COORDINATION AND ALLOCATION ON LAND MARKETS UNDER INCREASING SCALE ECONOMIES AND HETEROGENEOUS ACTORS – AN EXPERIMENTAL STUDY

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Abstract

Economies of scale and scope are often not exploited in Western agriculture. A general reason is probably that various types of transaction costs limit coordination among farmers. A more specific explanation is that coordination on land markets or machinery cooperation is difficult to achieve when farmers are heterogeneous as some kind of price differentiation is necessary for a Pareto-superior solution. This paper investigates experimentally such a coordination game with heterogeneous agents using an example inspired by agricultural land markets. The experimental findings suggest that a Pareto-optimal solution may not be found when agents are heterogeneous. The findings provide evidence for market failures and cooperation deficits as reasons for unexploited economies of scale in agriculture. Our findings are consistent with coordination failures that appear to be driven by behavioural factors such as anchoring-and-adjustment, inequity aversion, and a reverse form of winner's curse.

Keywords: Land Markets, Coordination and Allocation, Experimental Economics

1. Introduction

Western agriculture is characterized by small family farms and unexploited economies of scale and size. Moreover, these small farms do generally not - at least not to the extent as could be expected - establish and participate in different forms of horizontal cooperation that would allow them to benefit from the economics of size advantages of larger farms. The dominance and persistence of small family farms in this part of the world is likely to be a result of historical factors including present and past agricultural policies, and insufficient market mechanisms that do not support re-allocation to more efficient structures (Balmann 1995, Balmann et al. 2006). The establishment of more efficient structures may furthermore be mitigated by various transaction costs that limit vertical and horizontal coordination among farmers. Examples of such transaction costs include limited access to financial resources and opportunistic behaviour. A further potential explanation, which will be explored in this paper, is that there are specific difficulties to coordinate when actors are heterogeneous arising from behavioural factors.

Previous studies have shown that situations which require price differentiation among heterogeneous agents may lead to a market failure (e.g. Balmann, 1995; Aurbacher et al. 1997). Although machinery cooperatives often would lead to an improved economic situation for all involved parties[1], Aurbacher et al. (2007) show that the establishment of such may be organizationally difficult when the farmers are heterogeneous and, e.g., have differing amounts of sunk costs invested in their present machinery. Another example related to coordination on land markets discussed by Balmann (1995) is that the establishment of large arable farms in order to exploit increasing returns may require price differentiation when the existing smaller farmers have heterogeneous reservation prices for their land (due to, e.g., differencing sunk costs and managerial skills).

In order to better understand the under-exploitation of economies of scale in land markets as due to coordination failures, this study applies for the first time an experimental approach to analyze the problem of coordination and allocation in a situation with increasing returns and heterogeneous actors. If compared to an empirical examination, the experimental method offers

[1] Studies from Sweden have shown that partnership arrangements among farmers can contribute to increased profitability and secured economic variability (e.g. Andersson et al., 2005), and that they have a positive impact on overall farm efficiency (Larsén, 2010).

the chance to exactly implement all of the model's assumptions and therewith to directly compare individuals' performance with the normative benchmark. In this study, we rely on the land market example discussed in Balmann (1995). However, similar coordination situations could be identified for horizontal cooperation among farmers, such as machinery-sharing arrangements. The example considers a situation of increasing returns of an entrepreneur who wants to establish a large arable farm in a region dominated by small arable farms. For reasons of simplicity, the existing small farms are assumed to consist of physically identical land plots for which the farms have heterogeneous opportunity costs (reservation prices). These heterogeneous opportunity costs may be resulting from different amounts of sunk costs. The profit-maximizing entrepreneur is assumed to have no own initial land and therefore wants to "take over" land from the small farmers by buying/renting. For the assumed setting, which will be explained in greater detail in the following section, a transaction between the entrepreneur and a sufficiently high number of existing farmers increases the total welfare. However, in order for transactions to take place and a welfare gain to be realized, the entrepreneur cannot compensate all farmers by the same amount. Thus, farmers with low reservation prices for their land cannot be compensated with the same amount as those with high reservation prices. Accordingly, the entrepreneur has to differentiate the land prices, which requires that the farmers reveal private information about their reservation prices. This coordination problem is analyzed experimentally using an auction game in which the participants of the experiment (small farmers) repeatedly make a bid/ an ask (request a price) to a computerized profit-maximizing entrepreneur who in each round determines which bids to accept or reject. The number of accepted bids is thus an indicator of the level of coordination. The outcome of the experiments is compared with a game theoretic prediction obtained using an agent-based model with genetic algorithms in which the agents "learn" their optimal bids.

Besides trying to shed some light on the possibility of exploiting existing economies of scale by price differentiation, this study first implement and experimentally observes the effects of different rooms for negotiation and groups size in a complex coordination problem with heterogeneous players. In fact, this study also add to the knowledge on coordination games with large size groups, which is, with the exceptions of some market entry games (e.g. Rapoport et al., 2000), weak-link games (e.g. VanHuyck et al. 1990), and public goods games (e.g. Isaac and Walker, 1989), still at an early stage. Our experimental results first show the severity of the coordination problem: either many bids are accepted or hardly any. Although are bids generally correlated with opportunity costs, some players seem to fall prey to a reverse winner's curse (Thaler, 1988) by asking below their opportunity cost. Finally, and most probably the most severe obstacle to coordination, most players tend to ask for too much. We relate this behaviour to inequity aversion (Fehr and Schmidt, 1999; Bolton and Ockenfels, 2000) with respect to prices with the low opportunity cost players and with respect to profits with the high opportunity cost players. Inequity aversion essentially points at the fact that individuals both think in term of absolute and relative payoffs (Bolton, 1991) and its occurrence has been experimentally corroborated also in settings with fixed asymmetric endowments of players (Goeree and Holt, 2000) (which, because of the asymmetry of players, might be associated to our setting).

The remainder of the paper is structured as follows. In the following section, the example related to the land market and associated experimental setting will be described. Thereafter, a game-theoretic equilibrium, our normative benchmark, will be derived and the experimental results presented. The paper ends with conclusions and outlook for further research.

2. AN EXAMPLE RELATED TO THE LAND MARKET AND EXPERIMENTAL SETTING

The analyzed setting, based on an example defined in Balmann (1995), considers a situation with increasing returns to scale of a profit-maximizing entrepreneur who wishes to establish a large arable farm in a certain region characterized by small farms by taking over (by buying or renting) the land of the existing farms. The existing small farms are for simplification assumed to endow equally large land plots. While all farmers' land plots are assumed to have identical physical properties and thus being identical for the entrepreneur, the existing farmers have heterogeneous reservation prices (opportunity costs) for their land due to, e.g., differing sunk costs and/or managerial skills.[2] This is exemplified in Figure 1 by illustrating the average and marginal economic rent of the entrepreneur and average and marginal opportunity costs of the farmers. It is furthermore assumed that the total economic land rent of the entrepreneur, after a certain minimum number of land units, is higher than the aggregated opportunity costs of the farmers (for the example in Figure 1, this holds to the right of the point where the average economic land rent of the entrepreneur intersects with the average opportunity costs of the farmers). Thus, for the assumed setting, a welfare-improving situation is achieved if the entrepreneur is able to take over the land of a sufficient number of farmers. However, a realization of this means, for our

[2] Geographical localization of the land plots are for simplification not considered in this example.

setting, that the entrepreneur has to differentiate prices among the farmers as it is not possible for him/her to pay all farmers a price equal to the market price, P_m. A farmer is expected to only accept prices that satisfy his individual rationality constraints (i.e. the received price cannot not be lower than the reservation price), but is it organizationally possible to find a solution with differentiated prices? This was analyzed in an experimental setting where the subjects (students who participated in the experiment) represented farmers and the entrepreneur was computerized and profit-maximizing.

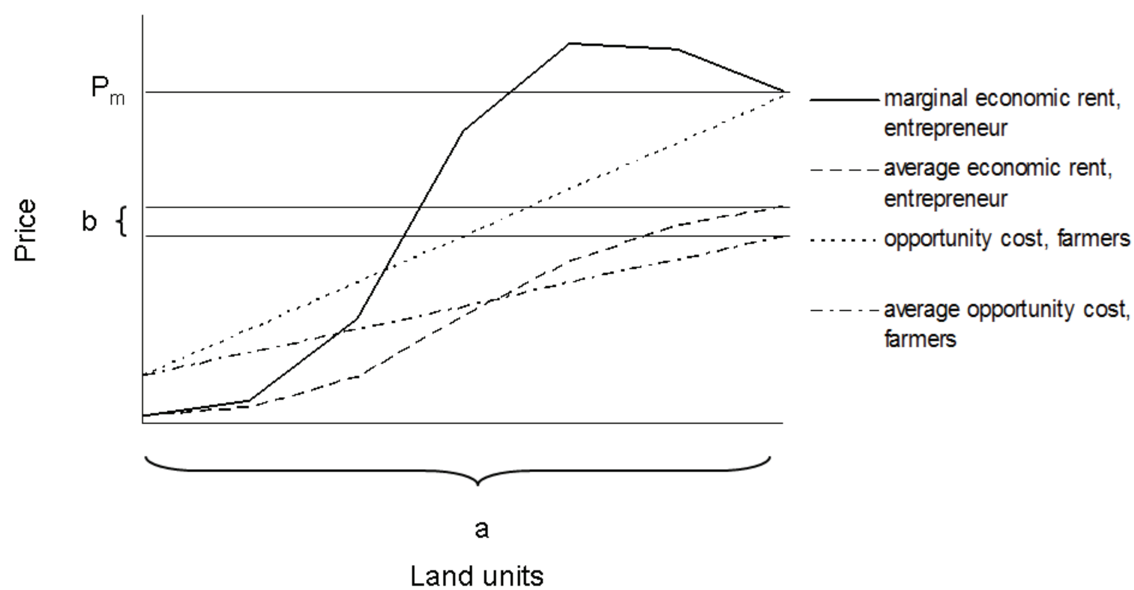

Figure 1: A land market example. Source: Authors.

The potential maximum welfare gain, i.e. the welfare gain that is realized when a transaction takes place between the entrepreneur and all farmers/players, equals the entrepreneurs total value of production subtracted by the sum of the players' reservation prices (area $a \times b$ in Figure 1). In order to analyze the impact of potential welfare gain and group size, four different treatments were used in the experiments (see Table 1): two different levels of potential welfare gain and two group sizes (7 and 14 participants respectively). The parameters where chosen so that the difference in the potential welfare gain is twice as high for treatments 2 and 4 compared to treatments 1 and 3 (704 and 352 units respectively). The assumed parameters, for the entrepreneurs production and the farmers/player, for all 4 treatments are displayed in Table 2 (it should be noted that these parameters where multiplied by 1000 in the experiment). With these treatment manipulations we expected that higher potential welfare gain and small groups of players make coordination easier and enlarge thus the number of transactions. Each experiment consisted of 40 repetitions. In each round, every participant was instructed to make an ask/a bid to the entrepreneur (i.e. to state an amount for which he/she was willing to sell his/her land for) while having information about its own reservation price for land, the distribution of the other participants' reservation prices and the total and average value of the production of the entrepreneur. In every round, each player received a new reservation price which was randomly drawn from the same distribution. This feature has been preferred toward assigning each player a fix reservation price throughout the game, in order to focus, for this first step of analysis, on the groups' capability to coordinate and rather control for learning effects in the form of adjustment. After every round, each participant received feedback on the total number of accepted asks, whether his/her own ask was accepted or not and the own pay-off. In case the bid was accepted by the entrepreneur, the participant received this amount. In case of a rejection of the bid by the entrepreneur, the player received his/her reservation price. In order to avoid strategic behaviour, reputation building, and envy, participants received no feedback on the others' asks and payoffs. The participants in the game received real incentives in the form of monetary compensation that were proportional to their performance in the game.

Table 1: Overview of the treatments. Source: Authors.

		Group size	
		"Small" (7 players)	"Large" (14 players)
Potential welfare gain	"Tight" (A-B = 352)	Treatment 1	Treatment 3
	"Generous" (A-B =704)	Treatment 2	Treatment 4

Table 2 Assumed parameters. * indicates parameters known by the players in the game.† Source: Authors.

Players		Entrepreneur					
		Treatment 1 – "tight room for negotiations"			Treatment 2 – "generous room for negotiations"		
Reservation prices* - 7 players	Total land units	Total value of prod.*	Marginal value of prod.	Average value of prod.*	Total value of prod.*	Marginal value of prod.	Average value of prod.*
Player 1: 80	1	12	12	12.0	14	14	14.0
Player 2: 160	2	52	40	26.0	74	60	37.0
Player 3: 240	3	232	180	77.3	314	240	104.7
Player 4: 320	4	732	500	183.0	874	560	218.5
Player 5: 400	5	1382	650	276.4	1634	760	326.8
Player 6: 480	6	2022	640	337.0	2374	740	395.7
Player 7: 560	7	2592	570	370.3	2944	570	420.6
Reservation prices* - 14 players		Treatment 3 - "tight room for negotiations"			Treatment 4 – "generous room for negotiations"		
Player 1: 40	1	6	6	6.0	7	7	7.0
Player 2: 40	2	12	6	6.0	14	7	7.0
Player 3: 80	3	32	20	10.7	44	30	14.7
Player 4: 80	4	52	20	13.0	74	30	18.5
Player 5: 120	5	142	90	28.4	194	120	38.8
Player 6: 120	6	232	90	38.7	314	120	52.3
Player 7: 160	7	482	250	68.9	594	280	84.9
Player 8: 160	8	732	250	91.5	874	280	109.3
Player 9: 200	9	1057	325	117.4	1254	380	139.3
Player 10: 200	10	1382	325	138.2	1634	380	163.4
Player 11: 240	11	1702	320	154.7	2004	370	182.2
Player 12: 240	12	2022	320	168.5	2374	370	197.8
Player 13: 280	13	2307	285	177.5	2659	285	204.5
Player 14: 280	14	2592	285	185.1	2944	285	210.3

† It should be noted that all parameters were multiplied with 1000 in the experiments.

3. Results

3.1 A game theoretic equilibrium for optimal bidding behaviour

What bidding behaviour is then to be expected from the participants in the experiments? In order to derive a game theoretic equilibrium for the bidding behaviour that can be used as a normative benchmark, an agent-based simulation with genetic algorithms learning was applied (cf. Marks 2002, Balmann and Happe 2000). In the agent-based model, the entrepreneur and the small farmers are modelled as agents with the entrepreneur being, as in the experiments, a strictly profit maximizing computerized agent. The farm agents in the model "learn" their optimal bids for a given opportunity cost by applying an individual genetic algorithm and the entrepreneur and the small farms interact repeatedly on the market until the model converges towards an equilibrium.

The steps of genetic algorithms are described in Appendix I, but can briefly be explained as follows. The first step is to define a genome (a set of test strategies or so-called genes) for each agent with a certain opportunity cost. The fitness of each of the different strategies is thereafter evaluated (where the fitness is in this case the profit or pay-off resulting from a certain bid). In the next step, the genetic algorithm operators – selection, crossover and mutation – are applied. The selection mechanism ensures that the best strategies survive and multiplied in the next generation (the new set of strategies/genes). The crossover and mutation operators create new strategies to be evaluated in the next generation. These steps are repeated until the model converges, i.e., the strategies are similar from one generation to the other and the strategies within the genome pool of the agent become homogeneous.

For the assumed parameters, the game theoretic equilibrium obtained using the agent-based model with genetic algorithms learning implies that a transaction will take place between the entrepreneur and all players. The players extract all rent (the entrepreneur thus makes zero profit) which is distributed equally among them with the exception of the players with the highest opportunity costs who cannot receive more than the market price (the marginal demand of the entrepreneur).

Formally, the game theoretic equilibrium implies that the predicted asks of player *i* equals $min\{oc_i + c; p_{max}\}$ so that $\sum_i ask_i = TW$ and c is maximized, where oc_i is the reservation price of player i, c is a constant (represented in the figure by the distance between the black and blue continuous lines for the first 6 players), p_{max} is the market price and TW is the total net potential welfare gain (i.e. 352 or 704). The equilibrium or predicted asks are illustrated for each of the treatments in Figures 3-5.

3.2 Experimental results

The experiments were carried out between September 2009 and April 2010 and the subject pool consisted of 112 participants/students of varying age and gender. A general observation from all experimental conditions is that exceptional asks occur quite frequently. For example, in each session some asks were lower than the respective opportunity cost of the player. The share of asks in each session that were lower than the respective opportunity cost varies between 0.4 – 14.6%. There were also some sessions with exceptionally high asks, for example more than ten times the opportunity cost. On the one hand, asking below opportunity cost is consistent with a reverse form of *winner's curse* (Thaler, 1988). People wanting to 'win' the deal, i.e., make the transaction, appear to increase their chances of trading by selling below opportunity costs – hence losing money. On the other hand, outrageous asks mean taking a risky gamble (maybe somebody is willing to pay so much), however, without any possibility of actually losing money.

3.2.1 Number of accepted asks

The distribution of the number of accepted asks in each of the treatments is illustrated in Figure 2. As already stated above, the chosen parameter values imply that a positive welfare gain only can be achieved if the entrepreneur is able to take over the land of more than a certain minimum number of players. Thus, if players act rationally (i.e., do not ask for less than their opportunity cost) the number of accepted asks in a given round is expected to be either 0 or higher than this minimum number (close to the group's size) corresponding to coordination failure and success, respectively. This coordination feature of our decision situation nicely shows up empirically in the bimodal distribution of accepted asks in Figure 2. Specifically, we get a distribution with very few, usually zero, accepted asks in some range between 1 and 5 (treatments 1 and 2) or 11-12 (treatments 3 and 4). Due to a small share of non-rationally acting players (that made a bid lower than their opportunity cost), there are a few cases/rounds with one accepted ask (for example in treatment 1).

From Table 3, we observe that the average number of accepted asks was, for all treatments, lower than predicted by the game-theoretic equilibrium (the benchmark case) and which is Pareto efficient (recall that, for the assumed parameters, the total welfare is maximized when the entrepreneur can take over the land of all players, which was also the game theoretic equilibrium). In fact, only 25-50% of the asks were accepted by the entrepreneur which has to be regarded as a highly inefficient outcome and a clear tendency towards coordination failure. It can be seen that, for a given group size, the average number of accepted asks is higher when the potential welfare gain is larger. It should also be mentioned that there was no improvement in the number of accepted asks over time (i.e. over the 40 rounds), although some cycles could be observed (e.g. several periods with 0 accepted asks followed by several periods of 6-7 accepted asks). In order to analyze learning effects (what was however not the purpose of our study), future experiments will be run assigning a fixed reservation price for each player throughout the game.

A non-parametric Mann-Whitney U-test was utilized to test for statistical significance of differences between the treatments with different potential welfare gains. This test is based on ranks with the null hypothesis that the two samples are drawn from identical populations. For the case of 14 players, the null hypothesis of no impact of welfare gain differences can be rejected at a 0.2%-level and for the case of 7 players it can be rejected at a 5.4%-level. Hence, higher potential welfare gains lead to a larger number of accepted asks.

It is furthermore interesting to compare the average share of accepted asks between the sessions with different group sizes but the same potential welfare gains (i.e. treatment 1 with 3 and 2 with 4). The average share of accepted asks was slightly higher for the smaller group in the case of 7 players, but no statistically significant differences between the treatments were found.

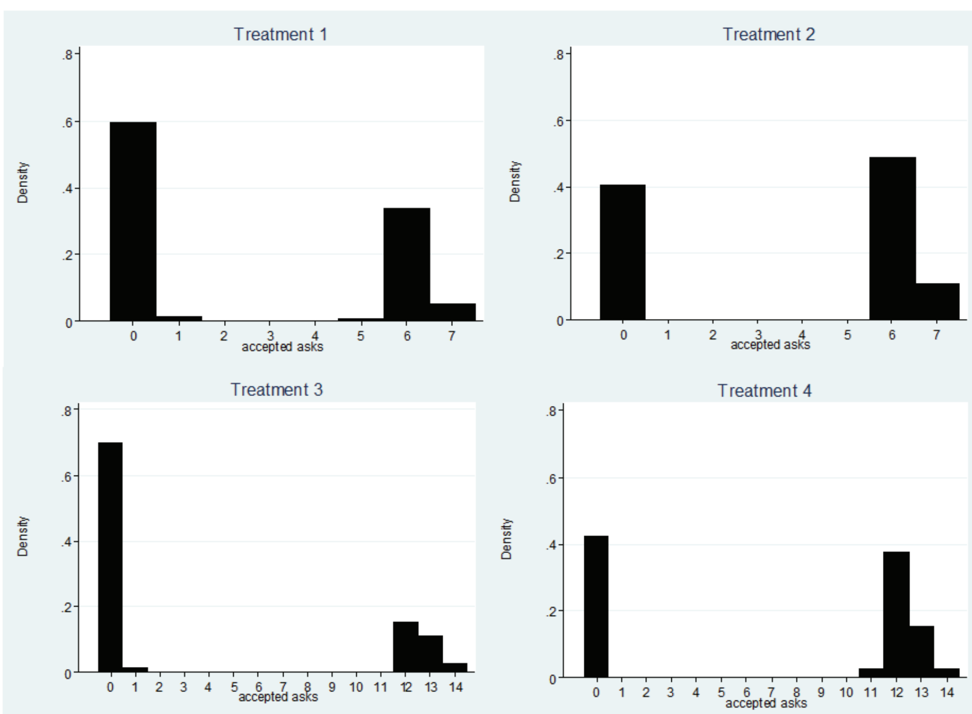

Figure 2: Distribution of accepted asks by treatment. Source: Authors.

Table 3: Average number of accepted asks by treatment. Source: Authors.

	Treatment			
	1 7 players, tight room (N=160)	2 7 players, generous room (N=160)	3 14 players, tight room (N=80)	4 14 players, generous room (N=80)
Average number of accepted asks	2.42	3.67	3.62	7.08
(Share)	(0.35)	(0.52)	(0.26)	(0.51)
Standard deviation	3.00	3.06	5.73	6.14
P-value, Mann-Whitney U-test	0.0003		0.0024	

Table 4: Average share of accepted asks by treatment. Source: Authors.

	Treatment			
	1 7 players, tight room (N=160)	3 14 players, tight room (N=80)	2 7 players, generous room (N=160)	4 14 players, generous room (N=80)
Average share of accepted asks	0.35	0.26	0.52	0.51
Standard deviation	0.43	0.41	0.44	0.44
P-value, Mann-Whitney U-test	0.28		0.96	

The fact that less than 50% asks are accepted in the treatments with “tight” room for negotiation and approximately 50% in the treatments with “generous” room for negotiation must be regarded as a highly inefficient outcome or coordination failure. Thus, the experiments do not support the hypothesis that auctions make players reveal private information about their opportunity costs. Smaller groups were on average slightly more efficient although this result is not statistically significant. This is not an especially surprising finding since fourteen players constitute a more complex coordination challenge than seven. Somehow related evidence on group size effects, proving that coordination is less efficient among large groups, comes e.g. from weak-link games (VanHuyck et al., 1990) as well as from public goods games (see the seminar work of Isaac and Walker, 1988).

3.2.2 Level of asks and comparison with benchmark case

We next turn to a comparison of the average levels of the asks with the predicted asks, i.e. the “optimal asks” that constitute the game theoretic equilibrium. The thick broken line in Figures 3-

6 shows the average asks in the experiment whereas the thick unbroken line represents the predicted asks (the exact numbers are displayed in Table 7 in Appendix II). There is a positive and statistically significant correlation between the actual asks and the predicted asks, suggesting that the experiment participants considered their opportunity costs when making the bids. This is consistent with earlier experimental findings indicating that individuals 'intuitively optimize' (Levesque and Schade, 2005) by adjusting behaviour upwards and downwards in the correct direction (applying 'anchoring and adjustment'; Tversky and Kahneman, 1974) but at the same time fall prey to certain biases and hence do not exactly meet the optimum.

It can furthermore be seen that, for low opportunity costs, the actual asks by the participants are on average higher than the predicted asks, suggesting that players with low opportunity costs on average ask for "too much". In all treatments except treatment 1, also high opportunity costs players asked for an average price higher than predicted by the benchmark case. In order to test for statistically significant differences between the actual and predicted asks, the non-parametric Wilcoxon signed-rank test was applied separately for each opportunity cost level (the p-values are reported in Table 7).[3] This test suggests that there are in almost all cases significant differences between predicted and actual ask.[4]

The often "too high" top-ups of the low as well as the high opportunity cost players could be related to some form of *inequity aversion* (Fehr and Schmidt, 1999), however, with an emphasis on different reference dimensions (what can be somehow related to the experimental results of Goeree and Holt, 2000). The high opportunity cost players appear to believe that they should receive the same top-up as the players with lower opportunity costs. At the same time, the low opportunity cost players may think that they should not be "punished" by receiving a lower price than the others. Specifically, whereas the relevant dimension of inequity aversion appears to be *price* with the low opportunity cost individuals, it rather appears to be *mark-up* with the high opportunity cost individuals. Most probably these are the dimensions that are considered 'scarce' or 'prominent' by the respective individuals.

[3] As the asks are not normally distributed, a t-test could not be used.

[4] Significant differences between actual and predicted asks where found even in some cases where the average ask is close the predicted ask, but this can be explained by the fact that this test do not make any distributional assumption.

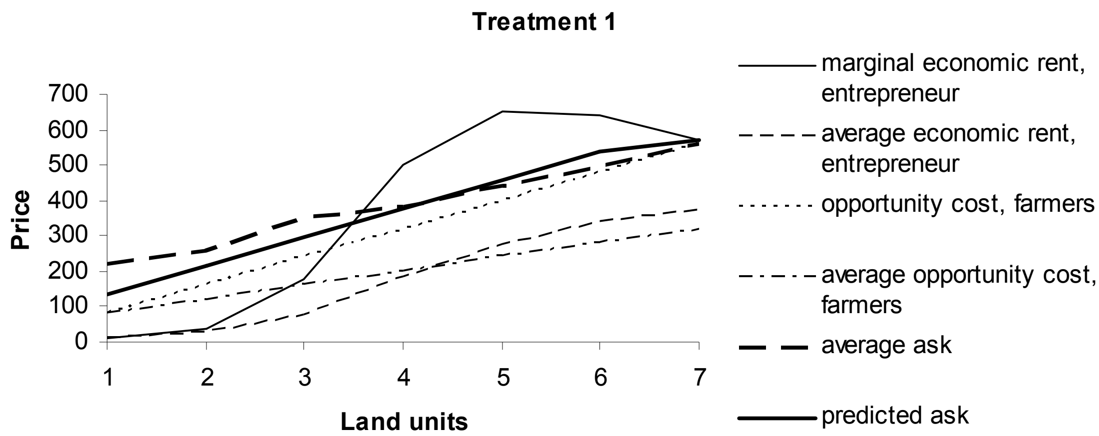

Figure 3: Comparison with benchmark, treatment 1. Source: Authors.

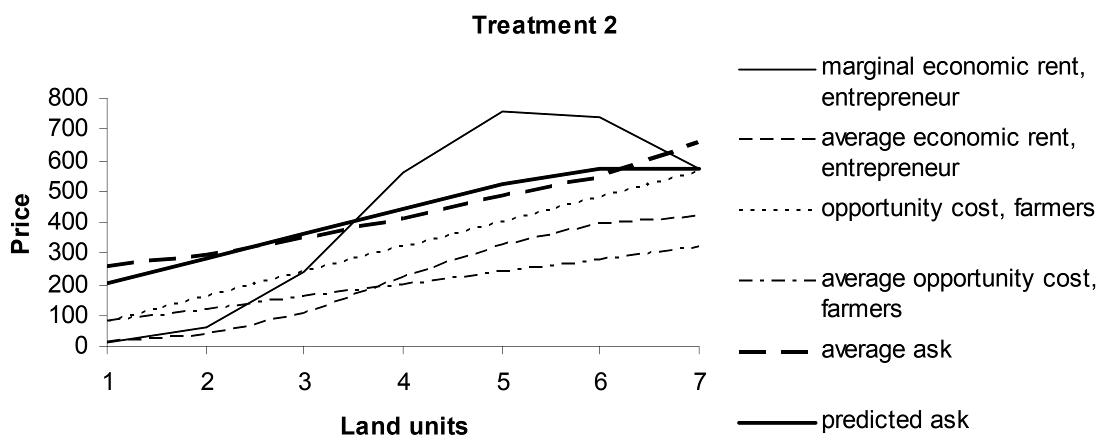

Figure 4: Comparison with benchmark, treatment 2. Source: Authors.

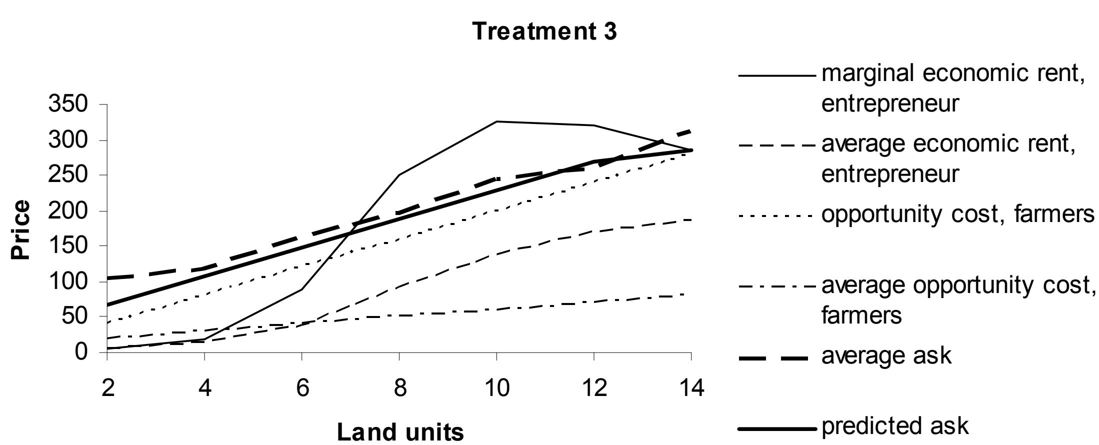

Figure 5: Comparison with benchmark, treatment 3. Source: Authors.

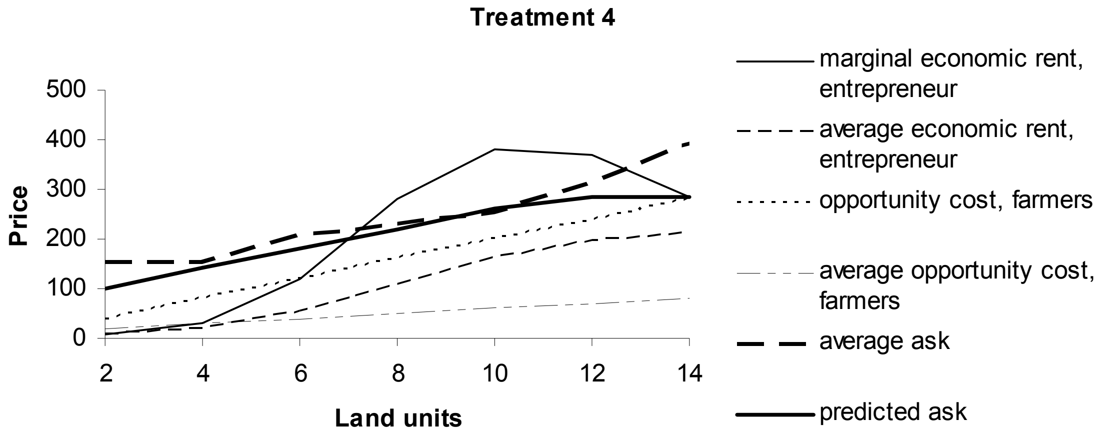

Figure 6: Comparison with benchmark, treatment 4. Source: Authors.

3.2.3 Regression results

The impact of the reservation price on the level of the players' asks as well as on players' net profits were analyzed separately for each treatment utilizing regression analysis. Net profit is here defined as the players' payoff from the round of the game (i.e. the level of the ask in case of acceptance or the opportunity costs in case the ask was rejected) minus the opportunity cost. Since experimental data exhibit a panel structure (containing observations for each participant over 40 repetitions), unobserved heterogeneity could be controlled by employing panel data methods. The fixed effects estimators are reported in Tables 5 and 6.[5]

The results in Table 5 suggest that the positive correlation between the level of the ask and the reservation price, that could be observed in the above figures, is statistically significant and robust against unobserved factors. Thus, although players on average ask for too much compared to the benchmark case, they do consider their individual reservation prices when making their bids. This confirms the above consideration on 'intuitive optimizing' and anchoring-and-adjustment. However, the coefficient of the opportunity costs is in all experiments smaller than one (in treatments 1 to 3 significantly lower than one at the 1%-level, while not significant in treatment 4). This supports the above finding that players with low opportunity costs in general ask for too much.

[5] Random effects (RE) estimators were also obtained but a Hausman test (Hausman, 1978) suggested that there were statistically significant differences between estimators in some of the treatments indicating the RE estimators are inconsistent in those cases. Therefore, we report the consistent fixed effects estimators for all treatments.

The results in Table 6 also suggest that there is a negative statistically significant correlation between ask and net profit. One possible explanation is related to the pricing mechanism according to which, in case of any accepted asks, the lowest asks are accepted first. A second explanation arises from the fact that low opportunity cost players ask for a higher mark-up than high opportunity cost players.

In addition to the models presented in Tables 5 and 6 that only used reservation prices as explanatory variable, other model specifications have also been tested. For example, the inclusion of a time trend variable (indicating the number of periods) showed that the period number had no significant impact on the level of the ask or the profit. In order to see whether acceptance/rejection in the previous round has an effect on asks in the subsequent round, lagged acceptance dummies were included as explanatory variables. In this case, the signs of the coefficients as well as the significance levels varied among the treatments (as well as among sessions and individuals). In some cases, rejection in the previous round led to a *higher* ask in the current round. This is surprising at first sight since one would expect players to reduce their ask if they were not successful. The opposite behaviour may indicate that some participants played some type of tit for tat in the sense that they "punished" other players when their own ask was not accepted by playing in an even less cooperative way in the next round.

Table 5: Fixed effects estimators – ask dependent variable. Source: Authors.

Dependent variable: Ask								
	Treatment 1		Treatment 2		Treatment 3		Treatment 4	
Variable	Coefficient	St.Error	Coefficient	St.Error	Coefficient	St.Error	Coefficient	St.Error
Constant	159100***	9170	166000***	14800	57100***	6330	86600***	19000
Reservation price	0.714***	0.026	0.825***	0.041	0.899***	0.035	0.979***	0.107

*, ** and *** indicate statistical significance on a 10, 5 and 1% level

Table 6: Fixed effects estimators – net profit dependent variable. Source: Authors.

Dependent variable: Profit								
	Treatment 1		Treatment 2		Treatment 3		Treatment 4	
Variable	Coefficient	St.Error	Coefficient	St.Error	Coefficient	St.Error	Coefficient	St.Error
Constant	43800***	4520	78700***	4100	9910***	1280	61700***	2930
Reservation price	-0.115***	0.013	-0.117***	0.011	-0.030***	0.007	-0.252***	0.016

*. ** and *** indicates statistical significance on a 10, 5 and 1% level

Looking at the experimental results from a different perspective, they support the view that it is typically not possible to achieve coordination among heterogeneous actors as this would require price discrimination. Nevertheless, the share of agreements seems to be affected by the potential welfare gains and the number of players.

4. Conclusions

This study used an experimental approach to investigate a coordination game with heterogeneous agents. The experimental design reflects a situation often encountered in Western agriculture in which economies of size are rarely exploited, possibly partly due to problems of coordination when actors are heterogeneous. The specific example analyzed in this study focused on allocation of land plots, but similar coordination situations are relevant for, e.g., horizontal cooperation among farmers such as machinery sharing arrangements.

The analyzed example considered an entrepreneur who wants to establish a large arable farm by buying or renting homogeneous land from a limited number of existing smaller farms with heterogeneous reservation prices. For the assumed setting, a Pareto-optimal solution is only feasible if the existing farmers accept heterogeneous prices and reveal their true individual opportunity costs. The experimental results suggest that it is typically not guaranteed that the entrepreneur finds an agreement with a sufficient number of sellers because of behavioural reasons, and that the degree of coordination indicated by the number of land plots sold is surprisingly low for all treatments (although somewhat higher for the treatments with larger space for negotiation). By comparing the experimental results with a game theoretic equilibrium obtained using an agent-based auction model in which the agents optimize their bidding by using a genetic algorithm (serving as normative benchmark prediction), it was found that players generally ask for a "too much". The results suggest some form of equity aversion among the players where the low opportunity cost players focus on prices and appear to think they should not be "punished" by lower prices and the high opportunity cost players focus on profit and want similar top-ups as the low opportunity cost players.

Assuming that the low allocative efficiency is not restricted to the auction type used in this example but also apply to the informal institutions often used in land markets, one of the reasons for the slow structural change in agriculture could be identified in the difficulty of solving a coordination problem with increasing economies of scale together with private and heterogeneous opportunity costs. The results of this study thus provide evidence for market failures and coordination deficits as reasons for unexploited economies of scale in agriculture.

Although this study provide some first experimental evidence for coordination failures in the case of heterogeneous actors, the impact of other types of auction schemes and/or the possibilities for negotiation among the farm agents and among the farm agents and the entrepreneur should be explored. The type of auction used, as well as the experimental setting, should reflect real land market transactions as far as possible. A further planned extension of this work is to conduct the experiments with real farmers instead of students.[6]

In the case that also future studies, relying on more realistic settings as well as on different information- and feedback-protocols, support the findings of this study, a next step is to identify what market mechanisms are needed in order to support coordination in the case of heterogeneous agents so that reallocation to more efficient outcomes can be achieved.

[6] This might be of particular interest also from the perspective of experimental economics, as some of the encountered behavioural effects, such as inequity aversion, have been shown to differently occur among different social and cultural groups (Kohler, 2008).

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APPENDIX I: GENETIC ALGORITHMS

An agent-based simulation with genetic algorithms learning was applied in this study in order to derive a game theoretic equilibrium for the players bidding behaviour. In this appendix, we will describe briefly the motivation for and general idea behind genetic algorithms (GAs), a computational intelligence method, originally introduced by Holland (1975), including an overview of the steps that most often are undertaken in a GA. After that, we will describe how we applied the GAs in our specific land market problem.

Short introduction to genetic algorithms

GAs have been used in a number of disciplines as tool for optimization, but also for determining equilibriums (such as game theoretic equilibriums in economic applications, e.g. Arifovic 1996). Although the GA is inspired by evolutionary biology – making use of evolutionary concepts such as selection, crossover and mutation -, the use of GAs have shown to be a promising method in many economic applications (cf. Balmann and Happe 2000) as these algorithms can be interpreted as models of learning behaviour of a population of adaptive agents. In economic applications, it is especially applicable in game theoretic contexts as it involves a population of competing strategies. An extensive description of GAs as a tool in economic models can be found in Dawid (1999).

The main steps that most GAs follow are the following:

Initialization: The first step involves defining a first generation of so-called genomes (a set of test strategies). This is usually done by using random values. In traditional GAs, the test strategies are coded into binary strings of 0 and1, but also other codings and even floating point numbers are possible.

Fitness evaluation: The fitness of each of the genomes in the population is thereafter evaluated using the relevant fitness function (in economic applications, it may for example be profit or the pay-off).

In the next steps, the genetic algorithm operators – selection, crossover and mutation – are applied:

Selection: The selection operator ensures that the strategies with the highest fitness survive and are multiplied in the next generation (i.e., the new set of genomes/strategies). The selection function often has a stochastic element so that also some of the less fit strategies may survive in the next generation. There exist different methods for the selection, including the so-called roulette wheel selection and tournament selection. The main objective of the selection is the reduction of the variety of solutions.

Recombination: This operator is the main mechanism for creating new strategies to be tried out in the next generation (the next population of genomes/strategies). It combines strategies with high fitness in order to create even fitter strategies. This step is also often called crossover, particularly in the cases when the test strategies are represented as binary strings. Also for this step, several different techniques have been used including the so-called one-point and two-point cross-over techniques.

Mutation: After the crossover operator has been applied, the mutation operator is usually applied. This mechanism changes with a certain probability some part (bit) of the genome and increases also the variety of solutions.

The steps above are repeated until the model converges, i.e., the strategies are similar from one generation to the other and the strategies within the string of genomes is relatively homogeneous.

The GAs can either be applied to the whole population of agents, in which case each agent is represented by a single genome (cf Arifovic 1994), or it can be applied separately to the individual agents, in which case each agent owns a population of genomes (cf. Balmann and Happe 2000).

The Genetic algorithm in the model

As mentioned above, the GAs can either be applied by representing each agent with a single genome, or each individual agent is associated with a genome population. In our application it is necessary to follow the latter, multiple-population, approach as the agents are assumed to be heterogeneous (having differing opportunity costs) and heterogeneous strategies are required for the equilibrium. Each agent is in our model represented by 15 genomes/test strategies in each generation. Below we will describe how each of the steps of the GA was implemented, which thus was done for each of the individual agents simultaneously, in our model.

Initialization: The initial values of the genomes were determined randomly.

Fitness: The fitness function, F, is in this application the pay-off for agent *i's* genome n in testing round t. The agents pay-off equals the level of the ask subtracted by his/her opportunity cost in the case that the ask is accepted by the entrepreneur (and 0 otherwise), who, as described in section 2, is strictly profit maximizing and will only accept asks such that his total profit is maximized and non-negative. The fitness function is specified in (A1)

$$F_{i,n,t} = \frac{1}{R_n} \sum_{k=1}^{R_n} \Pi_{n,k} \tag{A1}$$

$$\Pi_{n,k} = \text{ask}_{n,k} - \text{opportunity cost}_{n,k} \quad \text{if ask accepted the entrepreneur in test } k$$

$$= 0 \quad \text{if ask not accepted by the entrepreneur in test } k$$

Where R_n is the number of testing rounds the genome n was tested with its current value.

Selection: After evaluating and sorting the strategies of each genome population, we apply a selection mechanism that duplicates the three fittest strategies of each genome population and applies a stochastic element for the three genomes 4-6 (sorted according to descending fitness) in the sense that they are replaced with the fittest strategies with a probability of 0.2. The remaining 6 genomes are replaced by genomes 4-9. Thus, the 6 genomes with the lowest fitness do not survive in the next generation of genomes.

Recombination: Each genome is paired with another genome from the same population with a probability of 0.3. For a genome that is randomly chosen for recombination, the value, A, of new genome n to be passed on to the mutation step is determined as

$$A_{i,n,t} = (A_{i,n,t} \times A_{i,m,t})^{1/2} \tag{A2}$$

where genome m is a randomly drawn genome in the same population.

Mutation: The mutation operator is implemented in our model such that with a probability of 0.1, the genomes from the recombination step, are slightly modified according to

$$A_{i,n,t+1} = A_{i,n,t} \times 0.05(u - 0.5) \tag{A3}$$

where u is a random number drawn from a uniform distribution, i.e. $u \in [0,1]$.

The steps were repeated until the model converges.

APPENDIX II: COMPARISON WITH BENCHMARK CASE

Table 7: Experimental results and benchmark case. Source: Authors.

	Treatment 1					Treatment 2				
Reservation price	Predicted ask	Average ask	St.dev. (ask)	Diff.*	P-value. Wilcoxon signed-rank test***	Predicted ask	Average ask	St.dev. (ask)	Diff.*	P-value, Wilcoxon signed-rank test***
80	137	223	146	86	0.000	200.8	258	224	57	0.234
160	217	261	121	44	0.006	280.8	297	109	16	0.606
240	297	350	286	53	0.103	360.8	351	84	-10	0.000
320	377	383	94	6	0.363	440.8	410	79	-31	0.000
400	457	439	129	-18	0.001	520.8	485	65	-36	0.000
480	537	498	142	-39	0.000	570	550	89	-20	0.000
560	570	560	149	-10	0.000	570	659	522	89	0.000
Spearman's rho (p-value)	0.761 (0.000)					0.802 (0.000)				

	Treatment 3					Treatment 4				
Reservation price**	Predicted ask	Average ask	St.dev. (ask)	Diff.*	P-value, Wilcoxon signed-rank test***	Predicted ask	Average ask	St.dev. (ask)	Diff.*	P-value, Wilcoxon signed-rank test***
40	68.5	106	119	37	0.000	100.4	153	118	53	0.000
80	108.5	120	45	11	0.006	140.4	153	60	13	0.064
120	148.5	165	93	17	0.040	180.4	209	134	28	0.029
160	188.5	197	31	8	0.003	220.4	230	205	10	0.009
200	228.5	245	112	16	0.259	260.4	253	174	-7	0.000
240	268.5	261	25	-8	0.000	285	314	438	29	0.000
280	285	313	169	28	0.000	285	391	535	106	0.000
Spearman's rho (p-value)	0.881 (0.000)					0.661 (0.000)				

* Difference between predicted and average actual ask, ** Note that two players always received the same reservation price in the treatments with 14 players (treatment 3 and 4), *** Tests the null hypothesis: ask = predicted ask

APPENDIX III: INSTRUCTIONS, CONTROL QUESTIONS AND SCREENSHOTS

A III.1 Instructions

The instructions below were used in the experiments for the treatments with 7 players (translated from German).

Instructions

Welcome to this experiment and thank you for your participation!

Please read through the instructions carefully. If you have a question, please raise your hand. We will then come to you and answer your question. All participants in this experiment have received the same instructions as you.

The experiment will take approximately 80-90 minutes. Please read these instructions carefully as your earnings in this experiment will depend on your decisions.

Your will receive your total earnings in cash at the end of the experiment.

Feel free to use a pencil, a sheet of paper and a pocket-calculator available on your desk.

Please remain seated during the experiment.

Your earnings

The experiment consists of 40 rounds. In each game you have to collect as many “Taler” (our experimental currency) as possible as your earnings is proportional to the sum of the Talers which you gain during the game.

You will receive 1 Euro cent (0.01 Euro) per 10.000 Taler. All the other players will, just like you, receive 1 Euro cent for every 10.000 Taler during the experiment.

Introduction

Please imagine the following managerial situation.

Pretend that you, in each of the 40 games, operate an agricultural firm at your own land plot. Your firm/land plot is located in a region in which six additional agricultural firms operate. That is, there are, including yours, seven firms operating in the region.

Every firm disposes a land plot which has the same size as yours. As all firms are located in the same region, the physical properties of each land plot are identical. However, since each of you produce different crops/use different technologies; there are differences between your current profits from the land use. That is, the land has a different economic value for you and the other firms.

In every game the size of your profit will change. That is, the value of your land will change in every game (as if you in every game face different market conditions). The profit from your respective land use will be reported to you in the beginning of each new game.

Imagine now that an entrepreneur in your region would like to form an agricultural firm and that he therefore is interested in buying land. He does initially not have any own land. He is planning to use one and the same technology on all acquired land plots.

While yours and the other landowners profit from the land use differ (due to cultivation of different crops/different technologies), is the value of each land plot identical for the entrepreneur (i.e., the potential buyer).

The new entrepreneur is only interested in acquiring a specific *number* of firms/land plots, as his average profit increases with the number of acquired firms as a result of higher efficiency in production. In other words, the more land plots the new entrepreneur can operate at the same time, the more cheaply he can produce the higher is his average profit. His willingness to pay for the land plots is determined by this calculation but is unrelated to the profit of the individual firms.

Your decision

In each of the following 40 rounds, you should decide at which price you could imagine to sell your land plot. All the other 6 land owners will do the same. All requests are then communicated to the entrepreneur.

The entrepreneur is in this game implemented as a computerized player and maximizes his profit! Given all price requests and his own profit possibilities, he will choose his profit maximizing purchase strategy. This means that he will first accept the lowest requests (if any), and thereafter the next highest requests. Lower requests therefore have higher probabilities to be accepted. Again, please note that the average profit of the new entrepreneur depends on the number of land plots that he can acquire.

Every transaction, i.e. every land purchase, will occur at an individual price. The entrepreneur will either pay the requested price, or not buy at all. No negotiation will take place. As a profit maximizing strategy, the entrepreneur will accept requests up to the point where the most expensive sold land plot is cheaper than the increase of the profit through this purchase. This will have the following consequences for you:

- Your price request will be accepted when the bids of all more beneficial bidders already are accepted – or the most beneficial bidder – and with the purchase of your land plot related payment is lower than the profit gain, that the entrepreneur can achieve through the purchase of your land plot.
- Your request will otherwise not be accepted. You are thus not able to sell your land plot.

Irrespectively of whether your land is sold or not, you can participate in the next game. You will then receive a new land plot!

Your profit

In every game, your profit depends on whether your price request is accepted or not.

- When your price requirement is accepted, is the profit corresponds to the amount that you have demanded for your land.
- When your demanded price is not accepted, you will receive the value of your land plot.

Your information

As basis for your decision you have the following information:

- Your profit of your land use.
- The distribution of the profit of all seven land owners. That is, you know exactly how high or low the profit of the other owners in the area is and how they are distributed.
- The profit of the new entrepreneur is dependent of the number of acquired land plots: the more land plots he acquires, the more economically he can operate. In a table with the following information you are presented the situation facing the computerized entrepreneur:
    - Profit in relation to the number of acquired land plots.
    - Average profit per land plot in relation to the number of acquired land plots.

Please note that you, in the beginning of each game, will receive a new land plot and thereby new possibilities for making profits of the land use, independent on whether you have sold or not! The same hold for all other players.

All other players will have the same information as you.

Your feedback after each repetition

After you and the other players have made your individual price requests, you will receive the following information:

- whether your request has been accepted or not
- how many purchases that have taken place, that is how many firm purchases respectively how many land units the entrepreneur has acquired.
- your payment in the last game played.

All other players will after each game receive the same information as you. **None** of you will receive information about individual requests and individual payments of the other players.

Before the game begins we ask you to answer a few control questions at the monitor. They will make sure that you have correctly understood the rules of the experiment. Good luck!

A III.2 Control questions

The following control questions were used in the experiment to ensure that the participants had understood the rules (translated from German).

Control questions

Before starting the game, please, answer the following questions. This is to make sure, that you have understood the rule of the game.

Imagine, this is the game situation you have to play:

Your profit and the profits of the others from your respective land plots:		
Land owner	Profits (in Taler)	Land plots
A (you)	160000	1
B	80000	1
C	240000	1
D	560000	1
E	400000	
F	480000	1
G	320000	1

Profit function of the entrepreneur:		
Land plots acquired	Total profits (in Taler)	Average profits (in Taler)
0	0	0
1	12000	12000
2	52000	26000
3	232000	77300
4	732000	183000
5	1382000	276400
6	2022000	370300
7	2592000	370300

How much is your profit, in case you do not sell? […]

Which land owner has the highest profits? […]

Which land owner has the lowest profits? […]

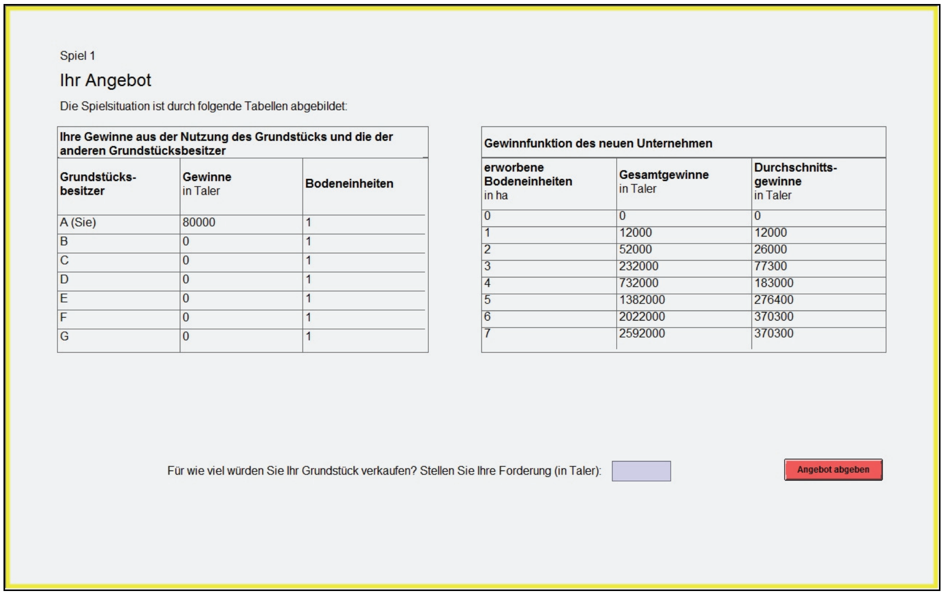
If 4 land plots get sold (i.e., if the entrepreneurs buy 4 plots), how much is the profit of the entrepreneur? […]

Imagine, your made a ask of 165000 Taler and it is accepted. How much is your payoff in this case? […]

A III.3 Screenshots

Below are two examples of the computer screens displayed to the experiment participants during the experiment.

Example of screen where players make their bid:



Example of screen showing the outcome of a round: