How appropriate are myopic optimization models to predict decision behaviour: A comparison between agent-based models and business management games

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Abstract

Agent-based models (ABM) are used in many cases of policy assessment in agriculture. But the behavioural assumptions of these models consider farmers as myopic optimizing profit maximizers. In this contribution we compare the behaviour of myopic computer agents with the behaviour of students playing a multi period business management game. We aim to answer the question, how far are agent-based models valid to map "real" human behaviour, so that ABM can be used well for policy impact assessment.

Keywords: Agent-based models, business management games, policy impact analysis

JEL classification: C63, C93, D22, Q18

1. INTRODUCTION

Policy impact assessment is one important field in agricultural economic research. Regulatory policies often aim to steer the behaviour of economic agents by changing their economic environment. Assessing the potential impacts of regulatory policies requires forecasts regarding how humans adapt to such changes. So far agent-based models (ABM) are used in many cases for policy impact assessment (cf. Happe et al. 2006 and 2008). The problem is that in such models the decision maker is considered to behave as myopic optimizing profit maximizers. In contrary real decision makers would also consider dynamic aspects, viz. longer term optimization but they have limited information processing capacities (Balmann et al. 2010, Mußhoff et al. 2009, Sandri et al. 2010). If real agents react on changes in general economic conditions different from agents in ABM, the results could be biased. The "right" policies for the "wrong" kind of decision maker would be "bad" policies. That is, for a meaningful policy impact analysis the decision behaviour of the economic actors has to be understood and adequately modelled. This is demanding: It includes modelling of decision-maker specific multidimensional entrepreneurial objectives and of bounded rationality.

Hengel et al. (2010) propose that BMG (business management games) can be used to contribute towards better understanding of the behaviour of real decision makers, since they provide an inexpensive opportunity to reach beyond existing anecdotal evidence concerning "behavioural anomalies". Within their work Hengel et al. (2010) demonstrate how bounded rationality can be quantified and separated into its two components: incomplete information and limited information processing capacities. The resulting data show that decisions made by participants in the game are strongly influenced by bounded rationality. They also show that both incomplete information and limited information processing capacities are relevant components of the bounded rationality displayed by players.

In this contribution we raise the question whether two sources of bounded rationality neutralize each other. On the one hand we have myopic optimizing agents in ABM and on the other hand the limited cognitive abilities of real actors. We will test, whether ABM can be used well for policy impact assessment. For this purpose we compare the behaviour of myopic optimizing computer agents with the behaviour of students playing the BMG "Field or Forest" (cf. www.planspiele.de.gg). The results of the real players in the BMG are used as a benchmark for the results of the ABM. To derive the optimal farm organization for computer agents we developed the model FarmDeS (Farmers Decision Simulator; for the entire ODD protocol (cf. Grimm et al. 2006), please visit FarmDeS (2010)). With FarmDeS we model the decision behaviour of farmers regarding production and investments. Based on the BMG "Field or Forest", the farm agents have to decide on how to use their land in order to maximize their terminal wealth. We ask the questions: Are the agents more successful in the game? How will the markets react due to the myopic optimizing behaviour of the computer agents? How far are agent-based models valid to map "real" human behaviour?

2. MODEL

The BMG and the ABM consists of ten periods. In the BMG and in the ABM all agents have an equal amount of monetary units (800,000 MU) and land (1,000 ha) at the beginning. They can use their land to grow maize silage or wood chippings (short rotation coppices). Furthermore, they can get money for setting aside their land or they can invest in bungalows (useful lifetime is five periods) which is the only landless production opportunity. There are also opportunities to rent and lease land. Regarding the liquidity the farmers are able to invest their available money for 3% p.a. at a bank or they have the opportunity to get long term loans (10% p.a.) and overdraft facilities (15% p.a.). To cultivate their fields the farmers need a hypothetical machine, which is able to seed and harvest for five periods, both maize silage and short rotation coppices. Cultivating maize silage is a one year production activity. In case of wood chippings, the short rotation coppices are flexible regarding the time of harvest. The yield follows a quadratic production function. Prices for the products maize silage, wood chippings and "overnight stay" are derived model endogenously, i.e., using demand functions. On the land market the amount of land which is traded and the price are given by the market equilibrium derived from the supply and demand of the participants.

The BMG was played in the summer term of 2010 and in the winter term 2010/11, with participants being mostly students of agricultural science at Göttingen University. In total, 83, resp. 71, participants were registered. Participants who went bankrupt were not included in the analysis.

The objective of the game is to accumulate the highest terminal wealth by the end of period ten. To provide incentive compatibility, we announced prize money for the five players with the highest terminal wealth. The rank of players was not disclosed until the end of the game to prevent players from dropping out because of poor performance. Besides the prize money for the top performers we also asked the players to make a price prediction at the beginning of each round for the following three periods. The best overall price prognosis was rewarded.

In the ABM a farm agent's decision is simulated by using mixed-integer programming and depends – aside from its capital – on its expectation of the future product prices. The initial price expectations vary randomly. In the beginning one period is simulated before the real simulation starts. This is done to get initial product prices, which are the basis for the following price expectations.

As in the BMG, one simulation run consists of ten production periods, i.e., ten years. In each period the following sequence of calculations is performed:

1. Price expectation: Every farm agent has its own price expectation function for the next and the after next period:

   The initial price expectations are different among the farmers; they vary randomly depending on the highest and lowest possible price according to the demand functions resp. observed range of land prices in the BMG: for maize silage between 0 and 33 MU, for wood chippings between 0 and 55 MU, for overnight stay between 0 and 25 MU and for rental price between 100 and 300 MU. After this initial round the price expectation is calculated as follows (Happe 2004, p. 51):

   - next period:

$$P_{ex}^{t+1} = {P_{ex}^{t}}^{\alpha} \cdot {P_{act}^{t}}^{1-\alpha} \qquad (1)$$

   P denotes the price, ex means expected; t the time period; α the weight of the actual price and the expected price in period t and act means actual. In our case we choose for α 0.5.

   - after next period:

$$P_{ex}^{t+2} = \frac{P_{ex}^{t+1}}{P_{act}^{t}} \cdot P_{ex}^{t+1} \qquad (2)$$

2. Production decision: The production decision is optimized by using mixed-integer programming. Considering the given constrains regarding money and production capacities, the mixed-integer programming model finds the production strategy which leads - based on the expected prices - to the highest terminal wealth.

   Each production activity has different variable costs and also fixed costs have to be taken into account. The fix costs are composed of 80,000 MU/year rental payments for initial land and 20,000 MU/year cost-of-living. The investment costs for bungalows are 50,000 MU/bungalow and for machines 70,000 MU/machine. Furthermore there are variable costs of 991 MU/ha maize silage, 600 MU/ha for planting and 485 MU/ha for harvesting a short rotation coppice and 500 MU per year and bungalow for maintaining. The payment for new rented land, as well as the income from leased land, depends on the land price at the year in which the transaction occurs. Additionally the farmers have the opportunity to extent the liquidity and land constrains up to a certain amount: They can rent additional land (see 3. Land market) and borrow in the short term up to 200,000 MU at an interest rate of 15% p.a. The amount of available long term loan depends on the lending limit of the investments (lending limit for machines equals to 50% and for bungalows equals to 80% of the investment costs). In this case the interest rate is 10% p.a. and the credit period matches the useful lifetime of the investment.

Each production opportunity has its individual yield: One bungalow produces 600 overnight stays per year for 5 years. One hectare maize silage yields 50 tonnes per year. The wood chipping amount is calculated by a growing function. It depends on the age of the short rotation coppice:

$$Y_{wood} = 28.2 \cdot a - 1.8 \cdot a^2 \qquad (3)$$

Y denotes the yield and *a* the age of the short rotation coppice in years.

3. Land market: As already mentioned above the farmers have the opportunity to rent additional land or to lease land. The land market is implemented as a double auction market, which means that buyers and sellers submit bids and offers in any order. Every year each farm agent can make a bid and an offer for a certain amount of land based on its price expectation for land. On the land market the bids and offers are summed up to one demand and one supply function. These functions determine the market equilibrium which means amount of land and price (point, where demand and supply function intersect).
4. Price setting: After the production decision the farmers should know how much they earn. Therefore they need a price for the output. This one comes out of the different demand functions for each product:

   Wood chippings:

   $$P_{wood} = \max\left(0; \quad 55 - 0.0028 \cdot \frac{M_{wood}}{N} + 0.00000003 \cdot \left(\frac{M_{wood}}{N}\right)^2\right) \qquad (4)$$

   Maize silage: $$P_{maize} = \max\left(0; \quad 33 - 0.0007 \cdot \frac{M_{maize}}{N}\right) \qquad (5)$$

   Bungalow: $$P_{stay} = \max\left(0; \quad 25 - 0.001 \cdot \frac{M_{stay}}{N}\right) \qquad (6)$$

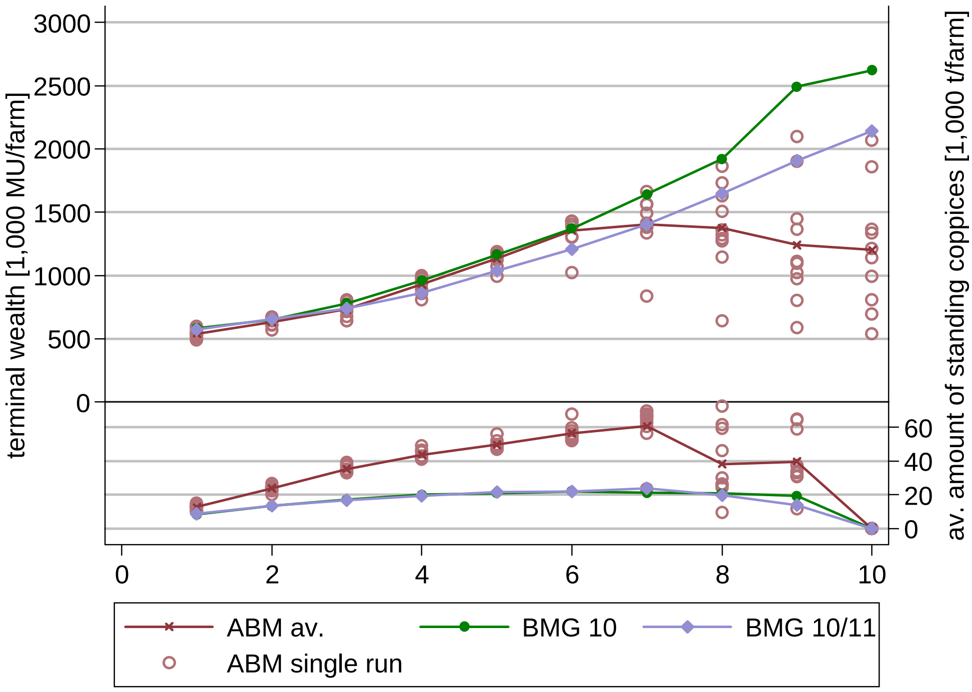
   M denotes the amount of product and *N* the total number of agents (including agents which are insolvent).
5. Actualisation:

   The production program is optimized in order to gain the highest expected terminal wealth on basis of the expectations regarding prices. There can be a difference between expected and realized values and actualisation is necessary.

3. RESULTS

We compared the mean of ten simulation runs of the ABM with the results of the two BMG runs. As a key figure of success we choose the development of the terminal wealth per solvent farm (Fig.1.). We have to clarify that the value of standing coppices is not in the terminal wealth. Therefore we added a plot showing the average amount of standing coppices per farm.

Fig.1. Development of terminal wealth per solvent farm



We find that in the first rounds there is hardly any difference between ABM and BMG. Also the results of the single ABM runs are close. But the growing impact of harvesting the short rotational coppices results in decreasing terminal wealth in the ABM. In the beginning the amount of wood chippings is increasing continuously (Fig.2.) while prices are decreasing (Fig.3.). Additionally the growing rate is decreasing over time and delaying the harvest is less and less worthwhile. Because of using linear programming for simulating the decision behaviour, eventually the critical point is reached where all other production opportunities are more favourable. Because of the underlying assumption for the price expectation of the after next period (see equation (2)) – projecting the actual price trend to the future – it is not worthwhile for the agents to wait anymore. As a result almost every short rotational coppice is harvested. As the starting point for cultivating short rotational coppice is the same for all agents (namely period one), all coppices are approximately at the same age. Therefore the agents decide nearly at the same point in time (around period eight) to harvest the majority of their short rotational coppices - with the effect that the price for wood chippings decreases dramatically. This indicates the starting point for a classical pig cycle (cf. Hanau 1928) which is illustrated in Fig.2. and Fig.3. In the second run of the BMG (BMG 10/11) one can also observe cyclic changes in the production and prices of wood chippings. But nevertheless it is not as strong as in the ABM. In case of the BMG, especially in the summer term 2010 (BMG 10), the amount of wood chippings in the last period is that high (and the price that low) because all short rotation coppices have to be harvested in the last production period. This is done automatically.

Fig.2. Production of wood chippings

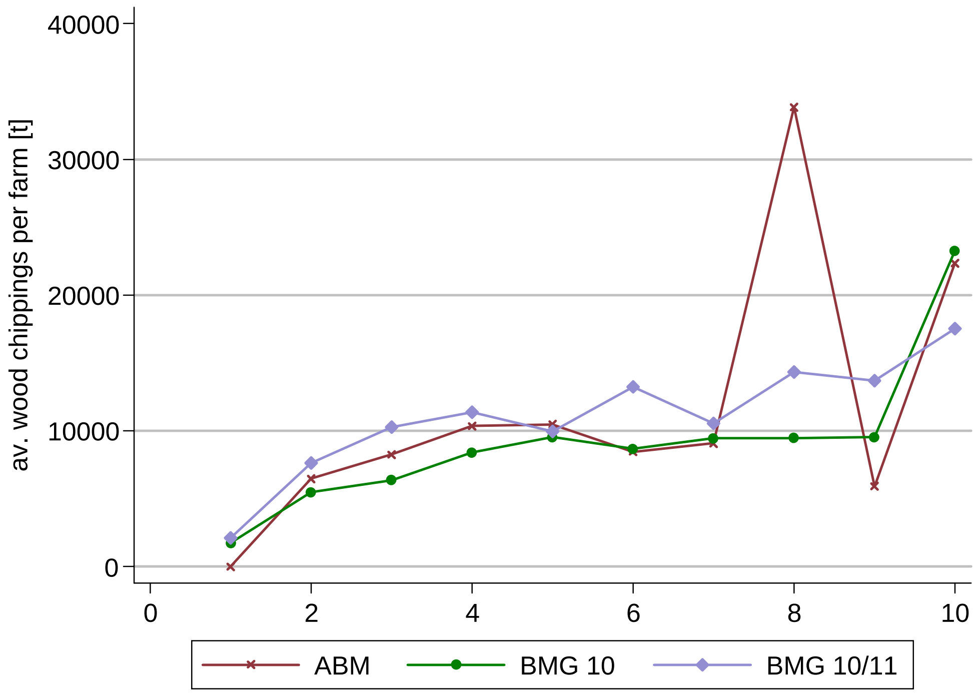
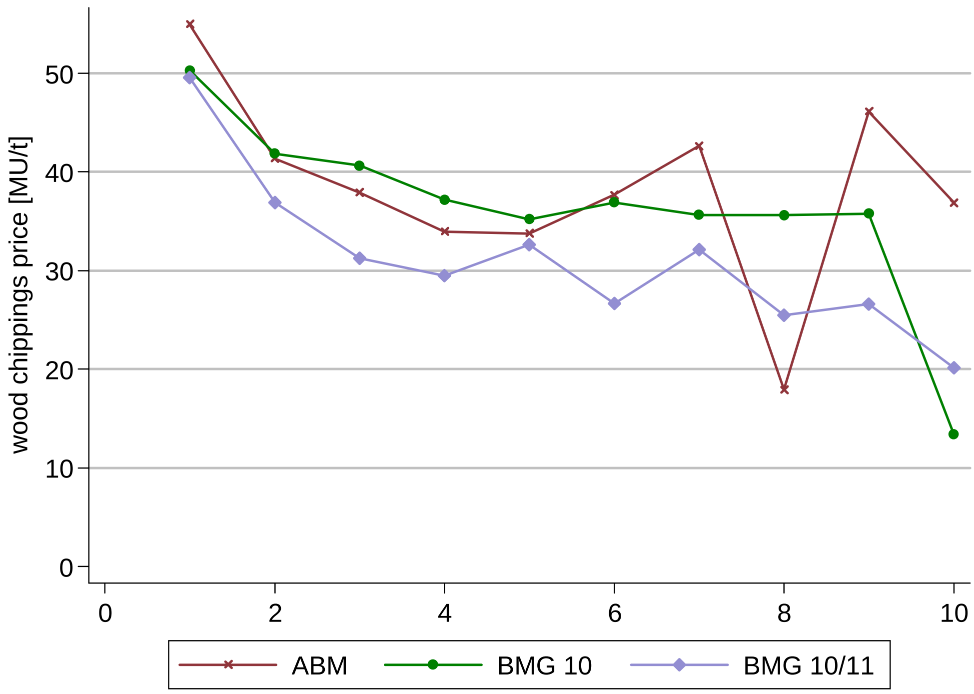


Fig.3. Development of the price for wood chippings



Additionally, one have to pay attention to the fact, that in the ABM more agents survive (stay solvent) than players in the BMG (Table 1). Illiquid farms are not considered in the analysis. Therefore the competition in the BMG becomes less hard over the course of time. Because hardly any agent in the ABM becomes illiquid, the competition is much harder and therefore the terminal wealth cannot increase as in the BMG.

Table 1. Amount of solvent actors [%]

Period	ABM	BMG 09/10	BMG 10/11
1	100	98.8	94.4
2	99.5	90.4	91.5
3	99.5	85.5	91.5
4	99.5	81.9	90.1
5	99.5	80.7	88.7
6	99.5	80.7	87.3
7	99.5	79.5	85.9
8	99.5	79.5	84.5
9	98.5	78.3	84.5
10	98.0	77.1	84.5

4. Conclusions

To conclude we can say that ABM could be reasonable in mapping the “real” human behaviour. Our analysis shows that especially in the first periods the model fits quite well the trends and results of the BMG, although the behavioural assumptions of the model are very rough. Several simulation runs (small circles in Fig.1) come really close to the BMG results even in the later periods. The myopia of the agents in ABM and the limited cognitive abilities of real actors seem to neutralize each other up to a certain extent. We have to remark that we can use only two BMG runs for this comparison. To draw even better conclusions, more runs of the BMG are desirable. But organizing and carrying out a BMG is time consuming. At the moment we are discussing the opportunity to play the BMG with a smaller group of students with more frequent repetitions. Compared to the effort of modelling an ABM and of organizing a BMG, the ABM is a cheap possibility, the results are reproducible and modifying is easier.

Additionally we presented one opportunity of testing and calibrating ABM in a relatively cost-effective way, because data of the BMG are cheaper to gather than data from field experiments. But one has to be aware of different effects resulting from the model design, like in case of the wood chippings that may cause problems. In our case we would propose a continuous design which means that the investments (short rotational coppices) are at different ages and such phenomena like the pig cycle can stabilize in the course of time.

It is impossible to detect human behaviour exactly but one has to decide in each individual case what amount of approximation is necessary or acceptable. Although we used really simple methods for simulating agent's behaviour, in some point the results are quite close to the BMG results. In the future we aim to improve the model to fit the observed behaviour in the BMG even better. The plan is to develop several sub models by using different methods (e.g. Bayesian networks, heuristics) of representing behaviour and try out which model correspond best to real human behaviour. In the end we can use these methods and apply them in larger models which are used for policy assessment.

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