

Seifert, Stefan; Hüttel, Silke

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Tel +49 (30) 2093 46845, Email [gabriele.wuerth@agrار.hu-berlin.de](mailto:gabriele.wuerth@agrار.hu-berlin.de)

**Agricultural Land Markets – Efficiency and Regulation**

# Common values and unobserved heterogeneity in farmland auctions in Germany

Stefan Seifert\* and Silke Hüttel\*\*

February 2020

**Abstract** In this paper, we test for the existence of a common component in agricultural land auctions in eastern Germany during the price boom 2007-2018 and discuss respective policy implications. Using a large, detailed dataset of auctions, we can rely on professional appraisals of the auctioned good that are privy to the seller to control for unobserved heterogeneity. We derive a new approach to disentangle valuations from observed and unobserved heterogeneity across auctions. For validation purposes we provide several model specifications; based on all models, we strongly reject purely private valuations. Based on the rich identification strategy, we conclude the existence of a common component in these auctions to be very likely. Our results first underline the importance of an adequate model specification to analyze farmland auctions. Second, from a policy perspective, the implied potential for a winner's curse can be seen as a warning sign for the sector.

**Keywords:** Farmland auctions, common values, unobserved heterogeneity

**JEL Codes:** C57, D44, Q12

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\*Corresponding Author. University of Bonn, Institute for Food and Resource Economics, Production Economics Group. s.seifert@ilr.uni-bonn.de

\*\*University of Bonn, Institute for Food and Resource Economics, Production Economics Group.

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# 1 Introduction

This article tests the presence of potential common values in land privatization auctions in eastern Germany during the price boom 2007-2018 and discusses its implications. Several empirical investigations suggest higher prices in first price land privatization auctions compared to negotiations (Hüttel et al., 2016; Visser and Spoor, 2011; Bulow and Klemperer, 1996). Besides privatization principles compliant with EU regulation asking for tendering procedures when selling by the public, auctions with public tenders offer an efficient search process to find the bidder with highest willingness to pay (WTP). The choice of this mechanism could be even strategic to influence specifically prices (Cai et al., 2013). The immobile nature and high spatial heterogeneity of farmland makes each transaction unique; in resulting typically thin land markets, this efficiency gain can be highly price relevant (Nickerson and Zhang, 2014; Polachek and Yoon, 1987).

The auction mechanism, however, will be efficient from a land allocation perspective only if the winning bid is submitted by the bidder with the highest valuation. In case of asymmetric bidders, for instance non-agricultural buyers may benefit from lower financial constraints (Clapp and Isakson, 2018), presence and type of competitors could influence bidding behavior. The weaker bidder, for instance farmer-buyers with financial constraints, could bid more aggressively to compensate for this disadvantage (Campo et al., 2003; Flambard and Perrigne, 2006). In farmland auctions with public tenders likely the number of potential bidders might be even higher compared to a (local) negotiation (cf. discussion in Hüttel et al., 2013), making the potential influence of number and type of competitors on price formation relevant. Even a buy-out of farmers by investors in land markets has been reported (Kay et al., 2015; Brady et al., 2017), where recently Croonenbroeck et al. (2019) took up this argumentation and investigated asymmetries in the German land privatization auctions at sealed bids. These authors conclude that bidder asymmetries are likely present but to be small in size and in effect on auction results. However, their investigation rests on the assumption that information for forming the bid is purely private without acknowledging potentially common components. When deriving the valuation of an auctioned lot of land, a potential bidder may consider (i) expectations about the returns from farming the land. While this component includes expectations about

common factors such as the development of output prices, a potential bidder has a private signal about the expected return depending on his skills as a farmer and a manager based on his own experiences (Croonenbroeck et al., 2019). This component is relevant only for farmers. (2) Returns from leasing: a buyer has expectations about a potential return from leasing out the land. Lease prices are publicly available at least at an aggregate level allowing each bidder to form his expectations. This component is available to farmers and non-farm investors. (3) Resale value component: each buyer has expectations about a potential return from reselling the land after winning the auction. Specific privatization auction rules allow resale after 15 years at the earliest; this implies bidders to form expectations about the development of the common resale value for many periods. This information is, however, not private: Because (potentially) competing bidders may also be potential buyers in the future, information about the signals of other bidders may influence the expected resale value. Thus, a bidder might update his valuation when learning about other bidders' assessment leading to a common value component in the valuation. Because this common component is unknown to all bidders, the bidder with the highest expectation about its value wins the auction. Being the most optimistic, however may be "bad news" after winning the auction, in particular if the number of competitors is large (Milgrom, 1981). Termed as the winner's curse, this phenomenon means that the winning bidder realizes to have paid more for the auctioned good than its actual value because of optimism.

Under common components, observing the winning bid begs the question whether the most optimistic bidder was a realist. In case of a winners' curse, the winner may realize a loss from the difference between the paid price and the actual value. In turn, additional cost may arise because the returns from owning the land may not pay out, by for instance non-realizations of capital cost reductions that would have been possible through ownership (Weber and Key, 2015), or reduced future lending limits. The discrepancy between price and actual value may challenge finding reliable mortgage values and could foster too high mortgage values and over-indebtedness of farms. In such a boom phase, especially the most productive farmers are optimistic and able to pay the high(er) prices in the short run, and thus likely win the auctions. However, it will be these farms suffering from the disadvantages and overpaying

during optimistic phases will increase their probability of bankruptcy. In case of land price bust periods, these farms can then not rely on financial buffer by ownership bearing the danger of a negative selection with the least productive farms surviving. Presuming non-agricultural buyers to be most optimistic, since land is scarce and finding suitable substitutes is often not possible, these auction winners can to a certain extent pass the winners curse through to the tenant. Tenants being able temporarily to pay higher prices might belong to the more productive group of farms. Overall too high rental rates will come at the cost of financial burdens, limited future possibilities of ownership and thus increases in capital cost. This may go along with higher risk of bankruptcy because of lower buffer and financial burdens making the farm less resilient ([Meuwissen et al., 2019](#)) and in case of bust cycles adverse survival may become likely. Such distorted prices may also send wrong signals to all potential bidders. Given that published auction results often serve as a reference in forming future bids, the bid will be based on optimistic estimates rather than on values with potential future misallocation of land as a consequence (cf. [Adamopoulos and Restuccia, 2019](#), for a discussion about consequences of distorted land ownership allocation).

From a policy perspective, the question whether the auction mechanism used for privatizing the land counteracts farmland regulation targeting at “preserving a healthy and sustainable farming structure” remains under debate. We argue, a profound understanding of bidder behavior and how bidders from their bid remains indispensable to investigate this question. Here, most relevant is how other bidders’ presence influences bidders’ valuations. Therefore the aim of this paper is to test the presence of a common component in valuations using the test of ([Haile et al., 2003](#)) and data from the eastern German privatization first price sealed bid auctions. The core idea of the test is to identify whether valuations systematically change with the number of actual bidders. Under a common value component, the winners’ curse gets more severe as the number of bidders increases, rational bidders should adjust their valuations according to the level of competition and valuations should on average decrease with the number of bidders. Therefore, valuations have to be identified from the observed winning bids, where we rely on the approach by [Li et al. \(2002\)](#).

In order to trace back the potential change in valuations in number of bidders to a

common component, other sources causing a potential relation between valuation and number of actual bidders must be ruled out. Immobility and the complex relation between natural conditions and potential profits from the land makes each transaction highly specific, resulting in large heterogeneity across auctions. We however, observe only a subset of covariates determining the bid such as size of the lot and soil quality. To remove this auction heterogeneity, we follow an indirect approach outlined by (Athey and Haile, 2007): each observed bid is homogenized to correspond to the bid that would have been submitted to an auction of a lot with average attributes. Other auction-specific information might be known among bidders and the seller but remains unobserved for the researcher. Omitting such aspects will influence value identification and thus any inference based on the common component test (cf. Haile and Kitamura, 2018). For instance, one auctioned land could be highly attractive for many bidders by its observed lot size and soil quality but also because unobserved issues such as future potential development options of the land. In this regard, Campo et al. (2003) and Haile et al. (2003) even use the number of bidders as an instrument arguing that better unobserved characteristics will attract more bidders. In order to control for this unobserved heterogeneity control function approaches (Compiani et al., 2019), mixture models (Kitamura and Laage, 2018) and measurement error approaches (Krasnokutskaya, 2011) have been proposed. Our rich data set offers us to rely on a different approach: we can rely on plot specific appraisal estimates by experts using previous auction results but adjusting for peculiarities. This information is private to the seller (the privatization agency selling on behalf of the Federal Ministry of Finance). Contrary to reserve prices based on appraisal (Roberts, 2013; Cai et al., 2013), we favor using these appraisals since these are not used as signals and should thus be independent from the competition for the lot. We can thus unbiasedly uncover unobserved heterogeneity at the auction level by decomposing the appraisal into an observed and unobserved component. Considering this unobserved component in the homogenization step and presuming a linear additive structure allows us to disentangle valuations from unobserved and observed heterogeneity. Based on the test results, we reject pure private valuations. In light of the rich identification strategy of the valuations, we conclude that the presence of common components is very likely.

The contribution of this paper is threefold. First, we are first to apply the test of [Haile et al. \(2003\)](#) in the land auctions context and second, we are first who discuss potential implications of a winners' curse in these privatization auctions based on a quantitative analysis. We therefore complement the investigation of [Croonenbroeck et al. \(2019\)](#) on potential sources of bias in land auction results with public tenders during the recent boom phase. Third, by making use of a rich and unique data set including appraisals private to the seller, we introduce a novel approach in order to acknowledge observed and unobserved heterogeneity. We base the homogenization step on three different model specifications and provide therefore a validity check and robustness analysis of this approach.

The remainder of the paper is structured as follows: we continue describing the general modelling of affiliated private values with common components and the testing procedure for uncovering common components. In section 3, we describe the privatization auctions in eastern Germany and introduce the data set. This is followed by the empirical strategy, where we first detail the approach to control for observed and unobserved heterogeneity, followed by the model specification basing the test of [Haile et al. \(2003\)](#). In section 5, we present the results; section 6 summarizes and discusses policy implications.

## 2 Model and testing procedure

### 2.1 The APV Model and Estimation

We analyze a first-price sealed-bid (FPSB) auction without reserve price. Our framework is the general affiliated private value (APV) model by [Milgrom and Weber \(1982\)](#). This structure allows diverse forms of dispersed information among bidders ([Athey and Haile, 2007](#)) including pure common value models, in which the unobserved value of the good is identical to all bidders, a common component in the valuation, and pure private values.

We borrow the notation from [Haile et al. \(2003\)](#) and upper cases denote random variables, lower cases are their realizations, and vectors are in bold font. We consider auctions with  $N \in \{\underline{n}, \dots, \bar{n}\}$  risk-neutral bidders but at least two participants ( $\underline{n} \geq 2$ ). Each bidder  $i$  has valuation  $U_i \in \{\underline{u}, \dots, \bar{u}\}$  for the auctioned good and



receives a private signal  $X_i \in \{x, \dots, \bar{x}\}$ .  $\mathbf{X}_{-i}$  denotes the signals of  $i$ 's opponents. Valuations and signals have a joint distribution  $\tilde{F}_n(U_1, \dots, U_n, X_1, \dots, X_n)$  with a positive joint density on  $(\underline{u}, \bar{u})^n \times (x, \bar{x})^n$ . Following [Milgrom and Weber \(1982\)](#), in the affiliated private value model (1)  $\tilde{F}$  is symmetric (i.e., exchangeable with respect to the indices); (2)  $U_1, \dots, U_n, X_1, \dots, X_n$  are affiliated; (3)  $E[U_i | \mathbf{X}_i = \mathbf{x}, \mathbf{X}_{-i} = x_i]$  is strictly increasing in  $x \forall \mathbf{x}_{-i}$ ; and (4), participation is exogenous, i.e.,  $n \leq \bar{n}$  and all  $u_1, \dots, u_n, x_1, \dots, x_n, \tilde{F}_n = \tilde{F}_{\bar{n}}$ . In this setting, bidders have private values if  $E[U_i | X_1, \dots, X_n] = E[U_i | X_i]$ , and common values if  $E[U_i | X_1, \dots, X_n]$  strictly increases in  $X_j$ . That is, opponents' private information would not affect a bidder's valuation if private values prevail. With common values, on the contrary, a bidder would consider other bidders' information when forming expectations about their own valuations. To differentiate between private and common values, observed bidder behavior can be used. In an auction with  $n$  bidders, a unique symmetric Bayesian Nash equilibrium exists and each bidder employs the strictly increasing strategy  $s_n(\cdot)$ . Bidder  $i$  assumes equilibrium bidding by his opponents and chooses his bid  $b$  to maximize his expected profit  $E[(U_i - b) \mathbb{1}\{s_n(x_j) \leq b \forall j \neq i\} | X_i = x]$ . [Milgrom and Weber \(1982\)](#) derive the corresponding equilibrium bid function

$$v(x, x, n) = s_n(x) + \frac{s'_n(x) F_n(x|x)}{f_n(x|x)} \quad (1)$$

with

$$v(x, x', n) \equiv E \left[ U_i | X_i = x, \max_{j \neq i} X_j = x' \right]. \quad (2)$$

$F_n(\cdot|x)$  denotes the distribution of the maximum signal of a bidder's opponents conditional on his own signal being  $x$  with corresponding conditional density  $f_n(x|x)$ .  $v(x, x, n)$  in equation (1) gives a bidder's expectation of his valuation conditional on his signal and on his equilibrium bid being pivotal. As shown by [Haile et al. \(2003\)](#), this expectation decreases in  $n$  only if a common value is present. While it therefore could serve as a basis of a test for CV, valuations  $v(x, x, n)$  are unfortunately unobserved.

To recover estimates of valuations from observed bids, [Guerre et al. \(2000\)](#) show that the joint distributions of signals and the joint distribution of bids are related in

equilibrium. With the subscript denoting the  $n$  bidder auction, they show that

$$F_n(y|x) = G_n(s_n(y)|s_n(x)) \quad (3)$$

$$f_n(y|x) = g_n(s_n(y)|s_n(x))s'_n(y) \quad (4)$$

where  $G_n(\cdot|x)$  is the equilibrium distribution of the highest bid among  $i$ 's rivals conditional on  $i$ 's bid being  $s_n(x)$ .  $g_n(\cdot|x)$  denotes the corresponding conditional density. Because  $i$ 's bid in equilibrium is  $b_i = s_n(x_i)$ , the FOC of the equilibrium bid in equation (1) is

$$v(x_i, x_i, n) = b_i + \frac{G_n(b_i|b_i)}{g_n(b_i|b_i)} \equiv \xi(b_i; n). \quad (5)$$

Because the joint distribution of bids is observed,  $G_n(\cdot|s_n(\cdot))/g_n(\cdot|s_n(\cdot))$  is non-parametrically identified, allowing identification of the distribution of  $v(X_i, X_i, n)$ .

For estimation, [Li et al. \(2000, 2002\)](#) and [Guerre et al. \(2000\)](#) propose non-parametric techniques that require some more notation. Consider that we observe  $T = \sum_n T_n$  auctions with  $T_n$  auctions with  $n$  bidders. In each auction  $t$ , bids  $B_{1t}, \dots, B_{nt}$  are submitted and we observe  $b_{1t}, \dots, b_{nt}$ . Using these observed bids, [Li et al. \(2000, 2002\)](#) and [Guerre et al. \(2000\)](#) show that  $G_n(b; b) \equiv G_n(b|b)g_n(b)$  and  $g_n(b; b) \equiv g_n(b|b)g_n(b)$  can be estimated non-parametrically with

$$\hat{G}_n(b; b) = \frac{1}{T_n \times h_G \times n} \sum_{t=1}^T \sum_{i=1}^n K\left(\frac{b - b_{it}}{h_G}\right) \mathbb{1}\{b_{it} \leq b, n_t = n\} \quad (6)$$

$$\hat{g}_n(b; b) = \frac{1}{T_n \times h_g^2 \times n} \sum_{t=1}^T \sum_{i=1}^n K\left(\frac{b - b_{it}}{h_G}\right) K\left(\frac{b - b_{it}^*}{h_g}\right) \mathbb{1}\{n_t = n\} \quad (7)$$

where  $b_{it}^*$  denotes the highest bid among  $i$ 's rivals,  $K$  is a Kernel, and  $h_G$  and  $h_g$  denote corresponding bandwidths. A sample of estimated valuations  $\hat{v}_{it}$ , called pseudo-values, can be calculated with equation (5) by evaluating  $\hat{G}_n(\cdot, \cdot)$  and  $\hat{g}_n(\cdot, \cdot)$  at observed bids  $b_{it}$  such that

$$\hat{v}_{it} \equiv \hat{\xi}(b_{it}; n_t) = b_{it} + \frac{\hat{G}_n(b_{it}; b_{it})}{\hat{g}_n(b_{it}; b_{it})}. \quad (8)$$

## 2.2 Testing for Common Values

To test the null hypothesis of private values, we use the approach by [Haile et al. \(2003\)](#). The test follows the idea that the winner's curse can only occur in a CV environment. Because the winner's curse gets more severe as the number

of bidders increases, rational bidders should adjust their valuations according to the level of competition. Thus, facing the risk of overbidding more competitors, valuations should on average decrease with the number of bidders. On the contrary, because no winner's curse can occur under pure private values, no such adjustment shall be observed.

Formally,  $E[v(X, X, n)]$  should be constant for different  $n$  under private values, but decreasing in  $n$  for common values. However, as pointed out by Haile et al. (2003), the sample of pseudo-values  $\hat{v}_{it}$  can not be used directly due to a potential error from the first stage of the estimation. Haile et al. (2003) propose using quantile-trimmed mean defined as  $\mu_n \equiv E[v(X, X, n)\mathbb{1}\{x_\tau \leq X \leq x_{1-\tau}\}]$ , where  $x_\tau$  is the  $\tau$ th quantile of  $\hat{F}_X(\cdot)$ . Using the  $\tau$ th quantile of the distribution of observed bids,  $\hat{b}_{\tau,n}$ , the sample analogue is

$$\hat{\mu}_{n,\tau} \equiv \frac{1}{nT_n} \sum_{t=1}^T \sum_{i=1}^n \hat{v}_{it} \mathbb{1}\{\hat{b}_{\tau,n} \leq b_{it} \leq \hat{b}_{1-\tau,n}, n_t = n\}. \quad (9)$$

Testable hypotheses are then

$$H_0 : \hat{\mu}_{\underline{n},\tau} = \dots = \hat{\mu}_{\bar{n},\tau} \quad (10)$$

$$H_1 : \hat{\mu}_{\underline{n},\tau} > \dots > \hat{\mu}_{\bar{n},\tau} \quad (11)$$

where  $H_0$  corresponds to private values, and  $H_1$  reflects situations with a common component or pure common values. Following Haile et al. (2003), we use a likelihood ratio test proposed by Bartholomew (1959). Denoting the inverse variance of  $\hat{\mu}_{n,\tau}$  with  $a_n$ , the test statistic is

$$\bar{\chi}^2 = \sum_{n=\underline{n}}^{\bar{n}} a_n (\mu_{n,\tau}^* - \bar{\mu}) \quad (12)$$

where  $\mu_{\underline{n},\tau}^*, \dots, \mu_{\bar{n},\tau}^*$  is the solution to

$$\min_{\mu_{\underline{n},\tau}, \dots, \mu_{\bar{n},\tau}} \sum_{n=\underline{n}}^{\bar{n}} a_n (\hat{\mu}_{n,\tau} - \mu_n)^2 \quad s.t. \mu_{\underline{n}} \geq \mu_{\underline{n}+1} \geq \dots \geq \mu_{\bar{n}}. \quad (13)$$

Under the null hypothesis, the test statistic follows asymptotically a mixture of Chi-square random variables with

$$Pr(\bar{\chi}^2 \geq c) = \sum_{k=2}^{\bar{n}-\underline{n}+1} Pr(\chi_{k-1}^2 \geq c) \omega(k; \Sigma) \quad (14)$$

where  $\chi_j^2$  is the standard Chi-square distribution with  $j$  degrees of freedom. Mixing

weights  $\omega(k, \Sigma)$  are the probabilities that the solution to the minimization problem in (13) has  $k$  distinct values if  $\{\hat{\mu}_{n,\tau}, \dots, \hat{\mu}_{\bar{n},\tau}\} \sim MVN(0, \Sigma)$ . Details on the implementation of the test are outlined in section 4.2.

The test is assumed to be exogenous entry of potential bidders. In our empirical set-up, bidding is not connected to high costs and the barrier of entry is low. No costs occur to obtain signals. In particular, farmers are experienced and estimate their potential returns. Past winning bids are publicly provided, which provides information about potential competition and valuations of competitors. Land lease rates can be obtained at regional level as well as from auction results for lease auctions. Likewise, expected sales prices are available at small regional scale based on past transactions (*Bodenrichtwerte*) and allow adjustments for particularities with publicly available factors. Lastly, entering the auction is not connected to fees.

### 3 Background and Data

Our empirical analysis focuses on farmland auctions in Eastern Germany carried out by BVVG (*Bodenverwertungs- und -verwaltungs GmbH*). Constituted after the German reunification, BVVG is a public authority with the mandate to privatize the and forest land owned by the former GDR. In total, since 1992 around 900,000 ha of farmland and 600,000 ha of forestland have been privatized. Still today, BVVG's transactions constitute a considerable share of the land market in Eastern Germany, with observed shares of up to 60% at the local level.<sup>1</sup>

In accordance with the German Privatization Principles, BVVG uses *inter alia* first-price sealed-bid auctions with public tenders. The auctions are listed on BVVG's homepage about two months before closing date with the auction rules. The listing includes detailed information about the offered lot and aerial pictures. Additionally, auction results from the last six months are posted online including winning bids and lot characteristics. The majority of auctions are open to all bidders (except for BVVG employees and other insiders) and no reservation prices are communicated. On the contrary, for around 8% of the auctions in our sample, some restriction exist, including listed reservation prices and bidding restricted to young farmers or for

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<sup>1</sup>We refer to Croonenbroeck et al. (2019), Wolz et al. (2009), and Hüttel et al. (2016) for more details on the privatization process.

organic farming only, and/or for labor-intensive production (BVVG, 2010). Nearly all posted offers invite buy bids. Additional lease bids can be invited for non-leased lots and a bidder may submit bids for both buying and leasing a lot. Bids can be submitted electronically, by mail or via fax. A valid bid consists of a brief form with contact details, the buy bid (and lease bid, if applicable), and a proof of financing (covenant of a bank or a bank statement). After the closing date, the auctioned lot is awarded to the highest bid, but BVVG reserves the right to not award it to anyone. If both buy and lease bids were invited, auction rules require awarding the lot according to the economically best bid, but no further details are provided. The sales contract bans resale within fifteen years after the transaction, virtually ruling out short-term speculations.

For our analysis, we rely on a unique dataset of all auctions carried out by BVVG in Eastern Germany between March 1, 2007 and August 27, 2018. For each auction, we observe information on the auctioned good including its location, lot size, lot type (shares of arable, grassland and other land), lot composition (number of parcels), and soil quality.<sup>2</sup> Additionally, we observe an appraisal of the auctioned land by local land market experts. This appraisal shall incorporate all price determinants including factors that are not included in the dataset. Our initial dataset consists of 9,821 auction. In a cleaning procedure, we remove 2,030 auctions with less than two bidders as there is virtually no competition. Also, three auctions in the city state of Berlin and in Western Germany are removed as the market environment strongly differs from the remaining auctions.<sup>3</sup> We also remove nine auctions with winning bids more than ten times higher than the appraisal because we suspect that appraisals may not included all heterogeneity that is valued by the bidders. Another seven auctions with winning bids above 1.75 million Euro are excluded as they strongly diverge from the remaining sample. Thus, our final dataset includes 7,764 auctions of in total more than 56.000 hectares of land generating revenues of around 900 million Euro.

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<sup>2</sup>The soil quality measure 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 (German Bundestag, 2007).

<sup>3</sup>BVVG auctions in Western Germany occur in one municipality that was on the territory of the GDR but joined Lower Saxony after reunification. It may therefore be structurally different (Grau et al., 2019).

Table 1: Descriptive statistics of 7,764 auctions 2007-2018

	Q1	Med	Mean	Q99	SD
<i>Characteristics of the auctioned good</i>					
Lot size (ha)	0.08	4.23	7.25	46.20	9.70
Arable land (ha)	0	2.17	5.39	41.04	8.54
Grassland (ha)	0	0	1.42	17.50	3.68
Other land (ha)	0	0.05	0.44	5.17	1.10
Soil quality (index)	16	40	43.58	95	17.24
Number of Parcels (#)	1	3	5.88	38	8.21
<i>Auction characteristics</i>					
Winning bid (1000 EUR/ha)	2.47	11.41	14.11	40.97	9.38
Average bid (1000 EUR/ha)	1.77	8.32	10.44	32.61	7.10
Appraisal (1000 EUR/ha)	2.25	8.99	11.52	34.30	7.75
Number of buy bids (#)	2	3	3.90	12	2.28
Lease bids (0/1)	0	0	0.22	1	0.42

Table 1 shows the descriptive statistics of our sample and indicates considerable heterogeneity across auctions: Lot sizes vary between less than a tenth of a hectare and more than 46 hectares. The plots consist mainly of arable land and more than the half are arable land only. However, besides grassland, on average five percent of unspecified other land is included. Soil quality varies strongly and ranges from 16 soil quality index points, which indicates very low quality, to more than 96 index points, which is close to the best soil quality available in Germany [German Bundestag \(2007\)](#). We observe a strong variation in appraisals and winnings bids which both varying between around 2.500 and more than 40.000 EUR/ha. On average, winning bids exceed the appraisals while average bids are below the appraisals.

For each auction, we observe the full vector of submitted buy bids, in total 30,278 bids. Bidder identities are, however, unobserved and we treat each bid as an independent observation. 14 non-competitive bids of one and two Euro in total are removed. As shown in Table 1, on average four bids are submitted, but the maximum is considerably higher with 22 bidders. Both buy and lease bids were invited in about 22 % of the auctions, which may increase the potential competition.

Figure 1 shows the distributions of the winning bids in EUR per hectare for different numbers of bidders with the number of auctions labeled at the top. The plot shows a strong variation among the winning bids for a given number of bidders underlining the importance of auction heterogeneity. Further, the plot indicates positive relationship

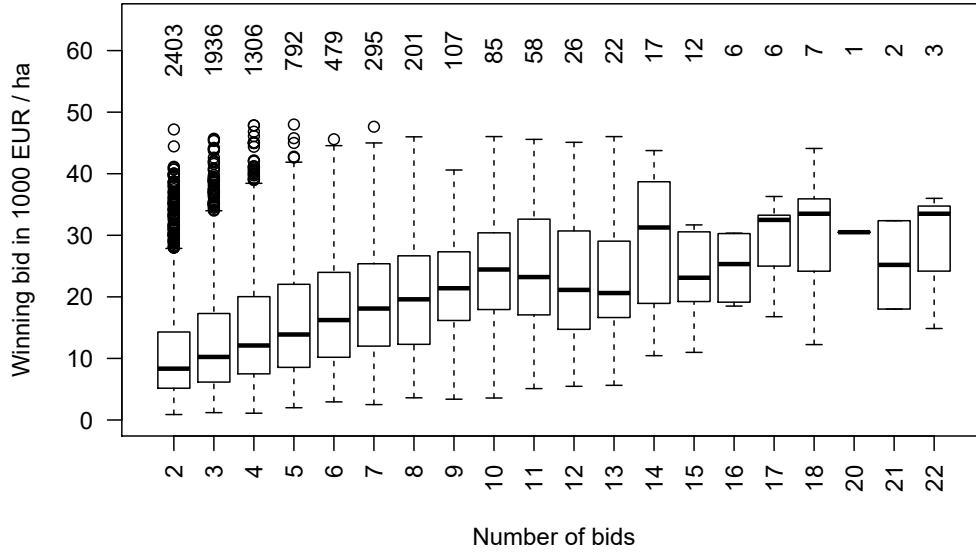


Figure 1: Number of bids, winning bids and number of observations

between winning bids and the number of bidders until ten bidders, but no clear trend afterwards. The distribution of average bids for different numbers of bidders shows a very similar trend but at a lower level (compare Figure 7 in the appendix). We note that around two percent of the auctions (169) attracted more than ten bidders. Due to this skewness, for the empirical analysis, we group auctions with seven to nine bidders as well as auctions with ten or more bidders. As a result, each group  $T_n$  contains at least 2,956 (10 or more bidders) and up to 5,808 bids (3 bidders).

Over the observation period, winning bids have increased strongly from around 5,919 EUR/ha in 2007 to around 21,000 EUR/ha in 2017 and 2018, while lot characteristics, such as lot size and soil quality, are rather stable over time. This reflects a general price rise in the Eastern German land market. In fact, in the public and in the academic debate (compare [Odening and Hüttel, 2018](#); [Croonenbroeck et al., 2019](#)), BVVG auctions have been discussed as a price driver, in particular due to low entry barriers. However, in the same period, competition was rather stable with only a slight increase in the average number of bidders in 2012 and 2013 (compare Figure 6 in the appendix).

## 4 Empirical strategy

### 4.1 Observed and Unobserved Heterogeneity

The auction model presented in section 2.1 refers to a repeated auctions of identical goods. Attributes of the auctioned land in our study, however, vary across auctions and observed bids likely depend on such attributes. To remove auction heterogeneity, we follow an indirect approach outlined by [Athey and Haile \(2007\)](#): each observed bid is homogenized to correspond to the bid that would have been submitted to an auction of a lot with average attributes. For this homogenization, we separate auction heterogeneity from valuations assuming an additive structure of the valuations such that

$$v(x, x, n, \mathbf{z}) = v(x, x, n) + \Gamma(z), \quad (15)$$

where  $\Gamma$  is a function to be estimated. As shown by [Athey and Haile \(2007\)](#), additive separability is preserved in equilibrium and allows to control for covariates using a regression of bids. That is, we use a regression of the form

$$b_{it} = \alpha(N_t) + \Gamma(\mathbf{z}_t) + \epsilon_{it} \quad (16)$$

where  $\alpha(N_t)$  is an intercept for auctions with  $N_t$  bidders and  $\epsilon_{it}$  is a mean zero conditional on  $\mathbf{z}_t$ . The estimate  $\hat{\Gamma}(\mathbf{z}_t)$  is then be used to calculate homogenized bids with

$$b_{it}^h = b_{it} - \hat{\Gamma}(\mathbf{z}_t). \quad (17)$$

Standard regression techniques deliver a consistent estimate  $\hat{\Gamma}(\mathbf{z}_t)$  and homogenized bids  $b_{it}^h$  correspond to bids in repeated auctions of identical goods with average attributes.

The approach requires that available auction covariates control for all heterogeneity. If additional heterogeneity commonly known among bidders but unavailable to the researcher exists, homogenized bids might be biased. In particular, they would likely indicate too high correlation within auctions, and too high variation across auctions. Therefore, to further control for unobserved heterogeneity, approaches for various auction settings have been proposed based on different assumptions and data requirements (see [Haile and Kitamura, 2018](#), for a review).



Although our data includes the main determinants of farmland prices (cf. [Nicker-son and Zhang, 2014](#)), additional heterogeneity might be prevalent. In this paper, we attempt to recover additional unobserved heterogeneity from an appraisal of the auctioned good derived by an appraiser specialized in land valuation. The appraisal is based on past auction outcomes for similar lots adjusted for particularities. These estimates should therefore incorporate all lot characteristics, including those otherwise not observable for us. As it is based on observed bidder behavior, the appraisal should correspond to the bidders' valuation of attributes of the auctioned. Thus, one might use the appraisal directly in equation 16.

To better understand the dimension and the impact of unobserved heterogeneity, we aim at recovering an estimate which enters the homogenization equation together with observed attributes of farmland. We assume that appraisals  $A$  are a function of observed ( $Z^o$ ) and unobserved ( $Z^u$ ) factors such that  $A = m(Z^o, Z^u)$ , where  $m$  is invariant across auctions. Thus, to estimate  $\tilde{Z}^u$  one can decompose the appraisals based on an estimate of  $m$ .

We assume that  $m$  is increasing in  $Z^o$  and, for instance, appraisals increase with lot size. Further, we assume that  $m(\cdot)$  is increasing in  $Z^u$  for all values of  $Z^o$  and higher levels of unobserved heterogeneity result in higher appraisals. Therefore, unobserved heterogeneity is one-sided and appraisals of observations with  $Z^u = 0$  form the lower boundary of potential realizations of  $A$ . We therefore define  $m$  as the lower boundary of the set  $m^*$  with

$$m^* = \left\{ (Z^o, A) \in \mathbb{R}^m \times \mathbb{R} \mid \exists \lambda \in \Lambda_K(\gamma) : Z^o \leq \sum_{k=1}^K \lambda_k Z_k^o, A \geq \sum_{k=1}^K \lambda_k A_k \right\}, \quad (18)$$

which contains feasible combinations of observable characteristics and appraisals of  $k$  ( $k = 1, \dots, K$ ) auctions, where the shape of  $m^*$  is governed by  $\Lambda$ . An estimate  $\tilde{Z}^u$  is then calculated as the distance between an observed  $A$  and an estimate of the lower envelope of this set. Figure 2 illustrates the approach for one-dimensional  $Z^o$  on the x-axis (e.g. lot size) and the appraisal on the y-axis. The solid line is the lower envelope of observed  $(A, Z^o)$ . The piece-wise linear shape follows from setting  $\sum_k \lambda_k = 1$  that enforces convex combinations. For  $k = 6$  the difference between the observed appraisal and the a linear combination of appraisals of  $k = \{1, 3\}$  estimates  $Z^u$ . For observation  $k = \{1, 3, 4\}$ , no unobserved heterogeneity is indicated.

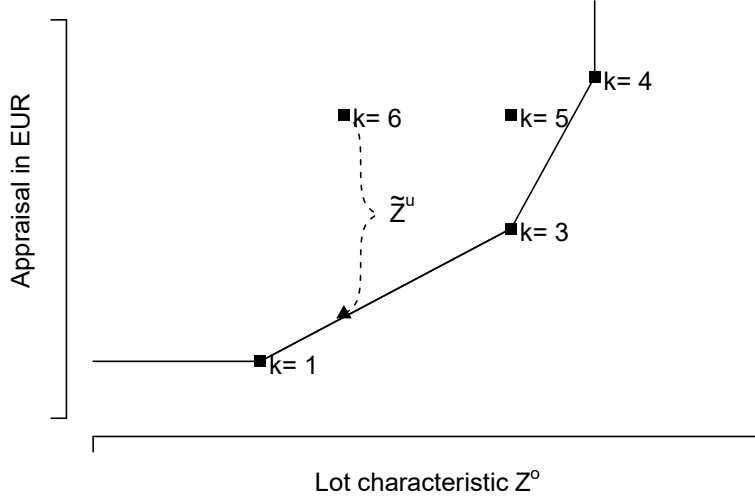


Figure 2: Example solution of LP to estimate unobserved heterogeneity  $Z^u$

We use the non-parametric and deterministic linear programming (LP) approach of [Banker et al. \(1984\)](#) to simultaneously estimate  $m$  and  $Z^u$ . That is, for some observation  $(A_0, Z_0^o)$  we solve

$$\min_{\theta_0, \lambda_1, \dots, \lambda_K} (1 - \theta_0) \quad s.t. \quad Z_0^o \leq \sum_{k=1}^K \lambda_k Z_k, \quad (1 - \theta_0)A_0 \geq \sum_{k=1}^K \lambda_k A_k, \quad \lambda \in \Lambda_K \quad (19)$$

to obtain weights  $\lambda$  that span a frontier by weighting  $K$  observations, and an estimate  $\theta$  that indicates the distance between  $(A_0, Z_0)$  and this frontier. Intuitively, the LP aims at contracting the appraisal  $A_0$  as far as possible while staying within combinations of observations with respect to  $Z^o$  and  $A$ .  $\theta$  describes the maximum contraction of the appraisal relative to  $m$  at  $Z_0^o$  in percentages. Thus,  $\theta = 0$  indicates that the observed appraisal is the lowest estimate conditional on  $Z$ , i.e., no unobserved heterogeneity. To translate this relative measure into monetary terms, we compute  $\tilde{Z}_0^u = \theta_0 A_0$ . To obtain estimates of  $\theta$  and  $\tilde{Z}^u$  for each observation, the LP has to be solved for each auction separately.

We use the obtained estimates in the homogenization of bids via  $\Gamma(z_t^o, \tilde{Z}_t^u)$  with the aim to better control for auction heterogeneity. The approach requires some assumptions: First, we assume that the seller is aware of all factors that bidders consider to form their bids and considers only those in the appraisals. This also means that the appraisal does not include auction characteristics, such as the expected

number of bidders. Further, our approach assumes that unobserved heterogeneity is unobserved only by the econometrician while the buyers and the seller know all characteristics of the auctioned good. In our application, the appraisal is in most cases privy to the seller. Contrary to the use of reserve prices (compare, e.g., [Roberts, 2013](#)), appraisals are not used as signals. Thus, contrary to an optimal reserve price that increases in the number of bidders as it can be used as a signal ([Cai et al., 2013](#)), the appraisals should be independent from the competition for the lot.

## 4.2 Model Specification and Implementation

We test for common values using three models, M1 to M3, that differ in the specification of the homogenization equation (17) as summarized in Table 2. All models use the log of the submitted bids in Euro per hectare as dependent variable but vary in the specification of the right hand side variables.

Model (M1) is a reference specification and includes observable factors. Based on [Croonenbroeck et al. \(2019\)](#) and [Kahle et al. \(2019\)](#), we control for the major determinants of farmland prices and include size and size squared, soil quality, a size-quality interaction, the number of parcels, the share of arable land, and the share of other land. A dummy equal to one if lease bids are invited controls for potential additional competition in such auctions. Spatio-temporal control variables are included in the form of dummies for the five federal states of Eastern Germany, a time dummy for each year, and interactions of state and time dummies. Model (M2) extends (M1) by a measure of unobserved heterogeneity. Using equation (19) with a specification outlined below, we estimate  $\tilde{Z}^u$  in 1000 Euro per hectare. In line with the dependent variable, we use the log and include  $\log(1 + \tilde{Z}^u)$  in the regression to allow for zero values. Model (M3) use only the log of the appraisal  $\log(A)$  in Euro per hectare to control for all price determinants, including those unobserved by us. To avoid multicollinearity, we also suppress spatio-temporal control variables in this model.

All specifications include the number of bidders  $\alpha(N_t)$  as dummy variables, where we group auctions to ensure sufficient sample sizes for each dummy. We include one dummy each for auctions with two to six bidders, a dummy for seven to nine bidders,

Table 2: Model specifications of homogenization equation

Model	Specification
M1	$\log(b_{it}^h) = \alpha(N_t) + \Gamma(Z_t^o) + \varepsilon_{it}$
M2	$\log(b_{it}^h) = \alpha(N_t) + \Gamma(Z_t^o, \tilde{Z}_t^u) + \varepsilon_{it}$
M3	$\log(b_{it}^h) = \alpha(N_t) + \Gamma(A) + \varepsilon_{it}$

and a dummy for ten or more bidders. The regressions include no intercept and the homogenized bid is calculated as the sum of the corresponding bidder dummy and the residual.

To estimate unobserved heterogeneity  $\tilde{Z}^u$ , we use the appraisal in Euro ( $A$ ) and three observable characteristics ( $Z$ ): the hectares of arable land and grassland both multiplied with soil quality, and the hectares of other land. The LP in equation (19) is solved for each auction separately including only auctions from the same year to form the frontier. We set  $\Lambda = \left\{ \lambda \in \mathbb{R}_+^K \mid \sum_{k=1}^K \lambda^k = 1 \right\}$  to impose a piece-wise linear form of  $m$ , similar to Figure 2. For each auction, we use the estimated  $\theta$  to derive  $\hat{Z}^u$  as unobserved heterogeneity in Euro. Further division by the lot size delivers a measure in Euro per hectare.

To estimate valuations out of homogenized bids, we use non-parametric regressions following [Guerre et al. \(2000\)](#) and [Li et al. \(2000, 2002\)](#). Estimation of  $\hat{g}_n(b; b)$  and  $\hat{G}_n(b; b)$  use triweight Kernels with bandwidths selected to minimize the asymptotic mean integrated squared error (AMISE) separately for each  $n$  and for each harmonization. To implement the test procedure for common values, we follow [Haile et al. \(2003\)](#) and estimate  $\Sigma$  using a block bootstrap of the quantile-trimmed mean. That is, in each bootstrap replication, we randomly draw auctions and include all of their bids to preserve any dependence between bids within an auction. To derive mixing weights, we use simulation of the quantile-trimmed means under the null hypothesis with a multivariate normal distribution  $MVN(0, \hat{\Sigma})$  based on the estimated  $\Sigma$ . Both block bootstrap and simulation use 5.000 replications.

## 5 Results

The following outlines the results of our analysis. First, we show results with respect to the unobserved heterogeneity and their relationship to observed bidder behavior. Second, we show the results of the homogenization procedure for the different model specifications. And third, results of the test for common values are presented.

### 5.1 (Un)observed heterogeneity

We aim to quantify unobserved auction heterogeneity using appraisals of the auctioned good. To explore the appraisals' explanatory power with respect to auction outcomes, Table 3 shows reduced form regressions for the winning bids on observed characteristics and appraisals. The estimated coefficients for the plot attributes are sensible and robust across specifications. The first column shows a high explanatory power of the observed characteristics with an  $R^2$  of around 0.72. However, we note that spatio-temporal controls play a very important role in this regression and their omission reduces the  $R^2$  to 0.46. In the third column, we omit all controls and include only the appraisals. The  $R^2$  of 0.77 indicates high explanatory of the appraisals for winning bids. When adding the appraisals as covariate to the observed factors (second column), the  $R^2$  jumps again considerable to 0.81. This indicates, that the appraisal does control for additional heterogeneity that is unobserved by us. In fact, comparing column 1 and 3 suggests that the appraisals control better for heterogeneity than all observed factors. However, the variance inflation factor for the appraisal (column 2) is close to the common threshold of five indicating problematic collinearity, which underlines that appraisals should contain information about all other variables.

Next, we outline the relationship between appraisals and observed heterogeneity and regress appraisals on lot characteristics and the number of bidders. Results of different specifications indicate that observed factors explain well the appraisals (compare Table 6 in the appendix). The number of bidders is only statistically significant if no spatial control variables are included, which suggests correlation between these factors. However, controlling for regional heterogeneity renders this factor insignificant, which supports our assumptions regarding unobserved heterogeneity (cf. section 4.1).

Table 3: Determinants of the log(Winning bid (1000 EUR/ha))

	(M1)	(M2)	(M3)
Constant	0.512*** (0.030)	0.268*** (0.025)	0.376*** (0.013)
Lot size	0.003*** (0.001)	0.002*** (0.0005)	
Soil quality	0.013*** (0.0003)	0.004*** (0.0003)	
# parcels	-0.004*** (0.001)	-0.001*** (0.0005)	
Share arable land	0.570*** (0.011)	0.147*** (0.011)	
Share other land	-1.230*** (0.043)	-0.568*** (0.037)	
Lease Bids [01]	0.132*** (0.013)	0.093*** (0.011)	
# Bids	0.039*** (0.002)	0.038*** (0.002)	
Log(A)		0.694*** (0.011)	0.917*** (0.006)
Year Dummies	Yes	Yes	No
State Dummies	Yes	Yes	No
Year $\times$ State	Yes	Yes	No
Observations	7,764	7,764	7,764
R <sup>2</sup>	0.718	0.812	0.765

*Note:* The dependent variable is the log of the winning bid in each auction in 1000 Euro/ha. Year and State indicate if dummies for each the observation year and the federal state is included, Year $\times$ State is their interaction. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01.

Using the LP outlined above, we estimate for each auction an indicator of unobserved heterogeneity which is the part of the appraisal that is not explained by observed lot characteristics. Estimates of  $\tilde{Z}^u$  are on average 6,541 EUR/ha, which corresponds on average to around 50% of the appraisal indicating substantial auction heterogeneity beyond the considered factors. Despite the deterministic nature of the estimator, only 213 of the 7,764 auctions are located on the boundary and obtain estimate of no unobserved heterogeneity. Figure 3 shows the estimates plotted against the winning bid. We observe a rather high correlation ( $\rho = 0.71$ ) with the winning bid, but also considerable dispersion with  $\tilde{Z}^u$  up to nearly 50,000 Euro per hectare. However, the observations with large estimates of  $\tilde{Z}^u$  are all small lots below one hectare leading to large numbers in per-hectare terms. Further, the Figure indicates estimates of  $\tilde{Z}^u$  partly exceed the winning bid. This is due to the construction of our estimator which allows only one-sided deviations from the appraisal for  $\tilde{Z}^u$  while winning bids may diverge from the appraisal in both directions.

Table 4 shows descriptive statistics of the measures for a different the number of bidders. The numbers suggests a positive relationship and competition increases for lots with higher unobserved heterogeneity. Over the observation period,  $\tilde{Z}^u$  also shows a considerable upward trend which reflects increasing prices and appraisals over

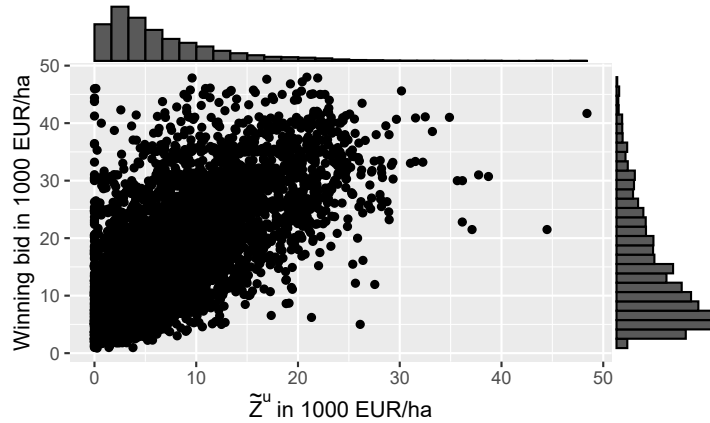


Figure 3: Estimates of  $\tilde{Z}^u$  and winning bids

the observation periods, while estimates of  $\theta$  do not increase over time (cf. appendix Table 7). The explanatory power of our estimates are evaluated in the next step when  $\tilde{Z}^u$  enters the homogenization regressions.

Table 4:  $\tilde{Z}^u$  and the number of bidders ( $T = 7,764$ )

n	2	3	4	5	6	{7,8,9}	$\geq 10$
1st Qu.	2.272	2.511	2.713	2.828	3.016	3.228	2.628
Median	4.159	4.620	5.091	5.276	5.452	6.007	6.486
3rd Qu.	8.060	9.112	9.280	9.216	10.466	10.209	10.177
Max.	34.886	37.751	36.164	36.149	48.399	38.717	23.431

## 5.2 Homogenization

Table 5 shows the results of the homogenization regression. Parameter estimates for the lot characteristics are generally statistically significant and their direction and magnitude is in line with other studies on the determinants of land prices (compare, e.g., [Nickerson and Zhang, 2014](#); [Kahle et al., 2019](#)). Control variables including state dummies, time dummies and their interactions reflect the steady increase in land prices in the observation period and underline regional variations (cf. appendix Tables 9 and 10). The explanatory power of all models is fair with  $R^2$ s between 0.48 and 0.52. Specifications (S1) shows significant impact for the explanatory variables. However, including  $\tilde{Z}^u$  in (S2) further increases the explanatory power of the model and the indicator for unobserved heterogeneity are statistically significant and in line with the assumption of positive impact on prices. Specification (S3), where we

only include the appraisal, also shows a satisfactory fit. Parameter estimates for the number of bidders are of similar magnitude in (S1) and (S2) corresponding to the average log bid. For S3, estimates are lower in magnitude and show a clearly increasing trend with the number of bidders. Thus, while the residuals of (S1) and (S2) are highly correlated ( $\rho_{S1,S2} = 0.96$ ), their correlation with (S3) is lower ( $\rho_{S1,S3} = \rho_{S2,S3} = 0.88$ ). Homogenized bids based on these estimates show a considerably lower variation than the raw bids with small but visible differences between the different specifications (cf. Figure 8 in the appendix).

Table 5: Hedonic homogenization regression of  $\log(\text{Buy Bid})$

	(S1)	(S2)	(S3)
# Bids: 2	7.211*** (0.029)	7.112*** (0.028)	0.776*** (0.050)
# Bids: 3	7.162*** (0.029)	7.066*** (0.028)	0.750*** (0.051)
# Bids: 4	7.140*** (0.029)	7.038*** (0.028)	0.743*** (0.051)
# Bids: 5	7.140*** (0.030)	7.043*** (0.029)	0.769*** (0.052)
# Bids: 6	7.182*** (0.030)	7.080*** (0.029)	0.822*** (0.053)
# Bids: 7	7.197*** (0.030)	7.087*** (0.029)	0.880*** (0.053)
# Bids: 10	7.201*** (0.032)	7.105*** (0.030)	0.995*** (0.054)
Lot size	0.010*** (0.001)	0.005*** (0.001)	
Lot size <sup>2</sup>	-0.0001*** (0.00001)	-0.0001*** (0.00001)	
Soil quality	0.015*** (0.0003)	0.013*** (0.0003)	
Lot size×Soil quality	0.00004* (0.00002)	0.0002*** (0.00002)	
# parcels	-0.005*** (0.001)	-0.003*** (0.0005)	
Share arable land	0.654*** (0.010)	0.430*** (0.011)	
Share other land	-1.421*** (0.040)	-0.963*** (0.040)	
Lease Bids [0\1]	0.107*** (0.012)	0.087*** (0.011)	
$\log(1 + \tilde{Z}^u)$		0.330*** (0.007)	
$\log(A)$			0.893*** (0.006)
Year Dummies	Yes	Yes	No
State Dummies	Yes	Yes	No
Year × State	Yes	Yes	No
R <sup>2</sup>	0.484	0.52	0.5
Observations	30,264	30,264	30,264
Res. Std. Error	0.621	0.599	0.611

*Note:* Dependent variable is the log of the bids. Year and State indicate if dummies for each the observation year and the federal state is included, Year×State is their interaction. Estimation suppresses the intercept and we calculate  $R^2 = 1 - \sum_i \hat{\epsilon}_i^2 / \sum_i (y - \bar{y})^2$ . \*p<0.1; \*\*p<0.05; \*\*\*p<0.01.

### 5.3 Valuations and testing for CV

Using the homogenized bids, we calculate bidders expected valuations according to equation 8. By visual inspection, estimated valuations monotonically increase with



the bids with few exceptions at the upper boundaries. Figure 4 shows the resulting distributions of these pseudo-valuations,  $\hat{F}_n$ , for  $n = \{2, 4, 6, 10\}$  for the different homogenization procedures. Following Li et al. (2002), valuations in this figure are trimmed to the interval  $[b_{min} + h_g, b_{max} - h_g]$ , where  $b_{max}$  ( $b_{min}$ ) is the maximum (minimum) bid in any  $n$ -bidder auction and  $h_g$  is the corresponding bandwidth. The resulting distributions show differences in shapes but generally similar orders for different  $n$ . Comparing  $S1$  and  $S2$  shows the effect of including our measure for unobserved heterogeneity. ECDFs are slightly steeper for  $S2$  and gaps considerably decrease. Nonetheless, for both models ECDFs indicate a left shift with increasing competition, which is in line with a common value framework. Compared to  $S1$  and  $S2$ , ECDFs for  $S3$  are shifted considerably to the left but show nonetheless similar orders. Gaps are less pronounced than for the other models. Thus, all models indicate a left shift of the valuations with increasing  $n$ . This shift is generally largest if  $n$  is small suggesting that information of an additional bidder is more important among fewer bidders. However, the distribution also suggest that models including some measure for unobserved heterogeneity ( $S2, S3$ ) result in smaller differences than if no such measure is included.

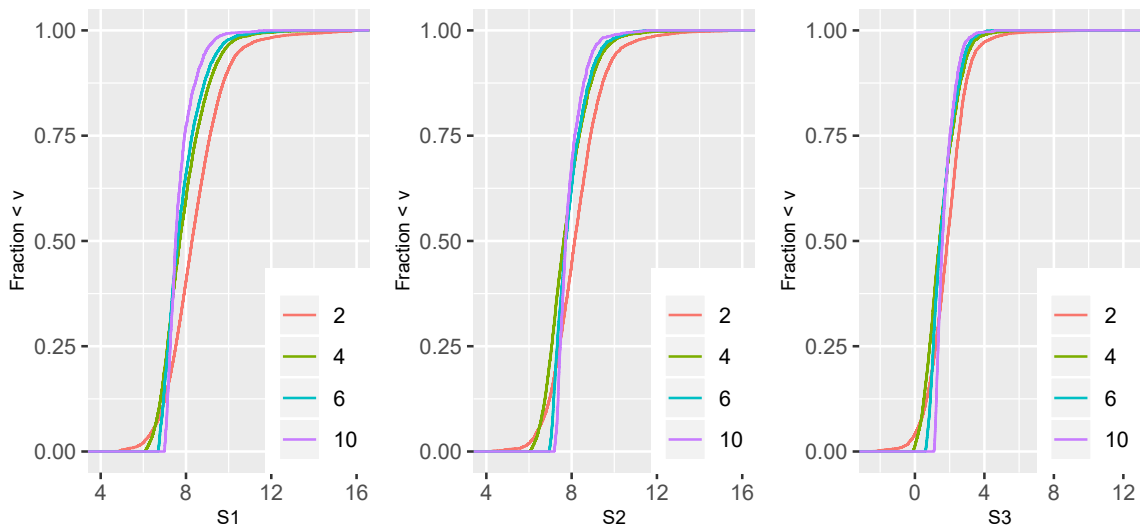


Figure 4: Distributions of estimated expected valuations

The presented empirical distributions of pseudo-valuations clearly suggest underlying the presence of a common value or a common component. To formally test this finding, we implement the test by Haile et al. (2003). Test results for our four speci-

fications are summarized in Figure 5 in terms of estimated trimmed mean valuations  $\hat{\mu}_{n,\tau}$  for  $\tau = 0.05$  and error bars for one standard deviation  $\sigma_{n,\tau}$ . All specifications show a decreasing trend with increasing competition. Standard errors obtained by block bootstrapping the means are small. The presented results lead to a strong rejection of the null hypothesis of pure private values with p-values being virtually one in all cases.

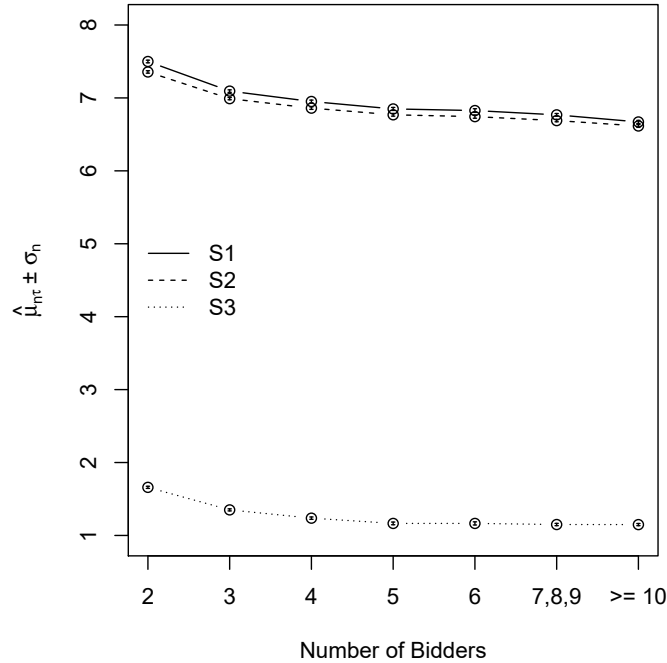


Figure 5: Estimates of  $\mu_{\tau,n} \pm \sigma_{n,\tau}$  for  $\tau = 0.05$

Because the choice of the trimming point  $\tau$  influences estimates of  $\hat{\mu}_{n,\tau}$  and its standard error, we also perform the test with  $\tau = \{0.01, 0.025, 0.1, 0.2\}$ . Resulting estimates show only small changes and lead to the same conclusion. Thus, overall, we find strong evidence for common values or a common component in the bidders valuation.

## 6 Discussion and Conclusions

This article tests the presence of potential common values in land privatization auctions in eastern Germany during the price boom 2007-2018. Based on a large and detailed sample of farmland auctions, we disentangle appraisals to control for auction heterogeneity and validate the approach with three different model specifications. Our analysis indicates considerable heterogeneity across auctions, where indicators for unobserved heterogeneity suggest considerable heterogeneity beyond observed factors. Nonetheless, tests for common values as proposed by [Haile et al. \(2003\)](#) provide strong evidence for common values, independent from the specification. Because optimal auction design crucially depends on the type of the bidders' valuations, the common component in bidders' valuations has considerable policy implications that require further discussion.

From a theoretical point of view, if a common component is present, optimal auctions (e.g., [McAfee et al., 1989](#); [McAfee and Reny, 1992](#); [Du, 2018](#)) would allow a complete rent extraction by the auctioneer but may not be practically useful due to their informational requirements (see [Brooks and Du, 2019](#)). Nonetheless, more practical implications can be directly drawn from the auction literature. In particular, more efficient auction design may increase total revenues of the seller while simultaneously decreasing the winner's curse for overly optimistic bidders.

First, in contrast to the current use of first-price sealed-bid procedures, theoretical results of [Milgrom and Weber \(1982\)](#) and empirical evidence (e.g., [Shneyerov, 2006](#)) suggests revenue superiority of open auctions in the APV model. However, survey data on German land markets ([Hüttel et al., 2020, mimeo](#)) suggests that potential buyers partly prefer to not publicly reveal their willingness to pay or their identities. Thus, open outcry auctions may reduce competition and efficiency of auction outcomes. However, anonymous open auctions, e.g. online auctions, may be considered. In particular, knowledge about the willingness to pay of other bidders, which is available in such a auction format, may simultaneously reduce bidders' uncertainty, overbidding and the winner's curse.

Second, following the linkage principle [Milgrom and Weber \(1982\)](#); [Cho et al. \(2014\)](#), provision of information by the auctioneer results in higher sales prices and increases efficiency as it reduces bidders costs of information acquisition. This suggest the

publication the appraisals as well as any other information privy to the auctioneer. Currently, only winning bids of past auctions are published, which allows potentials bidders to infer only on the valuation of the most optimistic bidder rather than on the distribution of valuations. Providing additional information on the bid structure (e.g., the three highest bids) can again increase the efficiency of the auction and may reduce the winner's curse. Likewise, publication of the decision rule for the award of a sales contract or a rental contract may help bidders forming their bids.

Third, in contrast to the current practice without reservation prices, optimal reservation prices (cf. [Li et al., 2003](#)) allow the auctioneer to reduce the winning bidders' informational rents and capturing more successfully their willingness to pay. However, reservation prices may result in failed auctions. In practice, this might slow down the privatization process and might not be of interest of BVVG.

And fourth, as shown by [Haile \(2003\)](#), a seller can only benefit from a resale opportunity for the auctioned good. This suggest that waiving the currently applied resale ban within 15 years after the auction increases revenues as it may increase bidders' valuations while also attracting additional bidders. However, while resales may increase market liquidity, they may interfere with BVVG's spatio-temporal supply strategy, which also considers the agrarian structure and economic considerations.

Regarding the validity of our results and implications, our study has several limitations. First, additional unobserved heterogeneity may be present and may further explain observed bidder behavior. Another issue may be the asymmetry among bidders, which may bias identification of valuations (see [Croonenbroeck et al., 2019](#), for a detailed discussion). Also, we acknowledge that our sample considers only a segment of the German land market. Auctions of farmland by other public institutions offer preferential conditions for former tenants, which may result in self-selection of bidders into auction formats. Lastly, our sample considers only auctions in eastern Germany with a given regulatory framework. Whether our findings apply to other regions with different institutional and regulatory settings requires testing in the specific context.

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# A Appendix

## A.1 Additional data description

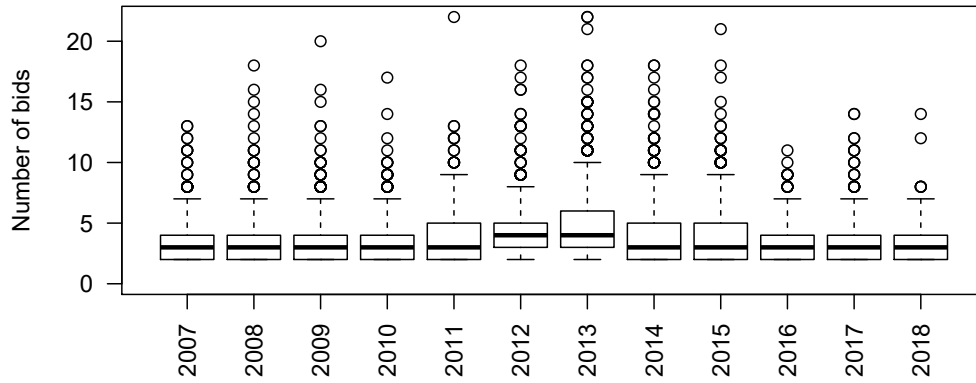


Figure 6: Number of buy bids over time

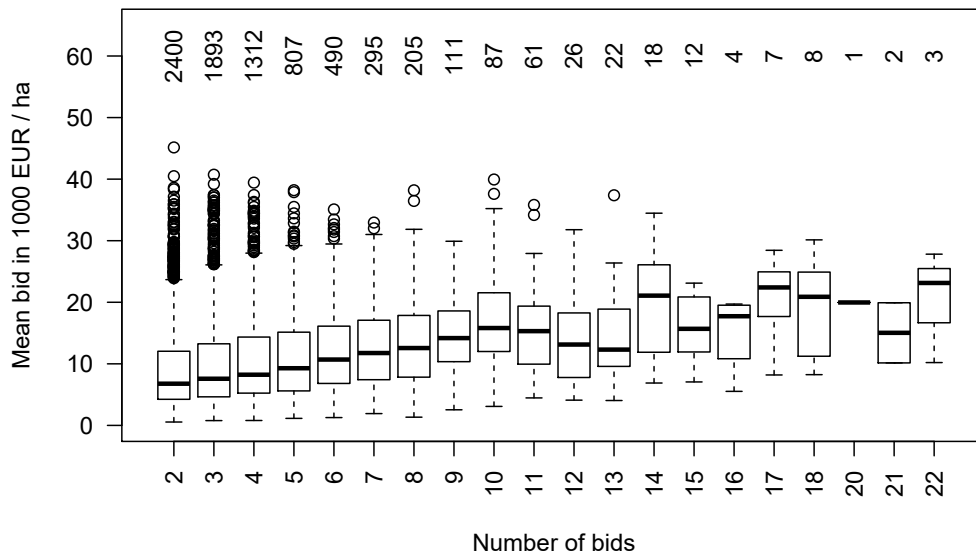


Figure 7: Number of bidders and median bids

## A.2 Determinants of the appraisals

Table 6: Determinants of the log(Appraisal)

	(M1)	(M2)	(M3)	(M4)
Lot Size	0.001 (0.001)	0.01*** (0.001)	0.002*** (0.001)	0.002*** (0.001)
Lot Size <sup>2</sup>	-0.0000** (0.0000)	-0.0000*** (0.0000)	-0.0000 (0.0000)	-0.0000 (0.0000)
Soil Quality	0.01*** (0.0004)	0.01*** (0.0002)	0.01*** (0.0003)	0.01*** (0.0003)
Arable land	0.66*** (0.01)	0.60*** (0.01)	0.61*** (0.01)	0.61*** (0.01)
Other land	-0.49*** (0.06)	-0.86*** (0.04)	-0.95*** (0.04)	-0.95*** (0.04)
Parcels	-0.01*** (0.001)	-0.01*** (0.001)	-0.004*** (0.001)	-0.003*** (0.001)
Lease Bids Allowed	0.24*** (0.02)	0.04*** (0.01)	0.06*** (0.01)	0.05*** (0.01)
Number of bids	0.004 (0.003)	-0.01*** (0.002)	0.0001 (0.002)	0.001 (0.002)
Year	No	Yes	Yes	Yes
State	No	No	Yes	Yes
Year × State	No	No	No	Yes
R <sup>2</sup>	0.430	0.729	0.879	0.785
Observations	7,764	7,764	7,764	7,764

*Note:* Dependent variable is the log of the appraisal in each auction. Year and State indicate if dummies for each the observation year and the federal state is included, Year×State is their interaction. Estimation suppresses the intercept and we calculate  $R^2 = 1 - \sum_i \hat{\epsilon}_i^2 / \sum_i (y - \bar{y})^2$ . \*p<0.1; \*\*p<0.05; \*\*\*p<0.01.

### A.3 Descriptive statistics $\tilde{Z}^u$ and $\theta$

Table 7: Summary statistics of  $\tilde{Z}^u$  in 1000 Euro per hectare

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Min.	0	0	0	0	0	0	0	0	0	0	0	0
1st Qu.	0.80	1.83	2.30	2.66	2.36	2.32	2.88	3.23	4.86	5.62	5.24	3.01
Median	1.45	2.86	3.45	4.68	4.05	4.12	4.79	6.40	9.23	10.39	9.46	6.76
Mean	2.01	3.43	4.13	5.22	4.87	5.37	5.89	7.22	10.14	12.29	10.78	8.16
3rd Qu.	2.37	4.26	5.10	6.94	6.84	7.91	8.12	10.24	14.55	18.41	15.43	12.48
Max.	17.23	34.89	26.11	29.32	18.84	35.66	29.18	26.37	48.40	38.72	37.75	26.19

Table 8: Summary statistics of  $\theta$  in % of the appraisal

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Min.	0	0	0	0	0	0	0	0	0	0	0	0
1st Qu.	0.27	0.46	0.45	0.49	0.41	0.38	0.37	0.39	0.53	0.60	0.44	0.26
Median	0.42	0.63	0.61	0.62	0.53	0.52	0.50	0.53	0.63	0.71	0.62	0.41
Mean	0.42	0.59	0.57	0.59	0.51	0.49	0.48	0.50	0.60	0.67	0.57	0.40
3rd Qu.	0.55	0.76	0.71	0.74	0.65	0.64	0.61	0.64	0.72	0.80	0.71	0.56
Max.	0.96	0.98	0.94	0.93	0.91	0.95	0.92	0.98	0.97	0.95	0.94	0.89

Table 9: Homogenization regression: spatio-temporal control I

	(S1)	(S2)
LandMV	0.069 (0.046)	-0.037 (0.044)
LandSN	0.031 (0.048)	0.018 (0.046)
LandSA	0.010 (0.053)	-0.025 (0.051)
LandTH	0.156** (0.065)	0.107* (0.062)
Year2008	0.231*** (0.035)	0.121*** (0.034)
Year2009	0.271*** (0.037)	0.061* (0.036)
Year2010	0.311*** (0.035)	0.063* (0.034)
Year2011	0.457*** (0.034)	0.253*** (0.033)
Year2012	0.400*** (0.034)	0.201*** (0.033)
Year2013	0.712*** (0.035)	0.455*** (0.034)
Year2014	0.752*** (0.037)	0.484*** (0.036)
Year2015	0.826*** (0.034)	0.451*** (0.034)
Year2016	0.924*** (0.038)	0.516*** (0.037)
Year2017	0.988*** (0.036)	0.656*** (0.035)
Year2018	0.936*** (0.048)	0.693*** (0.047)
R <sup>2</sup>	0.48	0.52
Observations	30,264	30,264
Residual Std. Error	0.621	0.599

*Note:* TH denotes Thuringia, SN is Saxony, BB is Brandenburg, MV is Mecklenburg-West Pomerania, and SN is Saxony-Anhalt. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01.

Table 10: Homogenization regression: spatio-temporal control II

	(S1)	(S2)
MV 2008	0.116* (0.059)	0.131** (0.057)
SN 2008	-0.010 (0.066)	-0.045 (0.064)
SA 2008	-0.114* (0.068)	-0.073 (0.066)
TH 2008	0.020 (0.081)	-0.003 (0.078)
MV 2009	0.284*** (0.058)	0.307*** (0.056)
SN 2009	0.001 (0.067)	0.044 (0.064)
SA 2009	-0.042 (0.064)	0.009 (0.062)
TH 2009	-0.041 (0.079)	0.078 (0.076)
MV 2010	0.267*** (0.057)	0.276*** (0.054)
SN 2010	-0.006 (0.065)	0.052 (0.063)
SA 2010	0.037 (0.064)	0.048 (0.062)
TH 2010	-0.124 (0.078)	-0.015 (0.075)
MV 2011	0.266*** (0.055)	0.218*** (0.053)
SN 2011	-0.168** (0.078)	-0.054 (0.075)
SA 2011	0.015 (0.061)	0.066 (0.059)
TH 2011	-0.173** (0.075)	-0.019 (0.072)
MV 2012	0.409*** (0.055)	0.303*** (0.054)
SN 2012	0.123* (0.067)	0.121* (0.065)
SA 2012	0.131** (0.063)	0.130** (0.061)
TH 2012	-0.081 (0.073)	0.043 (0.070)
MV 2013	0.178*** (0.056)	0.087 (0.054)
SN 2013	-0.032 (0.065)	0.017 (0.063)
SA 2013	0.071 (0.061)	0.079 (0.059)
TH 2013	-0.177** (0.072)	-0.035 (0.069)
MV 2014	0.260*** (0.058)	0.154*** (0.056)
SN 2014	-0.065 (0.067)	-0.025 (0.065)
SA 2014	0.092 (0.063)	0.046 (0.061)
TH 2014	-0.032 (0.072)	0.008 (0.069)
MV 2015	0.352*** (0.056)	0.265*** (0.054)
SN 2015	-0.0003 (0.067)	0.044 (0.065)
SA 2015	0.138** (0.062)	0.124** (0.060)
TH 2015	-0.023 (0.073)	0.030 (0.070)
MV 2016	0.245*** (0.060)	0.161*** (0.058)
SN 2016	-0.120 (0.078)	-0.106 (0.075)
SA 2016	-0.081 (0.072)	-0.048 (0.069)
TH 2016	-0.218* (0.115)	-0.157 (0.111)
MV 2017	0.277*** (0.058)	0.138** (0.056)
SN 2017	-0.245*** (0.071)	-0.274*** (0.068)
SA 2017	-0.065 (0.063)	-0.082 (0.061)
TH 2017	-0.241*** (0.086)	-0.126 (0.083)
MV 2018	0.223*** (0.068)	0.102 (0.065)
SN 2018	-0.057 (0.083)	0.006 (0.080)
SA 2018	-0.111 (0.074)	-0.060 (0.072)
TH 2018	-0.569*** (0.112)	-0.508*** (0.108)
R <sup>2</sup>	0.48	0.52
Observations	30,264	30,264
Residual Std. Error	0.621	0.599

*Note:* TH denotes Thuringia, SN is Saxony, BB is Brandenburg, MV is Mecklenburg-West Pomerania, and SN is Saxony-Anhalt. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01.

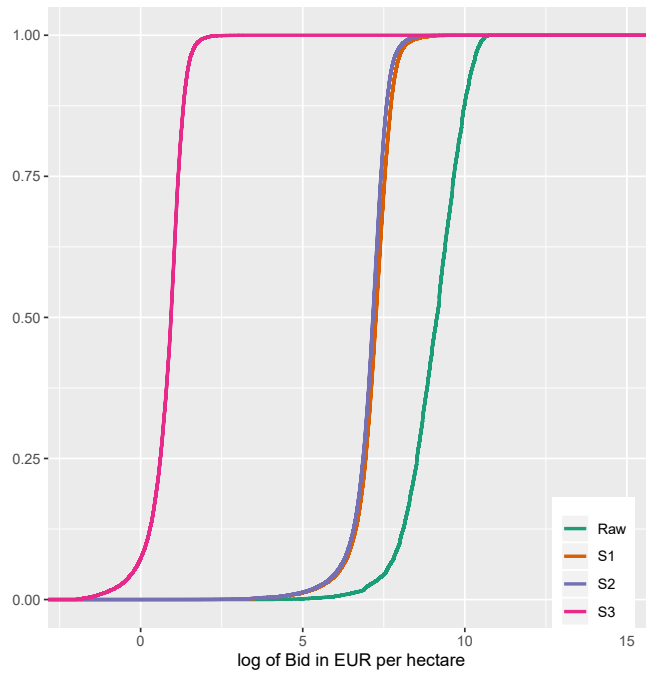


Figure 8: ECDFs of homogenized bids

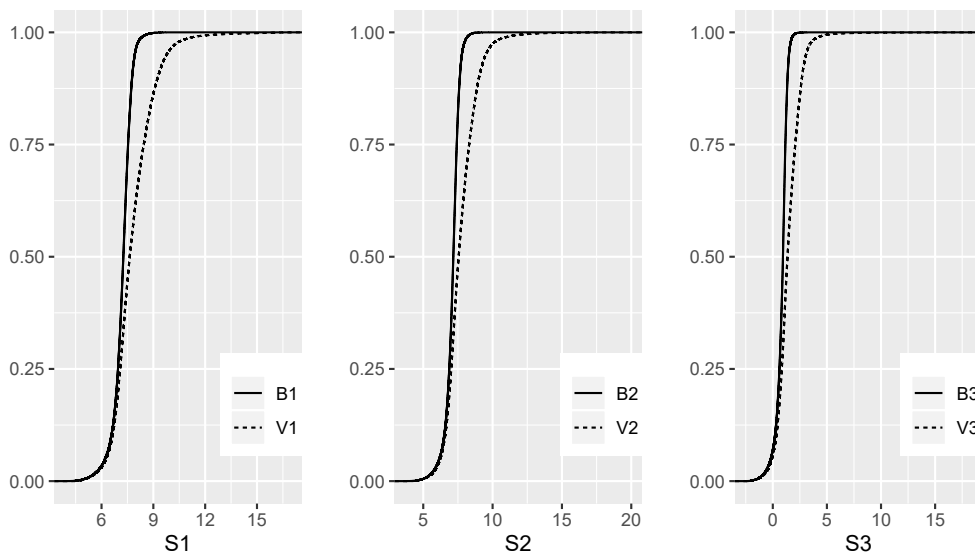


Figure 9: ECDFs of pseudo-valuations and homogenized bids