

Coordination and allocation on land markets under increasing scale economies and heterogeneous actors – an experimental study

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Introduction

- Economies of scale often not exploited in Western agriculture
 - dominance and persistence of small family farms (Balmann 1994, 1995)
 - „too little“ participation in collaborative arrangements that allow small firms to exploit economies of size (Aurbacher, Lippert, Dabbert 2007)

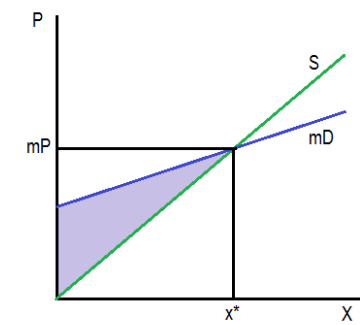
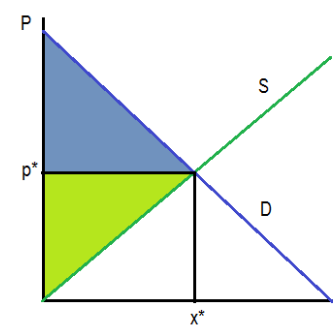
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Introduction

- Explanations for unexploited increasing returns
 - transaction costs limit, e.g., access to financial resources
 - naïve expectations prevents inefficient farms from exit
 - insufficient market mechanisms do not ensure appropriate re-allocation to more efficient structures
 - coordination failures among heterogeneous actors
- This study focuses on the last two explanations
 - Balmann (1994,1995)
 - establishing large arable farms can require price differentiation on land market
 - Aurbacher, Lippert, Dabbert (2007)
 - establishing machinery cooperation can require price differentiation for use₃

Introduction

- The problem of increasing returns / economies of scale
 - neoclassical market
 - increasing returns market



- exploitation of increasing returns often requires price differentiation!
- specific problem: private information of suppliers!

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Objective



- Question
 - Can the coordination and allocation problem be solved?
 - Application to the land market problem of Balmann (1995)
- Hypothesis
 - Auctions enable price differentiation
 - Auctions create incentives to reveal private information
- Approach
 - Laboratory experiments with students
 - Agent-based model with computationally intelligent agents using genetic algorithms provides normative benchmark solution (game theoretic equilibrium)

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Outline



- Description of land market example
- Experimental setting
- Benchmark case – simulations with ABM/GA
- Experiment results
- Conclusions and further research

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A land market example

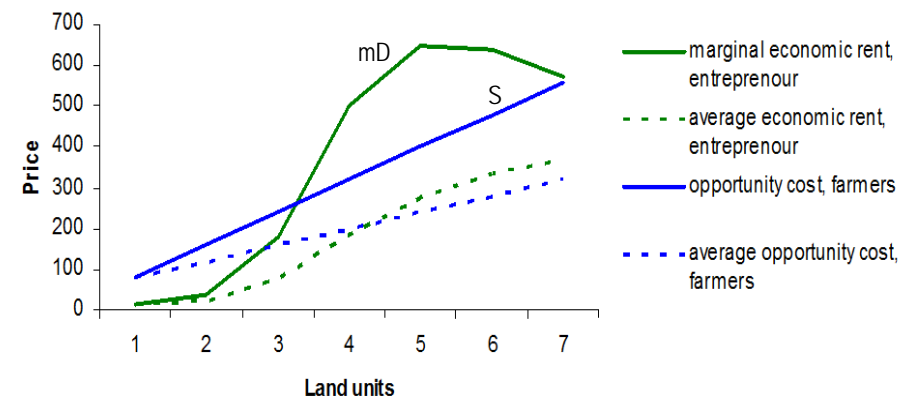


Imagine the following situation

- A profit maximizing entrepreneur characterized by increasing returns wants to „take over“ a certain number of smaller farms in a certain region
- The existing small farmers are assumed to
 - be equally large in terms of land
 - have land with identical physical properties
 - have heterogeneous reservation prices (opportunity costs) for their land
 - have private information on their reservation prices

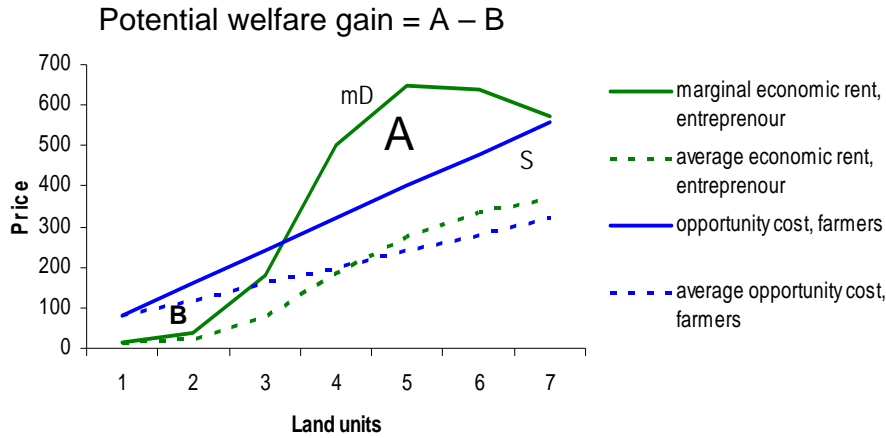
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A land market example



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A land market example



Experimental setting



- Four scenarios (treatments):
 - two different levels of potential welfare gain: „tight“ and „generous“ room for negotiation.
 - two group sizes: „small“ (7 players) and „large“ (14 players)

		Group size	
		„Small“ (7 players)	„Large“ (14 players)
Potential welfare gain	„Tight“ (A-B=352)	<i>Treatment 1</i>	<i>Treatment 2</i>
	„Generous“ (A-B=704)	<i>Treatment 3</i>	<i>Treatment 4</i>

Experimental setting



Example of parameters (treatment 1: 7 players, tight room for negotiations)**

Player	Sum of land units	Assumptions				
		Players		Entrepreneur		
	Opportunity cost of land unit*	Average opportunity cost	Total value of production*	Marginal value of production	Average value of production*	
1	1	80	80	12	12	12
2	2	160	120	52	40	26
3	3	240	160	232	180	77.3
4	4	320	200	732	500	183
5	5	400	240	1382	650	276.4
6	6	480	280	2022	640	337
7	7	560	320	2592	570	370.3

* Information known to the players

** Total potential welfare gain
 = Total value of production (at 7 players) - sum of players opportunity costs
 = 2592 – 2240 = 352

Experimental setting



- Each experiment consists of 40 repetitions of each treatment
- The entrepreneur is computerized and profit-maximising
- In each repetition (round), the opportunity costs are randomly assigned to the participants
- Each player is assumed to have the following information
 - His/her own opportunity costs
 - The distribution of the other players' opportunity costs
 - The entrepreneur's production function (and average production)
- Players are well informed!

Experimental setting



- After each round, each player receives feedback on
 - the number of transactions occurred
 - acceptance or declines the players own ask
 - the own payoff in the round
- The players are not informed about the other players' asks and payoffs (private information)

- The subject pool consisted of 98 participants (28 in treatments 2, 3 and 4; 14 in treatment 1)

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What should we expect?



- Benchmark case
 - game theoretic equilibrium for bidding behavior
 - agent-based simulation with genetic algorithm learning

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Benchmark case – simulations with agent-based model



Experiment by using an agent-based model

- entrepreneur and small farmers are modeled as agents
 - entrepreneur behaves like in the laboratory
 - small farmers “learn” optimal individual bids for given opportunity costs by applying individually a genetic algorithm (GA), i.e. GA defines optimal bid
- entrepreneur and small farmers interact repeatedly on market
- model converges towards an equilibrium

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Benchmark case – simulations with agent-based model



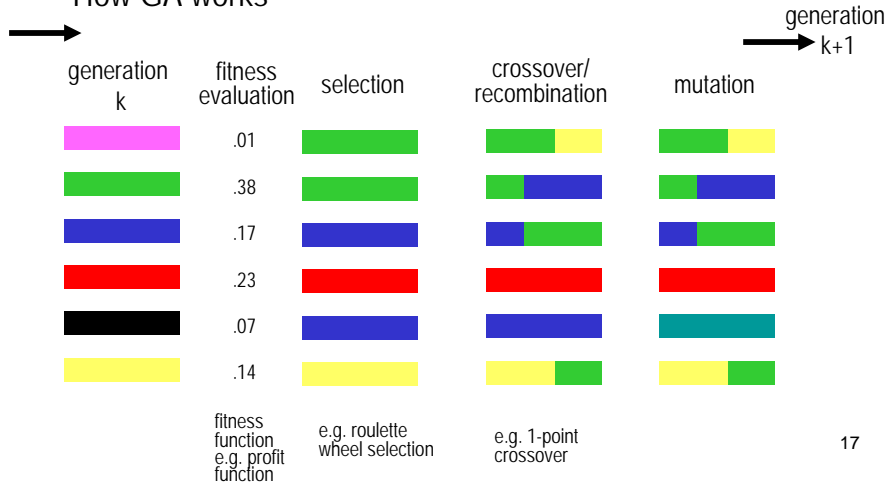
Steps to undertake in a GA

- provide genetic information:
 - encoding a strategy/solution as a string of genes
- define population of N genomes for each agent with a certain opportunity costs
- fitness evaluation by repeated simulations of the model
- apply genetic operators: selection, crossover, mutation

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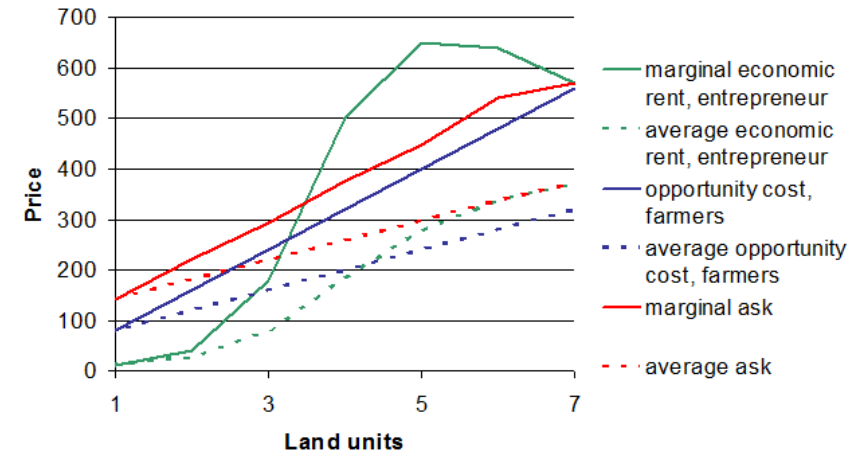
Benchmark case – simulations with agent-based model

How GA works



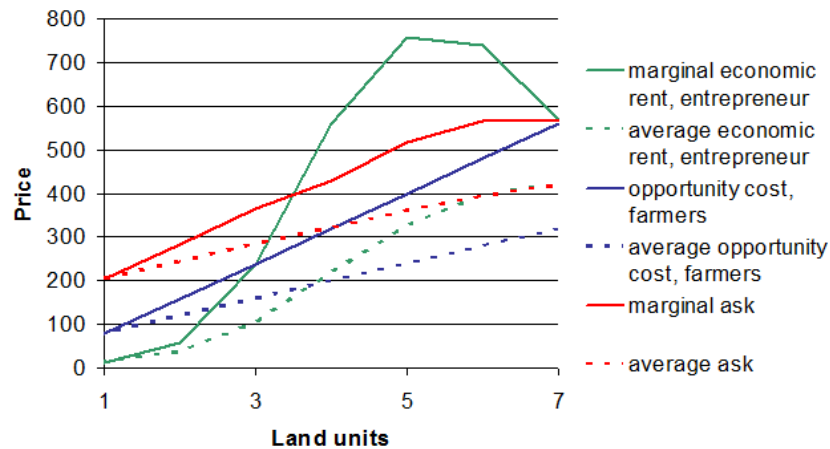
Benchmark case – simulations with agent-based model

Outcome of GA: treatment 1



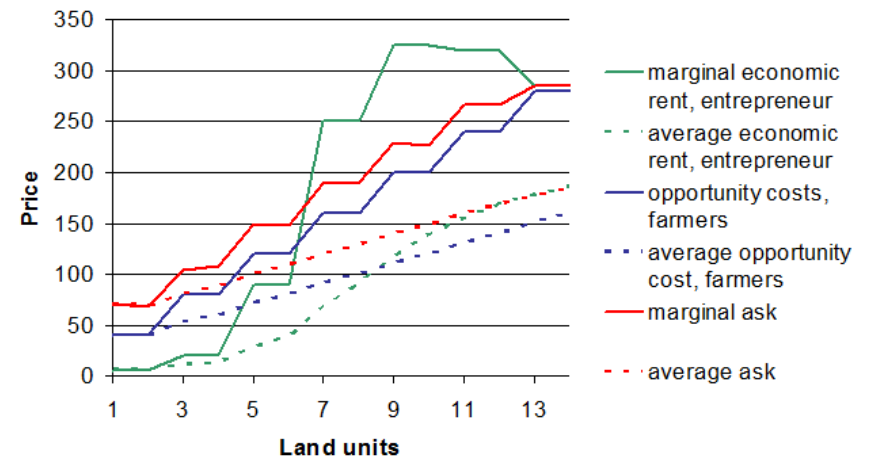
Benchmark case – simulations with agent-based model

Outcome of GA: treatment 2



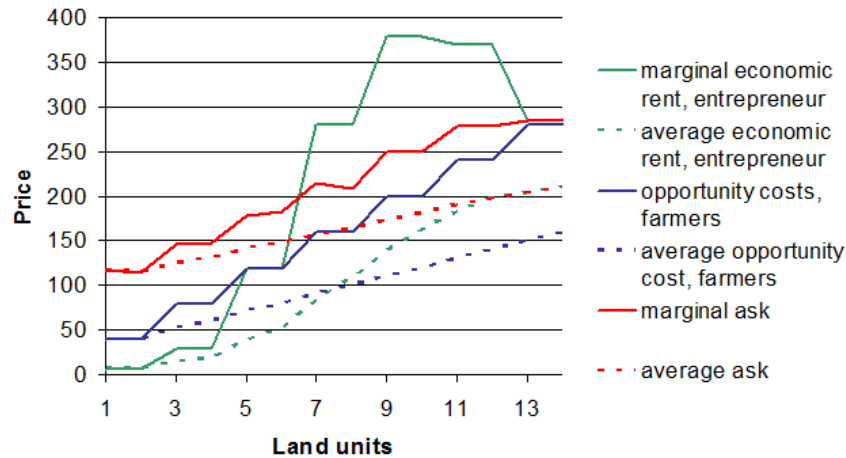
Benchmark case – simulations with agent-based model

Outcome of GA: treatment 3



Benchmark case – simulations with agent-based model

Outcome of GA: treatment 4



Benchmark case – simulations with agent-based model

The results from the genetic algorithms suggest:

Players add a value c to their reservation price (**top-up**) this can be found by solving the following optimization problem:

$$\max_{ask_1, \dots, n} c$$

subject to the constraints

$$ask_i = \min\{oc_i + c; p_{max}\} \text{ and } \sum_i ask_i \leq TV$$

where

ask_i is the ask of player i ,

oc_i is the opportunity cost of player i ,

p_{max} is the maximum price accepted (the market price) and

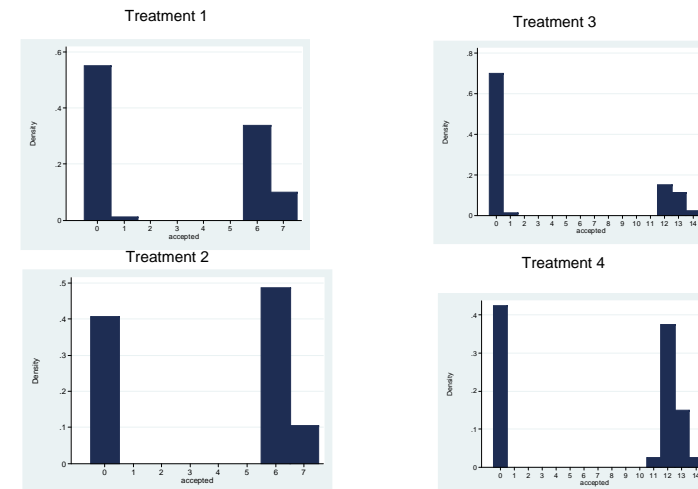
TV is the total net revenue if the entrepreneur can buy all land

Experiment results

- Experiments were carried out in September and October 2009 with students
- Some comments to the data
 - There are some exceptionally high/low asks
 - The subjects are not always acting rationally: in each session there is a number of cases with asks lower than the opportunity cost of player (varies between 0.4% - 8.9%)

Experiment results

Distributions of number of accepted asks per round



Experiment results



Average number of accepted asks by treatment

	Treatment			
	1 7 players, tight room (N=80)	2 7 players, generous room (N=160)	3 14 players, tight room (N=80)	4 14 players, generous room (N=80)
Average # accepted asks (standard deviation)	2.74 (3.11)	3.67 (3.06)	3.62 (5.73)	7.08 (6.14)
P-value, Mann-Whitney U-test*	0.054		0.0024	

* Tests whether the data comes from two different populations (the null hypothesis is that the two samples are drawn from identical populations)

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Experiment results



Share of accepted asks by treatment

	Treatment			
	1 7 players, tight room (N=80)	3 14 players, tight room (N=80)	2 7 players, generous room (N=160)	4 14 players, generous room (N=80)
Average share accepted asks (standard error)	0.39 (0.41)	0.26 (0.41)	0.52 (0.44)	0.51 (0.44)
P-value, Mann-Whitney U-test	0.74		0.96	

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Experiment results



Findings (I)

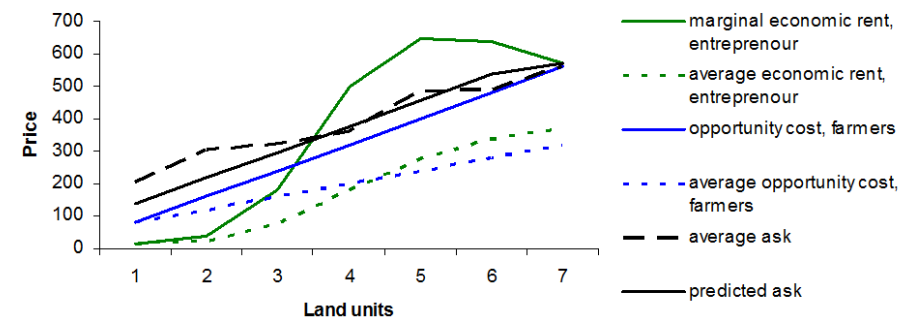
- In general the share of accepted asks is surprisingly low!
 - < 50 % in treatments with tight room for negotiation
 - ~ 50 % in treatments with high room for negotiation
 - highly inefficient outcome!
- Smaller groups are (slightly) more successful!
- Rate of acceptance does not increase over time!
 - players do not learn to coordinate (even after 40 rounds)!

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Experiment results



Comparison with benchmark case – Treatment 1



➢ asks correlated with opportunity costs (holds for all experiments)

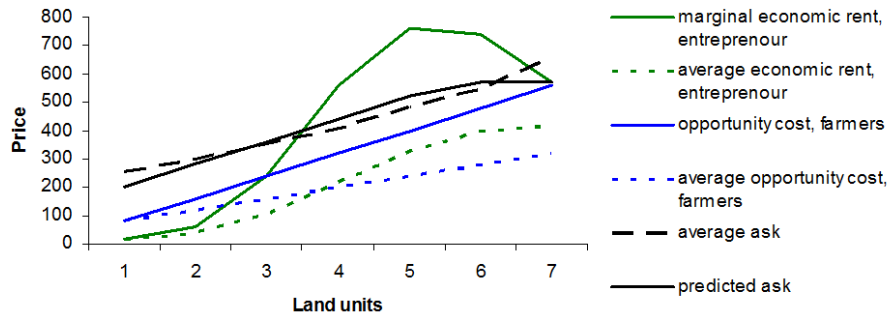
➢ in average far too high asks for low opportunity costs! (not just outliers!)

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Experiment results



Comparison with benchmark case – Treatment 2



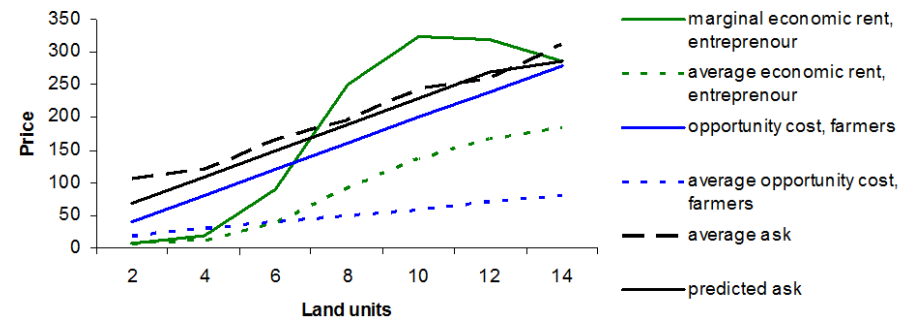
- in average too high asks for low and very high opportunity costs!
- bidding more efficient as too high asks are more costly!

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Experiment results



Comparison with benchmark case – Treatment 3



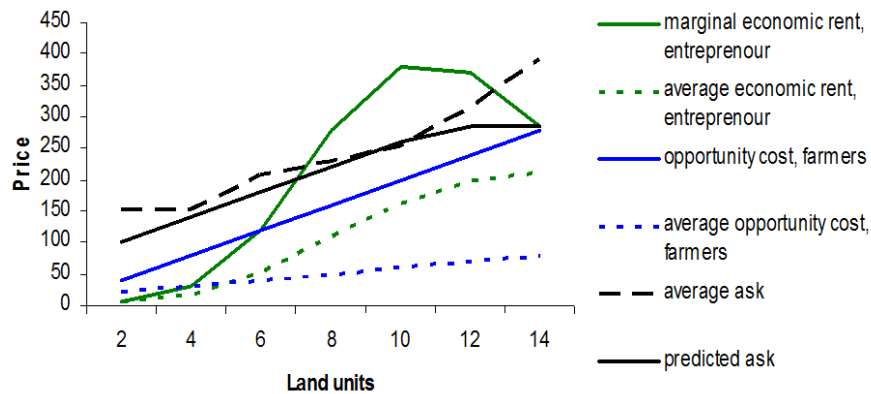
- in average far too high asks for most opportunity cost levels! (not just outliers!)

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Experiment results



Comparison with benchmark case – Treatment 4



- in average far too high asks for lower and high opportunity costs! (not just outliers)

Experiment results



Regression results

	Dependent variable: Ask			
	7 players		14 players	
	Tight room	Generous room	Tight room	Generous room
Constant	160900*** (22000)	167000*** (15200)	60600*** (6570)	89300*** (19300)
Opportunity cost	0.72*** (0.061)	0.82*** (0.042)	0.88*** (0.037)	0.96*** (0.11)
R-square	0.20	0.25	0.34	0.07

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Experiment results

Regression results

	Dependent variable: Profit			
	7 players		14 players	
	Tight room	Generous room	Tight room	Generous room
Constant	51900*** (7150)	78100*** (4190)	10600*** (1410)	60400*** (3150)
Opportunity cost	-0.14*** (0.020)	-0.12*** (0.042)	-0.035*** (0.037)	-0.24*** (0.018)
R-square	0.085	0.012	0.0080	0.15

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Experiment results

- Findings (II)
 - Individuals consider their opportunity costs
 - asks proportional to opportunity costs!
 - Problem: top-ups too high!
(most likely not just result of errors/trials!)
 - Players are too greedy!
 - Players suffer from greed!
 - Probably “fairness problem”
 - i.e., players with lower opportunity costs expect equal price
 - Question: Are players playing some kind of “tit for tat”?
 - in some treatments weak evidence that ask is lower if last asks successful

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Conclusions

- Auctions do not guarantee for Pareto optimal solutions!
 - Players do not reveal information although this is costly!
 - Players with low opportunity costs generally ask for „too much“
(compared to the benchmark case)
 - When potential gain is larger, the number of accepted asks is higher,
i.e., when too high asks are more costly
- Experiments provide evidence for
 - market failures
 - cooperation deficitsas reasons for unexploited increasing returns
- Other coordination strategies are probably more successful

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Further research

- Deeper analysis of results
 - Comparing the individual strategies of the players
(e.g. panel analysis)
 - Looking at the effects of learning
- Conduct the experiments with individualized opportunity costs
- Conduct the experiments with farmers instead of students
- Conduct the experiments with other auction schemes
 - eventually spectrum auctions

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Thank you for your attention!