How smart should farms be modeled?
Behavioral foundation of bidding strategies in agent-based land market models

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1 Abstract:

Land markets play a crucial role in agricultural structural change. Because the dynamics of structural change and land markets, respectively, mainly depend on the interactions between individual farms, agent-based modeling (ABM) has been established as a tool for understanding and explaining structural change and land market dynamics. This is particularly so because of ABM's ability to capture heterogeneity, non-convexity and dynamics. Unfortunately, the behavioral foundation of economic actors in ABM, i.e., of the farms, is often specified as *ad hoc* or simply based on "expert knowledge". In this contribution, the highly-detailed ABM AgriPoliS – which uses a myopic normative behavioral foundation – is coupled with a genetic algorithm (GA) to detect market equilibria on a land market. This is done in the dynamic context of the model and its heterogeneous, non-convex production functions. This approach enables the creation of a benchmark with a sound economic foundation for evaluating alternative behavioral patterns. As results illustrate, forming a rational strategy requires bidders that are able to anticipate size effects and their growth potential in a competitive situation. Moreover, the contribution shows that reaching the market equilibrium would imply "aggressive" bidding strategies.

JEL CODE: Q12, C6

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2 Introduction

Due to agent-based models' (ABM) ability to interpret complex systems from the "bottom-up", in recent years a broad range of research questions within the field of agricultural economics and natural resource management have been addressed with agent-based approaches (cf. Parker et al., 2003, Bousquet and Page, 2004). ABM in agricultural economics are most often application-oriented and used e.g. for policy and scenario analysis. A particular advantage of this approach is the flexibility in modeling individual behavior. Nevertheless, this flexibility has to be treated carefully with respect to the validation of models and their predictive power. The literature on ABM shows two main possibilities for creating underlying behavioral models: One approach is to derive behavioral assumptions empirically by interviewing real agents. Pioneering work in this respect was done with the so-called companion modeling approach using the CORMAS framework (D'Aquino et al., 2003). The drawback of this approach is that the behavioral models often lack a theoretical foundation, stressing the case study character and thus prohibiting generalization.

More promising in this respect are models with a normative behavioral foundation. Examples of a normative behavioral foundation in ABM can be found in Balmann (1997), Berger (2001), Happe (2004) and Hoffmann et al. (2003). Assuming rational actors, the task here is to answer the question of how actors *should* solve their decision problems. This is unproblematic in the case of decision problems where actors are assumed to be price takers. In the case that strategic behavior plays a role, as we later show for a land rental market, the problem is that the rational strategy is only analytically tractable for very limited cases with a restrictive assumption (e.g. 2-player, discrete finite action set, etc.). As a consequence, strategic aspects often remain unconsidered in ABM. Inevitably, behavioral assumptions serve at best as an approximation of economically-rational behavior. This is unsatisfying, because if the rational strategy of an actor, i.e., a normative evaluation criterion is unknown, it is not possible to evaluate alternative behavioral assumptions (e.g. empirically-derived ones). Indeed, a sound empirical or theoretical foundation for the agents' decision-making is, in most cases, only partly provided (cf. Parker et al., 2003).

This contribution tries to gap that problem. Taking the AgriPoliS model (cf. Happe, 2004) as an example, we show for the land rental market, as specified in AgriPoliS, how methods like genetic algorithms (GA) can be used to determine rational behavioral strategies in complex decision tasks. In a subsequent step, the identified strategies are fed back to AgriPoliS, where they serve as a normative behavioral model. These strategies are examined for both their short-term (static) and long-term properties (in the dynamic framework of AgriPoliS) with respect to their implications on structural change, efficiency and distributional effects. At the same time, these strategies are compared to alternative, more myopic, behavioral models. From a methodological point of view, this is an important contribution to the validation of ABM.

The outline of the paper is as follows: In Section 2 we give a brief introduction into AgriPoliS and raise some issues related to modeling land markets. In Section 3 the GA model is presented and we show how the model is connected to AgriPoliS. In Section 4 we present results and discuss the implications of different behavioral models.

3 Behavioral assumptions in agent-based models

The framework for the analysis is the AgriPoliS model (Happe, 2004), a normative, spatial and dynamic model of agricultural structures. Thus, an agricultural region is divided into quadratic cells of equal size which represent idealized plots with a homogenous land quality (arable land). Some plots in the region also serve as farmsteads. The spatially-distributed farms compete as agents on product and factor markets, where they act autonomously in order to maximize their household income. The core of the farm's decision-making is a mixed integer program specified as follows:

The farms have to simultaneously select from 21 production activities and 37 investment alternatives. In addition to the standard production activities, there are a number of auxiliary activities: A farm agent can hire labor on a fixed or per-hour basis; conversely, farm family labor can be offered for off-farm employment. To finance farm activities and to balance short-term liquidity shortages, farm agents can take on long-term and/or short-term credit. Unused liquid assets are invested at the assumed savings rate. Regarding prices, the farms have adaptive expectations.

The investment opportunities allow for scale effects, with further scale effects emerging if a farm's plots are adjacent. AgriPoliS aims to mimic the effect of technological progress and learning by decreasing production costs by a certain percentage in the case of re- (or new) investments. Investment costs are assumed to be sunk.

The internal state of a farm is organized as a balance sheet, which keeps track of factor endowments, the farms' age, and expectations about future prices, along with a number of financial indicators. Based on these indicators, a farm's further possible actions are derived. Farms can rent in additional land plots; farm agents decide whether to exit or stay in the sector. A farm exits either if its equity capital is zero, the farm is illiquid, or if opportunity costs of farm-owned production factors are not covered. After a farm agent has reached a certain age, a generational change takes place where higher opportunity costs are assumed.

Interaction between farms is defined via markets for factor inputs and products. For products, capital and labor, prices are determined via an exogenous price function with a given price elasticity and a price trend factor for each product. The land market, which has a central position in the model, is modeled as an auction where the farms directly compete for free land plots, as we will later describe in more detail.

For the base period the model is calibrated to the empirical data of the study region.

To summarize the decision-making process of a farm, Figure 1 displays the single stages of the farms` actions during one period. Figure 1 also shows that decision-making takes place on different levels. Whereas there are decisions such as calculating the production program, which can be taken independently from the behavior of the other assuming price takers, there are others where this is not the case. This is especially evident for the land market. In every period, free plots (i.e., plots for which rental contracts have ended) are allocated through a sequential auction. The latter means that in AgriPoliS, only one plot at a time is allocated through a first-price sealed-bid auction. These auctions are repeated until there is no further demand for land or no free plots.

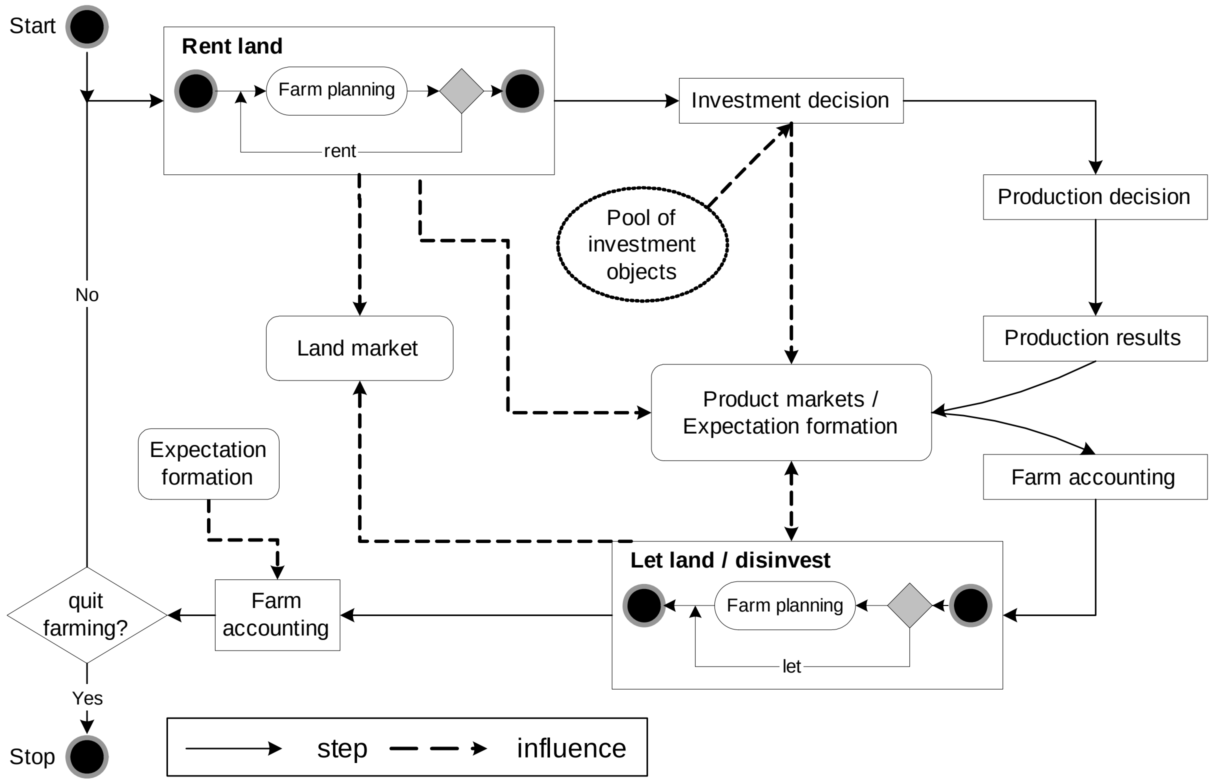

Figure 1: Course of action during one period in AgriPoliS. Source: Happe (2004)

In this context, one can ask how a suitable behavioral rule can be formulated for the agents' bidding behavior in this land auction. From a farm's viewpoint, there are two issues to consider:

a) Because of the indivisibility of the investments, the shadow price function for land is discontinuous and most notably non-monotone. To realize implicit scale and size effects, a bidder must formulate an expectation about his possibilities to get further land plots and the resulting benefits. Scale and size effects cause interdependencies between plots, which means that although it is possible to determine the value of a bundle of plots, it is *a priori* not possible to determine the value of a certain part of a bundle. Parts of a bundle can be complementary or substitutable for one another.

b) A bidder must have an expectation about the valuation of the other bidders because the offer of the bidder with the highest valuation should be only marginally above the second-highest bid.

Unfortunately, optimal bidding behavior in an auction setting, as it is defined in AgriPoliS, cannot be directly derived from auction theory. Known solutions are limited to cases where single, independent goods are traded and even additional assumptions, like e.g. uniformly distributed valuations are made (cf. e.g. Klemperer, 1999). Therefore, a strictly normative behavioral foundation must be given up due to the complexity of the strategic decision problem. For this reason, a combination of optimization and *ad hoc* rules is used in AgriPoliS to parameterize a number of alternative behavioral strategies in the model:

To circumvent the problem of formulating expectations about the valuation of other bidders, AgriPoliS has the option of using a second-price instead of a first-price auction. In the case of a second-price auction, the dominant strategy is to reveal the true valuation of a good, which results in a bid that equals the shadow price minus the transportation costs. Because the winner has only to pay the price of the second-highest bid, this implicitly allows the bidder to anticipate the valuation of the other bidders. Another possible option to reduce the bid, depending on the distribution of the valuation of the other bidders, is to set a parameter which defines the share of the bid of the shadow price.

Nevertheless, the first problem, that plots can be complementary to each other, remains unsolved. In order to consider this problem in AgriPoliS, a simple bidding rule is defined. Instead of calculating the shadow price for just one additional plot, the average shadow price for a fixed number (e.g. 8) of plots is calculated and the maximum value is chosen.

As argued above, the bidding in AgriPoliS relies on *ad hoc* formulated rules. This procedure is dissatisfying as long as we cannot quantify the effects of the chosen assumptions. Therefore, the knowledge of a strictly normative strategy would allow us to quantify these effects by serving as a benchmark. In the following section, we develop a methodological framework to create such a benchmark in the context of the AgriPoliS model using GA.

4 Determination of rational bidding strategies using genetic algorithms

The usage of GA for optimization problems dates back to the work of Rechenberg (1973) and Holland (1975). GA are a stochastic-numerical heuristic search technique, which uses evolutionary principles to structure the search space of an optimization problem. The procedure of the algorithm shows a direct analogy to the biological archetype. Starting off from a population of individuals, where each individual represents a solution of the problem, a value is assigned to each individual representing this individual's fitness (e.g. the profit of a strategy). After the fitness evaluation is done the genetic operators selection, crossover, mutation and migration are applied to the population.

Although GA are a heuristic search method, there exist a number of contributions where GA are successfully applied to game theoretic problems (cf. Birchenhall, 1995). For example, Arivofic (1994) uses GA to determine the supply in a Cobweb model. Price (1997) shows how GA can be used to determine Nash equilibria in Bertrand and Cournot Competitions. Andreoni and Miller (1995) show through simulation experiments that GA are able to determine Nash-strategies for a number of standard auction models. Marks (1992) uses GA to explain oligopolistic behavior. For agricultural land markets, Balmann and Happe (2001) show how GA can be used to explain oligopolistic behavior; the idea of the GA model in the current contribution is based on this study. Like in AgriPoliS, the region is interpreted as a GIS-like grid where the single cells represent the land plots in the region and the farms are allocated on these plots. Balmann and Happe (2001) use an estimated polynomial production function with a unique global optimum farm size. In the current contribution, however, the each farm's production function is defined via the AgriPoliS mixed integer programming model for a specific arable region in East Germany. For the land auction, every farm's bidding is derived via a GA with a farm-specific population of *n* genomes in which genome i (i=1..n) encodes the following parameters:

- Participation in the auction, T_i
- Initial bid, IG_i
- Bid differentiation coefficient , dG_i
- Maximum desired area, $B_{MAX,i}$

Dependent on these parameters, a farm's bidding function is defined as follows:

$$P_i(b_{x,y}) = \begin{cases} IG_i - dG_i \cdot b_i - TC_i(b_{x,y}) & \text{für } T_i = 1 \wedge b_i < B_{max,i} \\ \text{no bid} & \text{für } T_i = 0 \vee b_i \geq B_{max,i} \end{cases}, \tag{1}$$

where $b_{x,y}$ represents the plot currently being auctioned and $TC_i(b_{x,y})$ are the transportation costs to this plot. The structure of the model is as follows: One run of the model is divided into a number of generations for each production period (year), where each generation consists of 30 so-called test iterations. During one test iteration, every farm randomly picks a genome, i.e., a bidding function. Based on this bidding function, all free plots in the region are auctioned in a sequential first-price sealed-bid auction. Within an auction, a farm searches for the next free plot and formulates a bid according to their bidding function. At the end of a test iteration, the fitness of the chosen strategy is evaluated considering the resulting acreage. Fitness is determined by the objective value of the farm-specific programming model minus the expenses for rents and transportation costs, i.e., the farm's profit is the basis for the fitness of the strategy. After all genomes of all farm's are evaluated, the genetic operators are applied to generate, for each farm, the genome population for the next generation. This is repeated until the genome populations of the farms converge.

Because we assume non-convex, heterogeneous production functions, as well as a lack of a theoretical indication regarding the quality of the found solution, the resulting allocation is further examined. Rational behavior would imply that, for an auction setting, the resulting allocation should be economically efficient, i.e., there are no efficiency improvements possible by exchanging plots between farms. In an auction, this would mean that the bidder with the highest valuation receives the plot. In the case of convex production functions, this could be checked by screening the marginal land rents of the farms. However, as the production functions are non-convex and farm–specific, this would only provide an indication of the local properties of the solution. Therefore, we refer to the average economic land rent as an indicator for efficiency. To draw a normative conclusion, we nevertheless need a suitable reference scenario, i.e., we have to determine the allocation with the maximum possible economic land rent. Calculating such an allocation leads to a combinatorial problem, where already with a few farms and free plots in the region the solution cannot be obtained through full enumeration[1]. Because transportation costs exist, it is straightforward to exclude a large range of solutions in advance, and therefore to reduce the complexity of the problem to the standard 'cake division problem' (Steinhaus, 1948). This problem is solved in two stages: First we calculate the share of land of each farm which is maximizing the total economic land rent. Then, a transportation cost-minimizing allocation is chosen according to the defined shares. To determine the optimal shares we use a standard optimization algorithm, also based on GA.

To create a benchmark allocation, the models are combined as follows: First, AgriPoliS is initialized and simulated for one period. AgriPoliS' resulting state is then used to initialize the GA model, which means we carry forward the actual grid, the farms' mixed integer problems, the current factor endowments and farms' price expectations. The resulting land allocation is fed back into AgriPoliS in order to simulate a further production period. This procedure is repeated until the desired number of iterations is reached.

[1] In the case of *m* farms and *n* free plots, there are m^n possible allocations.

5 Results

For the current application, the model is calibrated to a region in Saxony, a state in the south-east of Germany (cf. Balmann et al., 2004); the model's area consists of approximately 500,000 ha of agricultural area, which covers about 54% of all Saxony. Eighty-six percent of the land in use is arable land. Of the region's approximately 2,900 farms, the predominant farm type is intensive crop farming (56.9%) followed by dairy farming (32.2%). The average farm size is 174 ha.

Based on this calibration, we conduct three different simulation experiments:

1) The standard AgriPoliS model, where we use a first-price auction and a bidding behavior with bids determined according to each farms' shadow price, minus transportation costs. This scenario is called FP.

2) The GA-Auction model, where the bidding strategies are determined by the GA model based on initial conditions given by AgriPoliS. This scenario is called GA.

3) To test GA's solution quality, we create a benchmark for the efficiency of the resulting allocation as described above. This scenario is called GA-ALLOCATION.

As can be seen in Figure 2, when we compare GA and GA-ALLOCATION, according to the Pareto-criterion there is not much space for improving the GA solution. The economic land rent could only be increased by an amount of 2€ per ha. To see how robust these results are, we conducted a sensitivity analysis, where we ran the simulation experiments depending on the same initial allocation, but with randomly chosen initial parameters for the GA. According to Figure 2, both GA and GA-ALLOCATION are quite robust, as the standard deviation is quite low for both scenarios. Also, because the farms in the region show some structural similarities, the resulting fitness landscape implies a large number of similar, local optima. Hence, there is a number of permutations of free plots, which shows similar properties according to the chosen evaluation criterion.

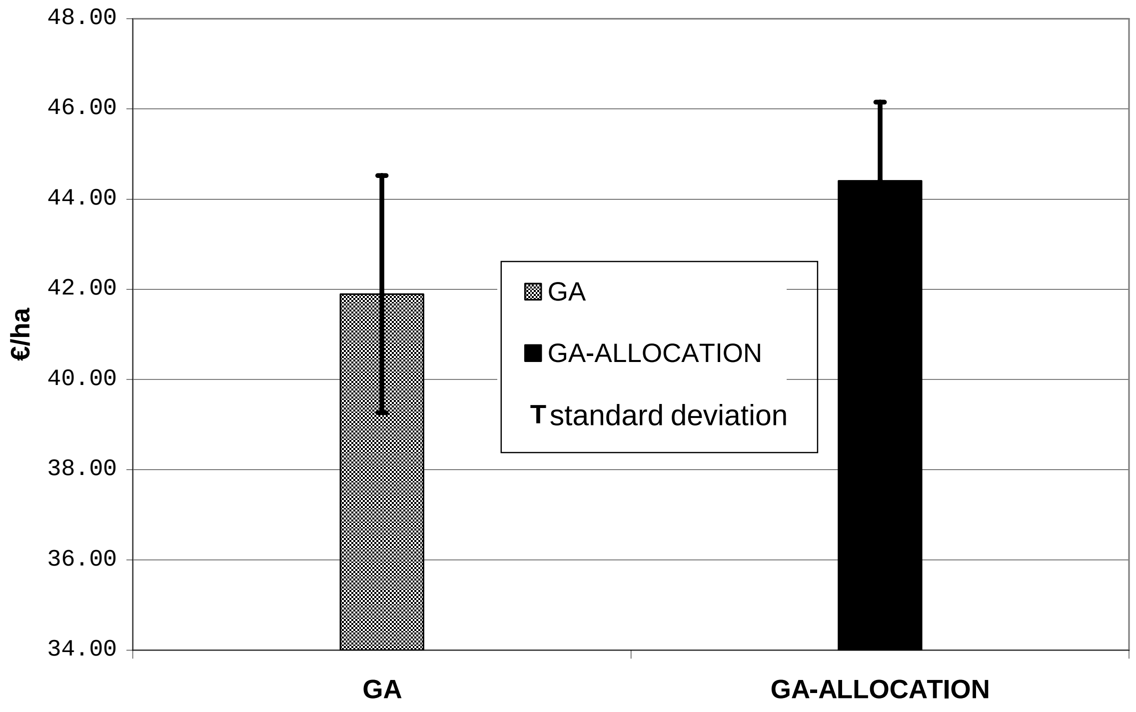

Figure 2: Efficiency gains compared to the standard AgriPoliS model

Overall we can conclude that, although GA is a heuristic method, it is able to determine rational strategies in complex decision tasks.

Next we want to compare this benchmark with alternative behavioral assumptions. If we assume the above-described myopic bidding behavior we can observe, as indicated in Figure 3, that the obtained economic land rent is, with 40 € per newly-rented plot, significantly lower than the economic land rent in the GA scenario. This becomes obvious if we look at the farms' individual production functions. One example of such a function is given in Figure 3, which shows the average and marginal shadow price per ha. Because of the indivisibility of investments, for example for machinery or employment, significant size effects can occur. If farms follow a naive bidding strategy in this situation, they grow only towards a local optimal farm size.

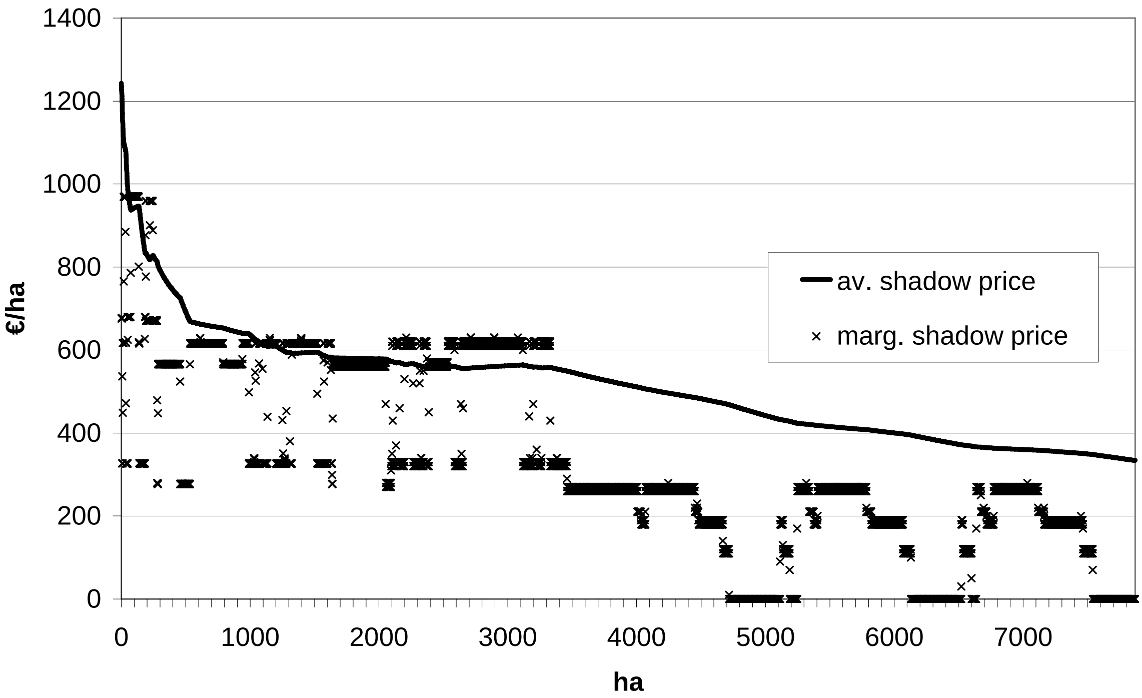

Figure 3: Average and marginal shadow prices resulting from an exemplary production function, source: own calculations

This becomes even clearer if we look at the distribution of paid rental prices as displayed in Figure 4. Obviously, farms grow until a point where a restriction in the farms' factor endowment hold and new investments would be necessary. In the case that all farms in the region reach some local optima, the allocation of the remaining plots takes place at a lower rent level until some farms reach an acreage where shadow prices increase again. Figure 4 shows this bimodal distribution. Overall we can state that the strategies found by the GA are able to a) anticipate size effects and b) form expectations about the possibilities of increasing their acreage. Accordingly, the distribution of rental prices in the GA scenario is relatively uniform.

Of further interest is that the GA scenario results in more "aggressive" growth strategies. This can be seen by the fact that, whereas in the FP scenario 43% of the farms rent at least one additional plot, in GA 65% of the farms could not realize any growth in acreage. On the other hand, there are some farms which increase their size by up to 800 ha, whereas in FP the maximal growth is 400 ha.

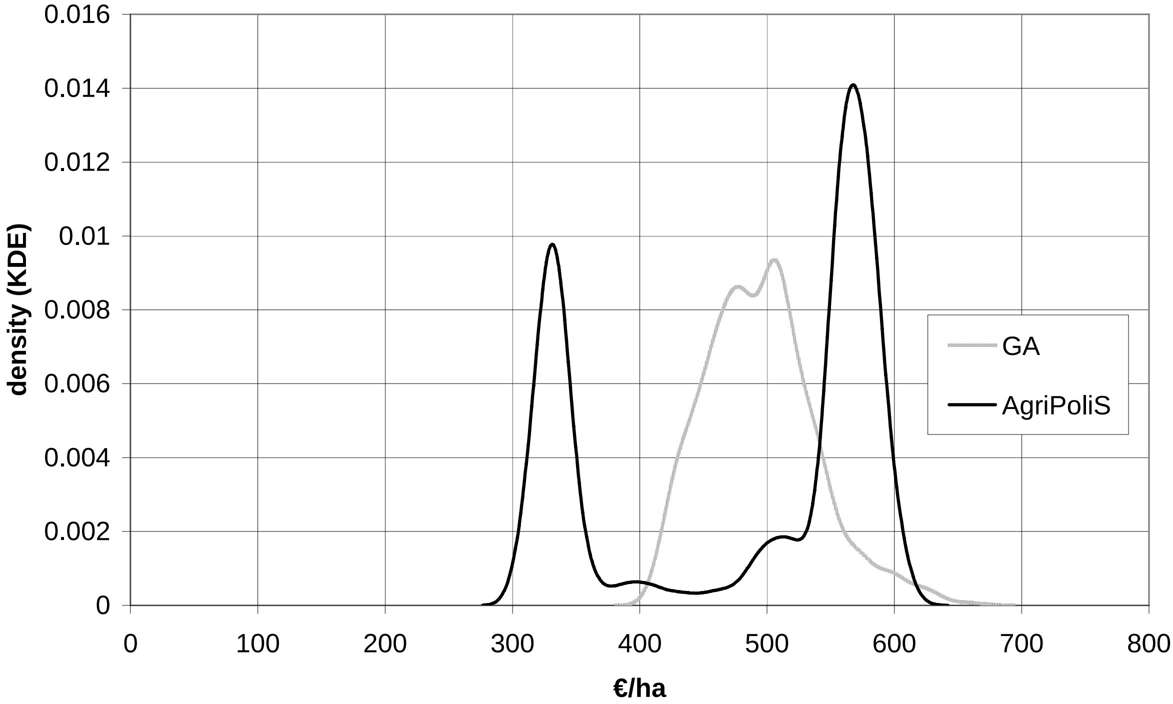

Figure 4: Distribution of land rental prices, source: own calculations

Regarding first implications, we can state that in addition to the considered rationality of farms, market transparency also plays a major role. Unless there is a certain degree of transparency, the farms have no basis upon which to estimate their growth potential and are thus forced to use more myopic strategies.

6 Conclusion

The current contribution attempts to overcome existing shortcomings in agent-based modeling, and especially the modeling of agricultural land markets. Therefore, we develop a methodological framework which allows a sound analysis of alternative behavioral assumptions for decision strategies on land rental markets. By using methods from computational economics, we are able to create a normative benchmark strategy to circumvent the problem that for complex decision problems, analytical solutions are seldom available. It turns out that GA is able to discover suitable strategies even in the presence of non-convex production functions.

In the current contribution we show that a rational bidding strategy would imply that farms are able to anticipate their growth potential resulting from size effects and their competitive situation. In comparison to myopic bidding strategies, this leads to more “aggressive” growth strategies, as well as short-term efficiency gains.

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