmers and other types, while no differences is found between non-tenant farmers and non-farmers. This suggests informational advantages are primarily present due to being familiar with local market conditions rather than due to knowledge about the expected returns from land use as we hypothesize. However, results for $TT3$ in the right figure show another picture indicating that prices for non-tenant farmers are highest for lots below around 20ha but decrease to the level of tenant farmers afterwards. Thus, they are able to better use their informational advantage with increasing lot size. This again supports our hypothesis that differences between farmers and non-farmers are more pronounced for large transactions.

buyer side ($TT2$, $TT3$), but changes in the baseline inefficiency result in identical marginal effects.

Figure 4: Predicted prices by buyer type for model $TT2$ (left) and $TT3$ (right)

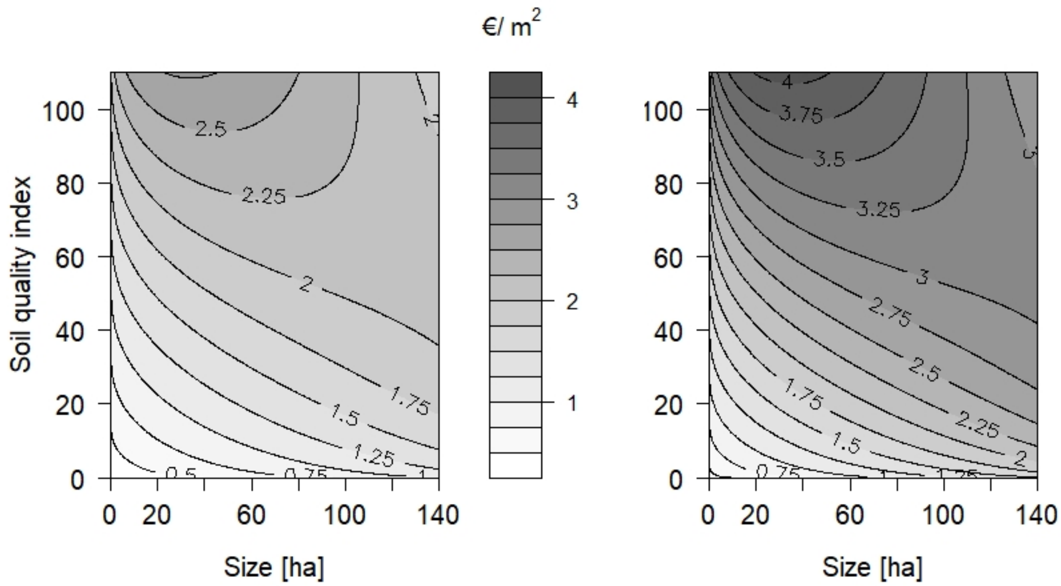


Lastly, to better visualize the effect for the seller side, Figure 5 shows the expected prices for a private seller (left panel) and the BVVG (right panel) as a function of lot size and soil quality while other variables are fixed at their sample means. The plots underline two important aspects: First, the gap between the prices of private sellers and the BVVG is small for lots of low quality, but substantial for lots of medium size and very high quality. Further, for both sellers prices are strictly increasing in soil quality. This is not the case for lot size and we observe decreasing predicted prices for large lots with high soil quality. However, few observations in our sample are located in this area and predictions might suffer from extrapolation bias.

5 Conclusion

This paper investigates the role of asymmetric information and search cost in the price formation in thin farmland markets. In particular, we analyze how asymmetries related to buyer and seller characteristics can explain price dispersion for the same fundamental value. For this purpose, we adopt an hedonic pricing framework with incomplete information. The model allows deviations from the competitive price due to informational costs, which in turn depend on buyers's and seller's characteristics. Our empirical application investigates the farmland market in the Eastern German state Saxony-Anhalt. This case is particularly interesting as information asymmetries are likely present: on the one hand, despite a drastic rise in prices since 2008, the market is thin and market information is scarce. On the other hand, as an

Figure 5: Predicted prices for private sellers (left) and sales by the BVVG (right)



artifact of the German reunification, the BVVG, a single, likely better-informed institutional seller dominates the supply side. To empirically assess such asymmetries for various buyer and seller types, we dispose of a comprehensive dataset of more than 10,000 transactions between 2014–2017. We estimate the model as a two-tiered stochastic frontier and a non-linear least squares estimator allows us to implement the theoretical framework without further distributional assumptions.

Our results indicate an important role of information asymmetries in Saxony-Anhalts' farmland market. While conventional hedonic characteristics such as lot size and soil quality determine land prices, price dispersion for the same fundamental value is well explained by buyer and seller characteristics. Additionally, our results indicate that losses due to information deficiency vary considerably stronger among sellers than among buyers. For the seller side, our results support the hypothesis that professionalism and experience allow lower information and search costs. In particular, we find that information deficiency decreases with specialization, and the BVVG achieves the lowest losses, followed by professional private sellers, public authorities, and, lastly, other sellers. We argue that this effect can be explained by the use of advanced sales strategies including for example public tenders and professional advertisement. This helps targeting potential buyers efficiently, which ultimately reduces the costs of searching the buyer with the highest willingness to pay.

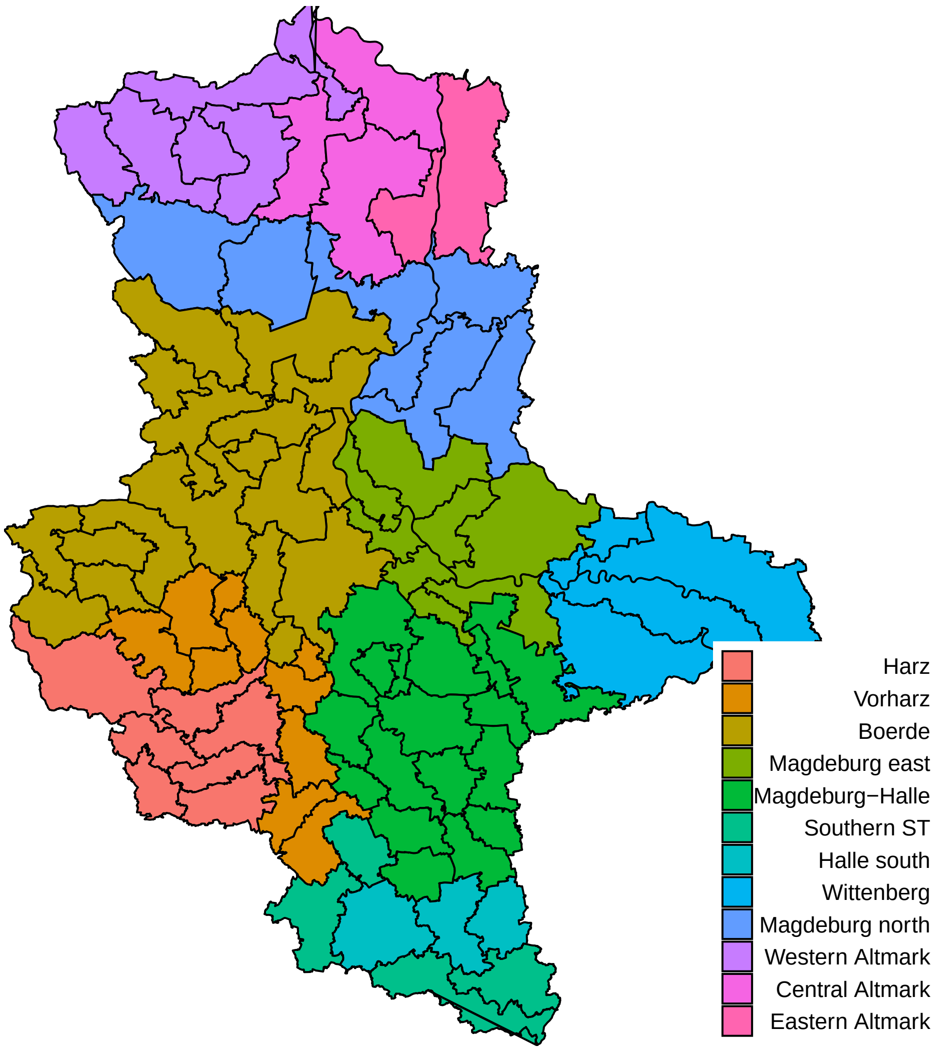
We also find evidence for informational asymmetries on the buyer side. We consider sector knowledge and knowledge about local market condition as determinants of informational costs and differentiate farmers and non-farmers as well as tenants and non-tenants. We find former tenants to be able to achieve lower prices supporting the importance of knowledge about the local market. On the contrary, the effect for farmers is, although statistically significant, rather negligible in monetary terms. For both groups we find informational advantages to increase with the transaction volume, for which we propose two potential explanations: First, smaller transactions may comprise additional heterogeneity, e.g., potential rezoning or alternative land use. Second, the group of non-farmers may be less heterogeneous for larger transactions and include for example non-agricultural investors. Both cases would ease identification because farmers' and tenants' alleged informational advantages would come into effect if pricing is governed by the conventional determinants.

While our findings are in line with the literature regarding determinants of farmland prices, our analysis underlines the relevance of the market micro-structure, information asymmetries and market mechanisms. From an academic perspective, the results emphasize that informational asymmetries need to be modeled explicitly to allow identification of the costs of incomplete information. Further, it should be noted that if information asymmetries are correlated with hedonic characteristics, their omission likely results in inefficient estimation and biased coefficients already for the hedonic function. From a policy perspective, our results imply that measures to increasing market transparency are necessary to foster efficient price discovery. In particular, our results emphasize the weak position of private sellers for which information about transactions of farmland are hard to get, costly, or outdated. Further, while market data is currently provided by the BVVG, this source of information will likely also disappear after completion of the re-privatization in 2030. Thus, to address market transparency and to support a more level playing field on the supply side, policies aiming at market efficiency should ease access to information.

Nonetheless, our study has certain limitations and results directly suggest directions for future research. First, our analysis indicates that a simple binary coding of farmers/non-farmers and tenants/non-tenants may not cover all relevant dimensions of information asymmetries resulting in a heterogeneous counterfactual. Moreover, such differentiation might hinder identification because of the strong overlap of the groups. Second, additional research is required concerning the role of local market power on demand and supply side accounting also for the interplay of sales and rental markets. Lastly, speculation effects and bargaining power should be explored.

6 Appendix

6.1 Map of location classes



6.2 Main Descriptives by Buyer and Seller Types

	Mean	Median	St. Dev.	Q1	Q99
Seller: BVVG					
Price (€/m^2)	2.43	2.42	1.00	0.60	4.77
Lot Size (ha)	8.17	3.38	14.73	0.03	90.66
Soil Quality (Index)	63.91	65.00	21.99	21.00	99.00
Lot Independence (1/0)	0.86	1.00	0.35	0.00	1.00
Wind energy area (1/0)	0.00	0.00	0.07	0.00	0.00
Lot is leased (1/0)	0.67	1.00	0.47	0.00	1.00
Seller: Professional Seller					
Price (€/m^2)	2.37	2.42	1.06	0.57	4.61
Lot Size (ha)	5.65	4.58	7.61	0.06	23.00
Soil Quality (Index)	70.71	75.00	22.29	22.00	99.00
Lot Independence (1/0)	0.94	1.00	0.23	0.00	1.00
Wind energy area (1/0)	0.01	0.00	0.07	0.00	0.00
Lot is leased (1/0)	0.69	1.00	0.46	0.00	1.00
Seller: Public Seller					
Price (€/m^2)	1.58	1.40	0.89	0.41	4.13
Lot Size (ha)	4.39	0.82	10.94	0.02	68.37
Soil Quality (Index)	59.18	58.50	23.13	20.10	100.00
Lot Independence (1/0)	0.72	1.00	0.45	0.00	1.00
Wind energy area (1/0)	0.00	0.00	0.00	0.00	0.00
Lot is leased (1/0)	0.48	0.00	0.50	0.00	1.00
Buyer: Farmer					
Price (€/m^2)	1.65	1.52	0.86	0.35	4.18
Lot Size (ha)	3.36	1.18	6.68	0.06	29.06
Soil Quality (Index)	64.93	67.00	22.42	21.00	100.00
Lot Independence (1/0)	0.89	1.00	0.31	0.00	1.00
Wind energy area (1/0)	0.01	0.00	0.09	0.00	0.00
Lot is leased (1/0)	0.78	1.00	0.41	0.00	1.00
Buyer: Tenant					
Price (€/m^2)	1.59	1.50	0.81	0.35	3.96
Lot Size (ha)	3.02	1.00	6.43	0.06	28.21
Soil Quality (Index)	65.50	68.00	22.32	21.00	100.00
Lot Independence (1/0)	0.89	1.00	0.31	0.00	1.00
Wind energy area (1/0)	0.01	0.00	0.09	0.00	0.00
Lot is leased (1/0)	0.88	1.00	0.33	0.00	1.00

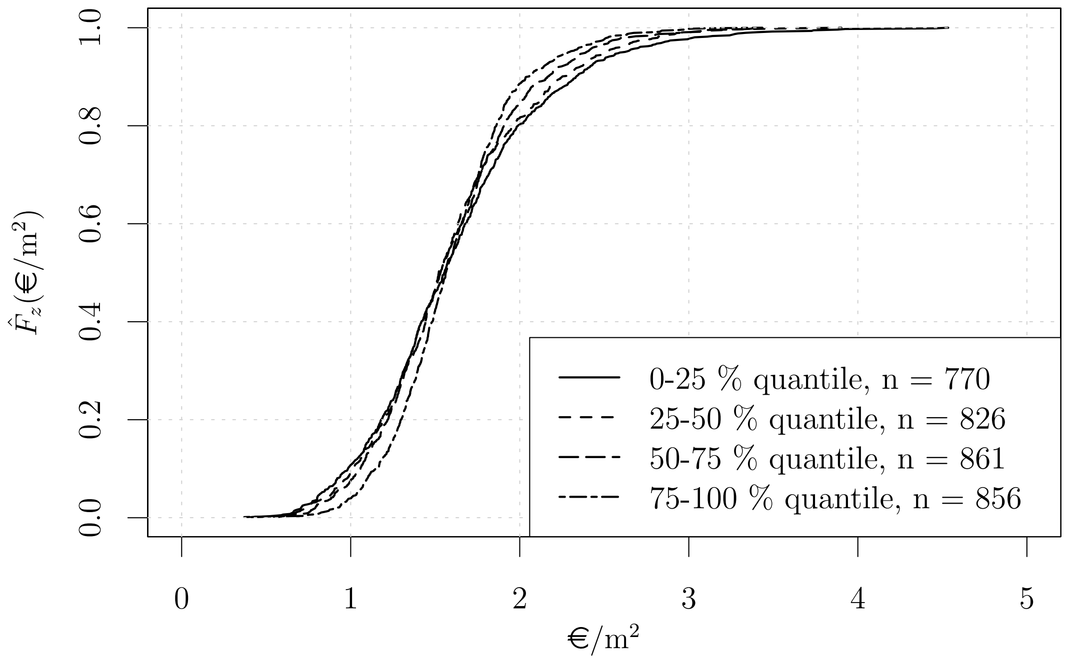
Table 5: Main descriptive statistics by seller and buyer types

6.3 Regression results: Spatio-temporal effects

N = 10,778	*LIN*		*TT1*		*TT2*		*TT3*	
Location classes								
Altmark-Mitte	0.343***	(0.075)	0.340***	(0.075)	0.341***	(0.077)	0.342***	(0.077)
Altmark-Ost	0.104	(0.094)	0.103	(0.094)	0.098	(0.093)	0.094	(0.093)
Altmark-West	0.287***	(0.068)	0.286***	(0.069)	0.278***	(0.070)	0.283***	(0.070)
Boerde	0.671***	(0.045)	0.670***	(0.044)	0.667***	(0.045)	0.668***	(0.046)
HAL-Sued	0.481***	(0.045)	0.475***	(0.044)	0.469***	(0.045)	0.465***	(0.045)
Harz	0.077**	(0.038)	0.075**	(0.038)	0.074*	(0.039)	0.074*	(0.038)
MD-HAL	0.515***	(0.032)	0.515***	(0.032)	0.514***	(0.034)	0.513***	(0.034)
MD-Nord	0.189***	(0.038)	0.187***	(0.037)	0.181***	(0.039)	0.186***	(0.038)
MD-Ost	0.461***	(0.048)	0.459***	(0.048)	0.460***	(0.049)	0.460***	(0.049)
ST-Sued	0.565***	(0.045)	0.562***	(0.045)	0.561***	(0.045)	0.555***	(0.046)
Vorharz	0.428***	(0.044)	0.427***	(0.044)	0.426***	(0.045)	0.427***	(0.045)
Time trend								
Trend	0.158***	(0.020)	0.158***	(0.020)	0.159***	(0.020)	0.160***	(0.020)
Trend^2	−0.012***	(0.003)	−0.012***	(0.003)	−0.012***	(0.003)	−0.012***	(0.003)
Interactions								
Altmark-Mitte · trend	0.012	(0.022)	0.012	(0.023)	0.010	(0.023)	0.011	(0.023)
Altmark-Ost · trend	0.040	(0.030)	0.040	(0.031)	0.040	(0.030)	0.042	(0.030)
Altmark-West · trend	0.010	(0.025)	0.010	(0.025)	0.012	(0.025)	0.012	(0.025)
Boerde · trend	−0.020**	(0.008)	−0.020**	(0.008)	−0.020**	(0.009)	−0.020**	(0.009)
HAL-Sued · trend	−0.024*	(0.012)	−0.023*	(0.012)	−0.023*	(0.012)	−0.020*	(0.012)
Harz · trend	0.011	(0.011)	0.011	(0.011)	0.012	(0.011)	0.012	(0.011)
MD-HAL · trend	−0.020***	(0.007)	−0.020***	(0.007)	−0.020***	(0.007)	−0.019***	(0.007)
MD-Nord · trend	0.007	(0.013)	0.007	(0.014)	0.008	(0.014)	0.007	(0.013)
MD-Ost · trend	−0.022*	(0.012)	−0.021*	(0.013)	−0.022*	(0.012)	−0.020	(0.013)
ST-Sued · trend	−0.015	(0.012)	−0.015	(0.012)	−0.015	(0.012)	−0.012	(0.012)
Vorharz · trend	−0.006	(0.012)	−0.005	(0.012)	−0.006	(0.012)	−0.005	(0.012)
Location classes	yes		yes		yes		yes	
Observations	10,778		10,778		10,778		10,778	
$\text{Cor}_{\text{P}, \hat{\text{P}}}$	0.676		0.676		0.676		0.677	
Residual Std. Error	0.326 (df = 10,738)		0.326 (df = 10,737)		0.326 (df = 10,738)		0.325 (df = 10,736)	

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

6.4 CDFs of homogenised prices based on TT3 by buyer farm size quartile



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