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Original Research Article

Human behaviour versus optimising agents and the resilience of farms – Insights from agent-based participatory experiments with FarmAgriPoliS

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A B S T R A C T

This paper aims to examine the extent to which human participants show higher resilience compared to computer agents in agent-based participatory experiments. We motivate and examine three types of resilient behaviour of farmers during a crisis or as response to competitive pressure: successful survival, loss-minimising farm exits, and path breaking respectively path creating growth strategies. Our experiments revealed that human decision makers recognised and exploited such resilient strategies in periods of crisis or under challenging circumstances in general better than myopic optimising agents, although they did not perform better on average. The reason can be seen in a substantial heterogeneity of human decision makers, for which we identified four categories: negligent gamblers, actors missing opportunities, solid farm managers and successful path breakers.

1. Introduction

Agricultural structures or farm populations may be described as complex adaptive systems of regular interactions between farms as well as between farms and their environment (Balmann et al., 2006). In general, structural changes occur in agriculture in a more gradual and path-dependent manner. Farms face fierce competition on both the input and output markets, especially on the land market. In particular, the concept of the technological treadmill (Cochrane, 1958) suggests that if new technologies emerge, farms either have to innovate, adapt, or exit the sector. The role that a farm takes within this complex process depends not only on the farm's characteristics, the characteristics of the farmer or farm manager, but also on local competition, available technologies as well as the economic, institutional and environmental conditions. For an adequate understanding of the underlying processes, it is important to capture not only the interactions amongst and between farms and their environment but also the farms' behaviour, i.e. their decision processes.

To capture these interactions, a large variety of economic modelling approaches has been developed. Examples include recursive programming models (Day, 1963), general and partial equilibrium models (for an overview cf. Balkhausen et al., 2006) and, in recent decades, agent-based models (e.g. Happe et al., 2006; Berger and Schreinemachers, 2006; Freeman et al., 2009). The agent-based models explicitly focus on modelling the interactions among farms to study emergent properties on the system level.

Traditional agricultural economics assume that farm behaviour is based on the concept of profit- or utility-maximising price-takers; which are considered to be perfectly rational. These behavioural assumptions serve as the basis of general and partial equilibrium models. Additionally, several agent-based models of the agricultural sector are based on this principle. Examples include AgriPoliS (cf. Happe et al., 2006), MP-MAS (cf. Berger and Schreinemachers, 2006; Schreinemachers and Berger, 2011) and SWISSLand (Möhring et al., 2016). The frequent application of maximisation concepts in agent-based models of the agricultural sector may be attributed to its high compatibility with linear, recursive, and positive mathematical programming farm models in the tradition of Earl O. Heady (1983), Richard H. Day (1963), Richard E. Howitt (1995) and others that inspired and dominated farm-level modelling in agricultural economics for many decades. The specific strengths of each of these approaches are related to their compatibility with farm-planning databases. At the same time, these approaches to modelling farm behaviour have several common weaknesses, all of which are related to decision-making in complex situations. These weaknesses include sensitivity of optimisation results to uncertain expectations, ignorance of strategic issues, and the assumption of perfect rationality amongst agents.

Agent-based models are, however, flexible with regard to modelling agent behaviour. Examples of behavioural approaches range from simple rules to computational intelligence, including learning. Some of these concepts and the modelling process itself are combined with participatory approaches such as companion modelling (Antona et al.,

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2003). An extreme case can be found in role-playing games where human participants play the role of an agent and the games themselves serve as the models (Barreteau et al., 2003). A further option of modelling agent behaviour may be found in behavioural experiments in a laboratory. Behavioural laboratory experiments are used to study human behaviour in controlled environments. Many behavioural experiments have shown that humans do not necessarily behave according to the fully selfish and rational profit maximisation, and that context matters (e.g. Harrison and List, 2004). These insights also apply to the behaviour of farmers (e.g. Schwarze et al., 2014; Howley, 2015; Rommel et al., 2017).

The objective of this paper is to analyse how different behavioural approaches perform under different conditions while considering the complexity of structural change in agriculture. In particular, we compare the behaviour and performance of human participants with that of optimising agents, which are used in AgriPoliS, an agent-based model of structural change (Happe et al., 2006). For this purpose, the business-management game FarmAgriPoliS (Appel et al., 2018) has been developed. FarmAgriPoliS allows a person to actively manage a farm within the agent-based framework of AgriPoliS. For the behavioural experiments students with a background in agricultural economics were selected. The experiments are then compared with simulations of the standard AgriPoliS model, where all farms are managed by optimising agents.

Of particular interest is the extent to which human participants show higher resilience in their behaviour compared to the optimising computer agents in the face of specific strategic challenges. Apart from that, we aim to improve our understanding of how human participants act in a strategic farm management context, how they differ in their behaviour, and how these differences affect a farm's performance. Finally, we aim to identify conditions under which the participants are more successful and more resilient than computer agents.

The theoretical part of this paper in Section 2 focuses on selected system-theoretic and economic concepts related to structural change in agriculture. Based on that, the concept of resilience is defined regarding its relation to farm behaviour within the process of structural change. The methodological part in Section 3 illustrates FarmAgriPoliS in more detail and motivates the experimental approach to examine the hypotheses developed in Section 2. The experimental findings are elaborated in Section 4. Section 5 discusses the results and conclusions drawn.

2. Theoretical background

2.1. Path dependence and resilience in agriculture

The agricultural structure of a region can be described in terms of farm sizes and numbers, tenure patterns, legal organisation (sole proprietorship, partnership, or corporation), production capacities, technologies, and activities (Tweeten, 1984). Farm structures can be highly heterogeneous, even within and between regions with similar agricultural conditions (climatic, soil, infrastructural, economic, social). To some degree, farm size distributions correspond to the Pareto law (see Sombart, 1967): Often, a relatively small number of large farms are responsible for the majority of agricultural production.

Balmann (1995) argues that agricultural structures are path-dependent, meaning that feedback mechanisms lead to a lock-in at a certain state that may be inefficient and prevent the system from transitioning towards an efficient state. The concept of path dependency (cf. Arthur, 1989; David, 1985; North, 1990; Cowan and Gunby, 1996; Pierson, 2000; Schreyögg et al., 2003) attempts to explain why similar systems may develop very differently due to historical events. That is, today's agricultural structures are shaped by history, and will also affect future structures. Path dependence not only emerges on the aggregate level of agricultural structures, but also on the individual level. In this regard, Balmann et al. (1996, 2006) refer in particular to the role of sunk costs of assets and human capital as well as frictions on land markets. Sydow et al. (2005) provide a more general overview and classification of different reasons as to why path dependencies emerge. These reasons include economies of scale and scope, direct and indirect network externalities, learning, expectations, expectations of expectations, coordination, and complementary effects.

A farm manager may have to overcome the specific frictions resulting from path dependence on the farm as well as the sectoral level in order to elicit change (voluntary exits and exploitations of new opportunities). Overcoming path dependence may be understood as either path creation or path breaking through a kind of mindful deviation from the previous or usually expected development path (Garud and Karnoe, 2001; Garud et al., 2010). With regard to farm development and structural change, Ostermeyer (2015) considers voluntary farm exits as a trivial kind of path breaking. Nevertheless, a voluntary farm exit may require mindful deviation in terms of overcoming a personal mental model as well as the mental models prevalent in the social environment. From a managerial point of view, more challenging and far less trivial is the case where a farm manager is able to manage unusually strong and profitable growth. From simulations with AgriPoliS, Ostermeyer (2015) found that a small fraction of some 2% of farms were able to show such behaviour, allowing them to gain substantial shares in total regional production. This small fraction of farms may partly be explained by the limits in the amount of land in the region, because farms can only increase their land bank if other farms decline or exit. Another explanation is that the small share of path-breaking farms found by Ostermeyer (2015) may be the result from limitations of agent strategies in AgriPoliS.

Although a specific agricultural structure may not be seen as a societal goal in itself, farm structures may still play an important role from a societal perspective. As structures change slowly, there will be long-term effects on economic, social and environmental outcomes. This may also be the reason why structural changes often raise public concerns (Balmann and Valentinov 2016; Chatalova et al., 2016). A distinction can be drawn between two core concerns regarding structural change. These concerns relate first to potential winners and losers, as structural change seldom leads to Pareto superior results. For the agricultural sector, this issue has been addressed by the technological treadmill (Cochrane, 1958) and more generally by the Schumpeterian notion of creative destruction (Schumpeter, 1942). Second, concerns regarding structural change may be related to the complexity of structural change itself, which may ultimately provoke an "ongoing discourse between the so-called industrial and agrarian philosophies of agriculture" (Chatalova et al., 2016, referring to Thompson, 2010).

Both of these concerns suggest that farm structures may affect the resilience and vulnerability of an agricultural system, and therefore its sustainability. Resilience refers to the ability of a system to withstand disturbances and the capacity to maintain function and state (Folke 2006; Holling 1973). As such, resilience concepts extend beyond vulnerability concerns; they explicitly address the ability to exploit new opportunities resulting from adaptations to environmental changes (Walker and Salt, 2012). Accordingly, the resilience of an agricultural region or a farm may also be evaluated regarding its ability to benefit from new opportunities.

Management literature sets forth a broad range of definitions of resilience. On a more conceptual and behavioural level, resilience is defined as "learning from adversity how to do better" (Wildavsky, 1988, p. 2), an outcome of organisational learning (Sitkin, 1992, p. 241) or the "positive psychological capacity to rebound" (Luthans, 2002, p. 702). From an outcome perspective, Gittell et al. (2006) define resilience as "a) the maintenance of positive adjustment under challenging conditions […], b) the ability to bounce back from untoward events […], and c) the capacity to maintain desirable functions and outcomes in the midst of strain" (p. 303, with reference to Sutcliffe and Vogus (2003), Weick et al. (1999) and Wildavsky (1988)).

Farms are directly affected by the complexity of structural change, which includes persistent fierce competition as well as pressures resulting from the technological treadmill. On this treadmill, farmers are directly confronted with the role of innovators changing the game, having to adjust to changes, or exiting. The question as to how strategic skills affect the future of a farm can be subdivided into two sub-questions: first, which opportunities exist to change or adapt, and second, what defines a successful strategy. Both sub-questions are related to the resilience of a farm and farm management.

Returning to the competitive pressure of farms as well as the external shocks previously mentioned, resilience may be expressed in many ways. A rather simple form of resilient management can be understood as whether a farmer is able to survive an unexpected crisis through adaptation. However, exiting farming in an ordered way that minimises losses from devaluation and deterioration of fixed assets, or serves the well-being of the involved persons may also be understood as a strategy serving resilience. In this regard, even farm exits can be understood as entrepreneurial behaviour and vice versa, farm survival might not be a necessary condition for resilience. On the other hand, adaptation to external shocks or a changing business environment may also lead to completely new opportunities. The ability to exploit new opportunities may also express resilience. Both types of path breaking or path creating behaviour to adapt to changing environments can be considered as resilient.

2.2. Behavioural theories and hypotheses

Usually, neoclassical approaches evaluate agricultural policies based on the assumption of rational decision makers, typically following the model of the *homo economicus* (e.g. Pareto, 1906; Camerer and Fehr, 2006). This model assumes that farmers are profit- or utility-maximisers responding to (monetary) incentives. These assumptions have been questioned by research on behavioural economics (e.g. Ariely, 2008; Kahnemann, 2011; Thaler, 2012). Accordingly, humans are best described as boundedly rational, and are subject to numerous cognitive biases. They often ignore substantial parts of the available information and use heuristics rather than optimisation when making decisions. This means that the behaviour of human participants may deviate from that of computer agents in maximising profits. With regard to our behavioural experiments, this leads to Hypothesis 1:

- Behaviour differs between human participants and optimising computer agents. Compared to the optimising computer agents, the participants in a game tend to pursue a deviating investment and growth strategy.

  The prospect theory developed by Kahneman and Tversky (1979) further specifies cognitive biases that affect behaviour under uncertainty: Humans generally evaluate deviations from the current state (gains and losses) rather than absolute values (see Kahneman and Tversky, 1979, p. 277) and that "losses loom larger than gains" (p. 279). This leads to Hypothesis 2:

- Compared to optimising agents, the participants tend to be more effective at avoiding losses than at realising gains.

  Recent applications in organisational theory recognise the role of cognitive processes and social-emotional aspects in the concept of path dependency. Mental models of the protagonists involved may be particularly relevant to path dependence in agriculture. According to Jones et al. (2011), "(m)ental models are personal, internal representations of external reality that people use to interact with the world around them. They are constructed by individuals based on their unique life experiences, perceptions, and understandings of the world. Mental models are used to reason and make decisions and can be the basis of individual behaviours. They provide the mechanism through which new information is filtered and stored." In general, farmers may have varying mental models even if they work under similar conditions in the same region (cf. Ostermeyer, 2015). The reason is that mental models serve specific purposes and have different roots. This leads to Hypothesis 3:

- The participants differ in their behavioural patterns, and clusters of behavioural patterns exist among the participants.

  Starting from the assumption that path dependencies may cause a potential inefficiency, the question arises as to whether and under which circumstances a change towards a more efficient path is possible. Actors becoming aware of the inefficiency of the current path may try to escape from this path dependence. A starting point for overcoming path dependences can be found in a particular entrepreneurship of the actors. Garud and Karnøe (2001, p. 2) describe entrepreneurs as reflective and self-determined actors: "In our view, entrepreneurs meaningfully navigate a flow of events even as they constitute them. Rather than exist as passive observers within a stream of events, entrepreneurs are knowledgeable agents with a capacity to reflect and act in ways other than those prescribed by existing social rules and taken-for-granted technological artefacts." Overcoming path dependence through path creation or path breaking (Garud and Karnøe, 2001; Schreyögg et al., 2003) emphasises the role of entrepreneurs and how they can intentionally create desirable new paths. This leads to Hypothesis 4:

- (At least) some human participants exhibit path breaking or path creating behaviour in specific situations.

  Both prospect theory (Hypothesis 2) and the concept of path breaking and path creating behaviour (Hypothesis 4) are important aspects in the resilience of businesses: Prospect theory is related to the aim and ability to withstand disturbances and the capacity to maintain the own function and state (Folke, 2006; Holling, 1973), whereas path breaking and path creation aim towards exploiting new opportunities resulting from environmental changes (Walker and Salt, 2012). Following these behavioural approaches, we would expect that in contrast to the optimising computer agents, human participants exhibit a variety of strategies: Some may aim just to survive while others either follow a loss minimising exit strategy or exploit potential profits. Each of these strategies can address a specific form of resilient behaviour under harsh conditions: robustness, adaptability, transformability. This leads to Hypothesis 5:

- In general, participants display more resilient behaviour than optimising computer agents through successful survival in cases of crisis, loss-minimising exits, and successful growth strategies. Additionally, the participants are particularly successful under challenging conditions.

3. Methodology and model description

3.1. Economic experiments

Economic experiments have become popular and are increasingly used to inform policy makers (Colen et al., 2016; Viceisza, 2015). There is an ongoing academic debate on the best methods for investigating specific field contexts as "it is not the case that abstract, context-free experiments provide more general findings if the context itself is relevant to the performance of subjects" (Harrison and List, 2004: 1022). A wide spectrum of experimental tools ranging from simple and abstract (e.g. Hellerstein et al., 2013; Torres-Guevara and Schlüter, 2016) to complex decision environments have been adapted to specific field settings (e.g. Fiore et al., 2009; Reutemann et al., 2016). On the one hand, abstract laboratory experiments yield clean data at relatively low cost. However, the external validity of experimental results is limited.

On the other hand, empirical data from field studies has greater external validity, but identifying causal effects is often difficult. Framed field experiments using context-specific software environments may bridge this gap (Harrison and List, 2004; Fiore et al., 2009; Reutemann et al., 2016). Realistic agent-based models may provide this context-specific environment and participants can become part of the agent-based simulations. Guyot and Honiden (2006) describe this type of experimental setting as an agent-based participatory experiment.

3.2. The FarmAgriPoliS model

3.2.1. Software

FarmAgriPoliS can be understood as a business management game or experimental platform providing participants with a software-based environment of a simulated agricultural region. Within FarmAgriPoliS, one farm is managed by a human participant. The participant is assumed to manage this farm and to compete with computer-simulated optimising farms (agents) that derive their decisions from mixed-integer short-term profit maximisation (Appel et al., 2018). FarmAgriPoliS is based on AgriPoliS (Agricultural Policy Simulator; Happe, 2004; Happe et al., 2006; Kellermann et al., 2008) which represents a spatially explicit and dynamic agent-based model that simulates structural change in an agricultural region. Fig. 1 provides a flowchart that illustrates the course of actions per year of AgriPoliS and FarmAgriPoliS. Both models allow simulating farms, regional farm populations and structures, markets, agricultural production, and so on. Sahrbacher et al. (2014) provide a detailed documentation of AgriPoliS following the ODD standard protocol (Overview, Design concepts and Details). FarmAgriPoliS uses identical specifications routines for regions and specified farms as AgriPoliS does. In AgriPoliS, and therefore also in FarmAgriPoliS, the farms affect each other primarily through the land rental market. The farms in the model region compete for available land (i.e. land that is currently not rented) via a repeated auction. Within the auction, every farm first selects the available plot that is most valuable for the farm and then calculates a bid for this plot. Every farm's bid equals a specific proportion (e.g. 80%) of the marginal gross margin of this additional plot. The bid considers transportation costs that are assumed to be proportional to the distance between plot and farm. The farm with the highest bid receives the plot and is able to use it for a specific contract length (cf. Kellermann et al., 2008, p. 28 et seq.). Afterwards, all farms can again submit bids that are compared again. For a given period, this procedure continues as long as land is available.

Apart from renting land, participants have to formulate price expectations and to decide in every period on farm exit or continuation and on investments in durable and capital-intensive assets such as buildings and machinery. In case of a farm exit, farms will continue to receive incomes for the production factors owned by the former farm. In particular, they receive the rent paid by the leaseholder for their owned land, wages for off-farm working family members in the case of family farms, and interest on their liquid capital. At the same time, the closed farms are affected by depreciations and interest costs for existing debts (cf. Kellermann et al., 2008, p. 44). The grey boxes in Fig. 1 highlight the situations in which a participant has to make a decision. For FarmAgriPoliS, one can assume that participants face a comparable salient context that induces decisions similar to those faced by actual farm managers (cf. Guyot and Honiden, 2006) as can be assumed for the use of AgriPoliS. The participants compete with other farms controlled by the computer, which also make their decisions on investments, exits, and land rentals by means of mixed-integer but short-term optimisation. Thus, experiments with FarmAgriPoliS provide insights into how human participants behave in these competitive situations compared to computerised optimising agents as used in AgriPoliS.

A typical experiment lasts twenty rounds (equivalent to twenty simulated years). The participants' decisions on farm exit or continuation, bidding strategies for land, and investments in durable and capital-

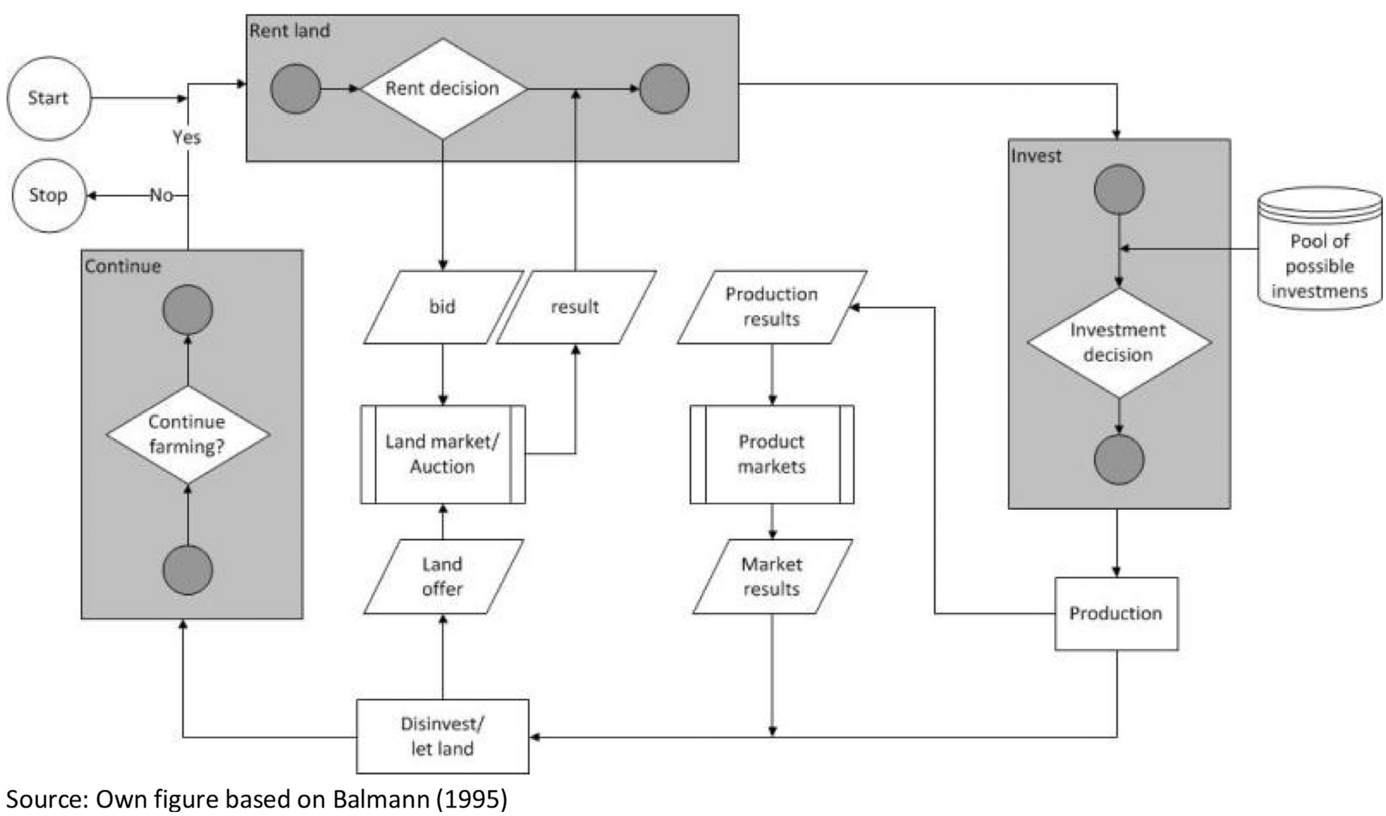


Fig. 1. Flowchart of one period in AgriPoliS and FarmAgriPoliS.
Source: Own figure based on Balmann (1995).

intensive assets such as buildings and machinery can be considered strategic decisions that drive a farm's performance in the long run. Short-term optimisations such as planning of the annual production are considered as non-strategic. It is therefore assumed that these can be made by the computer programme on the basis of the participants' price expectations and using mixed-integer optimisation. For the strategic decisions, participants may access information on how a computer agent would decide, which provides a default for rental bids and investments from which participants can, however, deviate. Appel et al. (2018) gives a more detailed description of FarmAgriPoliS.

3.2.2. Region

For our experiments, we defined an economic environment adapted to the characteristics of the Altmark region located in the German Federal State of Saxony-Anhalt. The Altmark captures important features of the large-scale agricultural structures of eastern German agriculture. The study region has a comparatively high proportion of grassland at almost 27%, the soil quality is poor and the yield levels in arable farming are low. Most of the land is cultivated by farms with more than 200 hectares (ha). Farm sizes are, however, heterogeneous. In terms of numbers of farms, individual full- and part-time farms as well as partnerships are predominate in the Altmark. Although corporate farms (mainly limited companies and producer cooperatives) only account for some 10% of the farms, they use almost 45% of the agricultural land. Most farms have a high share of loan capital and rented land. Larger farms in particular mostly operate through the use of hired labour. Livestock production is dominated by farms with large stocks. Fattening pigs are mainly kept in herds of more than several thousand animals and dairy cows in herds of up to more than five hundred. Around 40% of the dairy cows and 53% of the specialised dairy farms in Saxony-Anhalt are located in the Altmark, although the region covers only 23% of the agricultural acreage of Saxony-Anhalt (in 2007, StaLa, 2008, 2014), emphasising the relative importance of livestock production. Ostermeyer (2015) gives a detailed description of how the Altmark region is implemented in AgriPoliS.

The Altmark region may be seen as more vulnerable than other agricultural regions in Germany due to the weak capital base, high share of rented land, high share of hired labour, and low proportion of high-quality arable land. It is often argued that smaller farms which rely on their own labour, land, and capital are less vulnerable as it is easier for them to tighten their belts in times of crises (e.g. low agricultural prices) (see Weiss, 1999).

For the experiments, a portion (approx. one fifth) of the Altmark is simulated to shorten the computation time and to avoid longer waiting times for the participants during the experiments. However, the region is large enough to represent the specific characteristics of the region and relevant neighbourhood effects.

3.3. Design of behavioural experiments and subject pool

In order to study the decision-making of the participants in a competitive agricultural context, nine different scenarios were defined for the behavioural experiments. We defined three specific farm types with different sizes and individual production cost levels. These farms represent either larger family farms, partnership farms, or corporate farms (limited liabilities or producer cooperatives) which engage in arable and dairy farming. The farms are characteristically typical in terms of production, land use and employment for the study region. We also defined three different milk price developments (see Fig. 2) to study how participants respond to changing environmental conditions. Both factors, i.e. farm types and price scenarios were combined into a full factorial design. The scenarios are presented in Table 1.

Participants for our experiments were students recruited from three German universities in 2014 and 2015. A total of 49 students participated. Participants studied agriculture and related subjects (80%) either at Humboldt University Berlin (20%), Martin Luther University

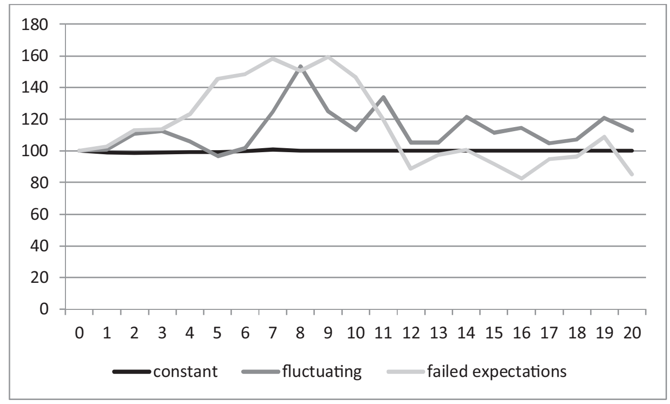


Fig. 2. Index of milk price developments used for the experiments (Period 0 = 100).

Halle-Wittenberg (53%), or Georg August University of Göttingen (27%). Participants were on average 25.1 years old (SD = 3.45), 35% were female, 63% already had a Bachelor's degree, and 63% had some practical experience in agriculture.

Participants were randomly assigned to scenarios and each participant had to play up to three different scenarios (drawing from an urn without replacement). In total, data sets of 144 experiments are available for the analysis. Every scenario was also simulated by replacing the respective participant by a computer agent which managed the farm through the standard optimisation routines of AgriPoliS with identical initialisation. These runs provided benchmarks for comparisons with the respective participant's behaviour.

Before the experiments, the participants were introduced to FarmAgriPoliS and were asked to maximise the final equity capital of the farm over the period of twenty rounds (years) in every experiment. They were also informed that they would receive payments contingent on their performance in the experiment. In addition to a fixed show-up fee of 20 euros, subjects received a euro for every two-percent increase in equity capital relative to the computer benchmark; the equity bonus was limited to a maximum of 30 euros per experiment. In those scenarios in which the respective computer agent went bankrupt in terms of negative equity capital after 20 periods, the reference for payment calculation was replaced by a simulation run with an informed human participant investing just enough effort to ensure positive equity capital. Apart from the calculation of payments, the computer agent served as the benchmark for the subsequent analysis in all scenarios. Detailed instruction in the software followed to ensure sufficient comprehension. Participants also had the opportunity for a test run, which was widely used. The participants were supervised by a researcher, who assisted them with the software, throughout the experiment.

3.4. Data collection

During the experimental session various data was collected. We logged the decisions of the participants and various indicators for the participants' farm as well as of all other computer farms, such as farm investments, land rentals, farm sizes, financial results, rents paid etc. As we have these data for every farm, we can reconstruct each single simulation run in detail and aggregate the farms' data to observe regional patterns as well.

In addition, a post-experimental questionnaire was used to collect data on the personal background (age, gender, educational level, etc.) and perceptions of the experiment. The participants were asked to answer without reference to their decisions in the experiments. Two item batteries based on validated psychological scales were used to identify decision-making styles (GDSM; cf. Scott and Bruce, 1995; Mann et al., 1997) and to distinguish satisficing and maximising behaviour (cf. Schwartz et al., 2002). Scott and Bruce (1995) defined decision-making

Table 1
Scenarios.

Scenario	Milk price (trend)	Farm	Production cost factor[a]	Size	Number of experiments
1	Price 1 (constant)	Farm 1	Good (0.9)	Medium (665 ha)	15
2	Price 2 (fluctuating)	Farm 1	Good (0.9)	Medium (665 ha)	20
3	Price 3 (failed expectations)	Farm 1	Good (0.9)	Medium (665 ha)	15
4	Price 1 (constant)	Farm 2	Normal (1)	Large (1480 ha)	16
5	Price 2 (fluctuating)	Farm 2	Normal (1)	Large (1480 ha)	8
6	Price 3 (failed expectations)	Farm 2	Normal (1)	Large (1480 ha)	24
7	Price 1 (constant)	Farm 3	Poor (1.15)	Medium (665 ha)	31
8	Price 2 (fluctuating)	Farm 3	Poor (1.15)	Medium (665 ha)	11
9	Price 3 (failed expectations)	Farm 3	Poor (1.15)	Medium (665 ha)	13

Note:
[a] Factor multiplied with the variable costs of the farm for each production activity.

styles as learned, habitual behaviour patterns applied in decision-making situations. They developed a questionnaire measuring rationality (information collection and careful consideration of alternatives), intuitiveness, dependence (relying on other people), avoidance, and spontaneity in decision-making. The General Decision Making Scale (GDSM) is measured on a five-point-scale. A modified version of the Maximisation Scale by Schwartz et al. (2002) was used for measuring the maximisation tendency. The German translation of the items was taken from Greifeneder and Betsch (2006). Although the maximisation tendency is usually measured on a nine-point scale, we opted for a five-point scale to improve the fit to GDMS. Data on risk attitudes was gathered by self-assessment from participants and an incentivised Holt and Laury lottery (HLL; Holt and Laury, 2002). We applied an eleven-point scale for self-assessment with questions worded from the socio-economic panel (see Ewald et al., 2012, referring to DIW, 2010, p. 27).

3.5. Analysis

3.5.1. Descriptive

A descriptive analysis is used to systematically analyse the differences in the behaviour and performance between the participants and agents. In this regard, performance refers to financial indicators, as the participants were incentivised to maximise the farm's equity capital at the final period. As financial indicators we use liquidity, revenue, profit and equity capital, where

- Liquidity is the amount of money that is readily available for a farm for investments, production, savings and consumptions.
- Revenue is the farm's monetary returns from farm production.
- Profit is the money that a farm earns above the costs to produce the goods. A farmers' profit is calculated as:

  Profit = Revenue − Production costs + Interest on working capital + Subsidies − Rental payments – Interest paid – Wages paid – Current upkeep of machinery and equipment – Depreciation – Farming overheads – Transportation costs

- Equity capital is the difference between the value of the farm's assets and currents on the positive side and its liabilities on the negative side.

3.5.2. Regression

To analyse the determinants of the participants' performances in the experiment, we conducted ordinary least squares regressions (OLS) where the relative difference in equity capital from the computer benchmark (Eq. 1) was used as the dependent variable. This accounts for different initialisations as well as the performance of the respective computer agents, which serves as the benchmark.

$$\text{Equity}_{relative} = \frac{(Equity_{Participant} - Equity_{Benchmark})}{Equity_{Period=0}} \quad (1)$$

The analysis was based on equity in the final round of all scenarios. For the regressions, we accounted for the panel data structure by clustering standard errors for participants. We used two dummy variables for farm type and two dummy variables for price movement to control for the two factors we manipulated in the scenarios. We included the amount of time that a participant played on average per scenario and period (duration) to assess the potential effect that some participants may have been more careful in their decisions than others and whether it was the first, second, or third experiment played by the participant during the session (order) (Table 2, Model 1). Further demographic variables were included such as gender and age (Table 2, Model 2) and the participants' general decision behaviour, represented by a psychological decision-making-style scale (GDMS; Scott and Bruce, 1995), a maximisation tendency scale (Schwartz et al., 2002), and risk attitude (HLL; Holt and Laury, 2002) (Table 2, Model 3).

3.5.3. Trajectory clustering

After comparing participants with computer agents, a cluster analysis was used to analyse and systematise the differences between the participants. To this end, we used a Stata plugin developed by Jones and Nagin (2013) to calculate group-based trajectories, where the trajectories measure the course of the relative equity compared to the corresponding benchmark farm (Eq. 1) over time. Group-based trajectory modelling (Nagin, 2005) is a specialised form of finite mixture modelling and provides the opportunity to identify distinctive clusters of individuals following similar developmental trajectories within a population. The model parameters are estimated by using maximum likelihood, where a general quasi-Newton procedure is used to locate the parameters that maximise the likelihood function.

Subsequently, a one-way analysis-of-variance (ANOVA) with Stata was applied to test for significance in the differences observed between the clusters resulting from the group-based trajectory modelling. The resulting pairwise comparison between the cluster groups was adjusted for multiple comparisons using the Bonferroni method.

4. Results

4.1. Descriptive analysis

Based on a descriptive analysis, we examined how the participants performed compared to the computer agents which served as benchmarks. This analysis focused on systematic differences in the behaviour and performance between the participants and agents. In this regard, performance refers to financial outcome, as the participants were incentivised to maximise the farm's equity capital in the final period.

The first surprising result was that the participants were not more successful than the computer agents in total. In 52% of the experiments analysed, the participants reached an equity capital level below the benchmark at the end of every experiment.

The scenarios were designed in such a way that some of them

Table 2
Regression of participant performance at the end of the experiment (difference in equity capital compared to benchmark relative to initial equity).

	Model 1 Coef.	Robust std. err.	Model 2 Coef.	Robust std. err.	Model 3 Coef.	Robust std. err.
Farm 2 (large)	**1.482****	0.545	**1.662****	0.531	**1.758***	0.653
Farm 3 (medium)	**1.365****	0.496	**1.481****	0.485	**2.148*****	0.547
Price 2 (fluctuating)	**0.7313***	0.335	**1.115****	0.346	**1.375****	0.401
Price 3 (failed expectations)	**3.397*****	0.547	**3.445*****	0.536	**3.445*****	0.661
Duration	0.0347	0.139	−0.0493	0.149	0.145	0.175
Order	−0.249	0.240	−0.2889	0.239	−0.264	0.382
Female			−0.404	0.543	0.137	0.882
Age			**0.221***	0.083	**0.226***	0.096
Knowledge of farm management[a]					**0.728***	0.331
HLL (safe choices)					0.262	0.134
Risk (self-assessment)[b]					−0.101	0.171
Maximising[c]					−0.66	0.451
Rational[d]					−0.02	0.887
Intuitive[d]					−0.251	0.567
Dependent[d]					0.094	0.319
Avoidant[d]					0.111	0.279
Spontaneous[d]					−0.05	0.355
Const.	−1.785	1.001	**−7.436****	2.368	−4.213	6.158
R^2	0.291	0.347	0.445			
F	10.22	9.40	4.51			
Number of obs	144	144	105			

Note: significance level:
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$; standard errors clustered for participants.
[a] I have sound knowledge of agricultural management. - 1 = strongly disagree, 2 = disagree, 3 = neither agree nor disagree, 4 = agree, and 5 = strongly agree.
[b] 0 = highly risk-tolerant, …, 10 = completely risk-averse.
[c] 1 = strong satisficing behaviour, …, 5 = strong maximising behaviour.
[d] 1 = very low expression of the resp. characteristic, …, 5 = very high expression of the resp. characteristic.

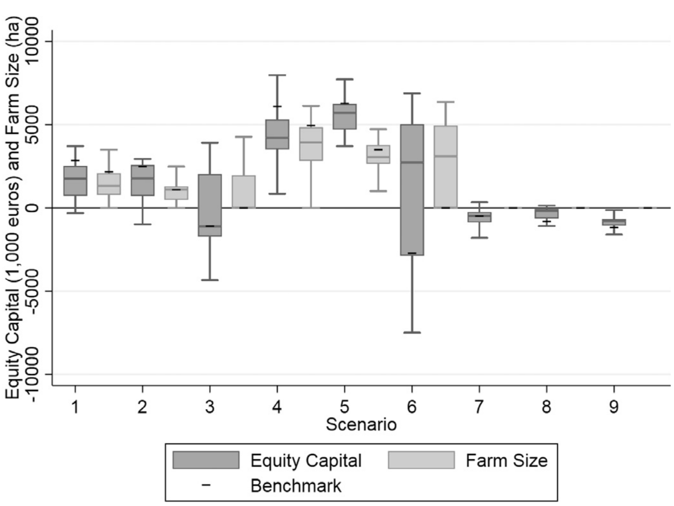


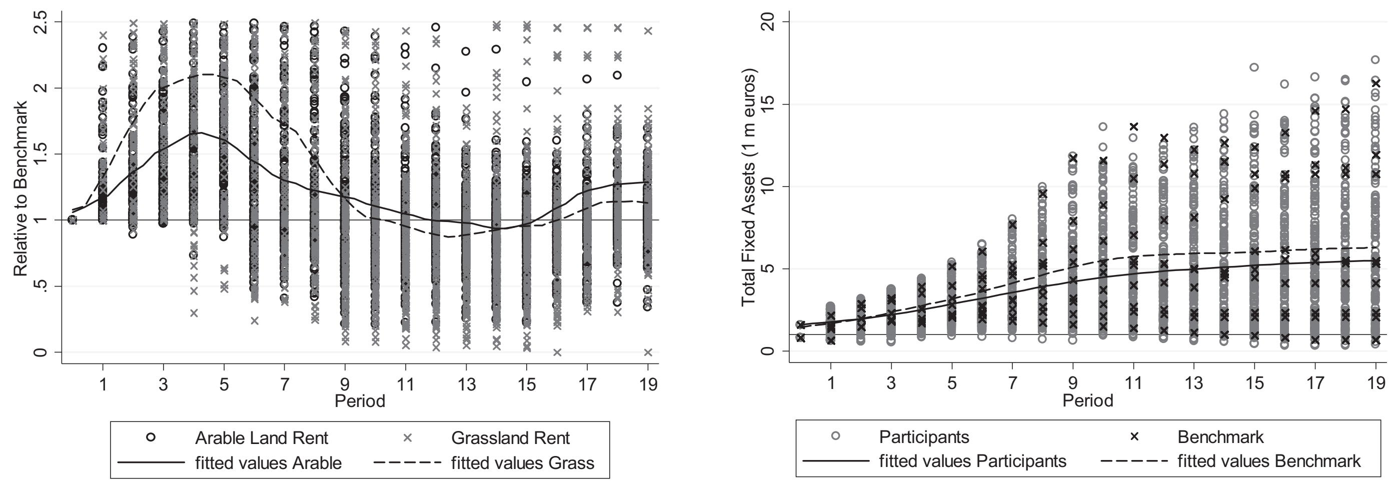
Fig. 3. Boxplot of equity capital and farm size at the end of the experiment. Note: Negative equity capital indicates bankrupt farms.

provided promising growth opportunities (scenarios one, two, four and five) while others created more competitive pressure (scenarios three, six, seven, eight and nine). In these more challenging scenarios the benchmark farms (computer agent) went bankrupt and ended with negative equity capital. Prospect theory by Kahnemann and Tversky (1979) indicates that the participants would be more engaged in avoiding losses than in realising gains compared to the computer agents. Fig. 3 shows that the participants were more successful on average in scenarios where the benchmark farm went bankrupt. Table A1 gives an overview of the statistical significance of these results. At the same time, participants showed a lower performance on average in cases where the computerised agents were profitable. In principle, this finding could be seen as the result of a selection bias – that is, that the computer agents may have been more or less successful by chance in certain scenarios. However, those scenarios in which the computer agents were more successful are scenarios with stable or positive market environments as well as scenarios in which the selected farms had a comparative cost advantage. Human participants were more successful on average in those scenarios characterised by price pressure and comparative disadvantage in the farm, so the differences can be considered as systematic.

In scenarios where the agents were more successful in financial terms, computer agents tended to pursue a stronger growth strategy and therefore operate in the end on larger farms than the participants (see Fig. 3 and Table A1). There were also significant differences between computer agents and participants regarding their behaviour on the land market. Participants in general tended to rent more land, especially in the more challenging scenarios where the respective farms faced volatile returns and comparative disadvantages resulting from high costs (scenarios three, six, seven, eight and nine; see Table A1).

The third key figure analysed was the difference in the value of production. Overall, participants tended to invest and produce less as reflected in the lower revenue in Table A1. This is interrelated: Funds used for a more intensive growth strategy regarding the farm's land bank detract from funds available for investment in production facilities such as stables, equipment and biogas plants. The remaining participants in agriculture only produced more in those scenarios where the benchmark farms quit.

The participants were informed about the expected marginal gain in profit, respectively, gross margins in every decision-making situation for rentals and investments. In addition, they were informed which decision the computer agent would make. According to the experiments, the participants deliberately differed from these suggestions.



(a) Rental prices for arable land and grassland (relative to benchmark)

(b) Investments in fixed assets

Fig. 4. Evolution of land rental prices and investments.
Note: Fitted values: kernel-weighted local polynomial smoothing; in addition to the fitted line, the graphs provide the corresponding single observation to give an impression on the distribution.

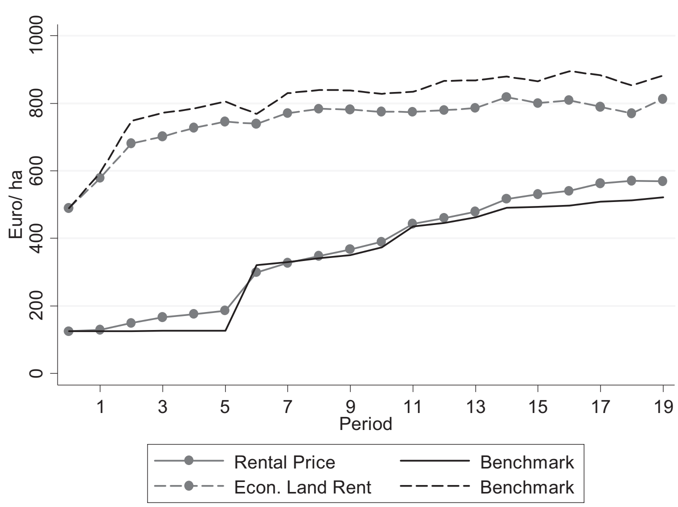


Fig. 5. Average development of rental prices and economic land rent in scenario one for participants and computer agents (Benchmark).
Note: Economic land rent is an imputed variable and measures the economic value of using the production factor "land" which is comparable to the Ricardian (Ricardo, 1817) or von Thünen (1826) land rent. Rental price is the average rental price paid to the land owner.

This often led to higher bids on the land market (and therefore higher rental prices, see Fig. 4a) and lower investments in other assets (see Fig. 4b). The participants rented land at prices which were clearly above the benchmark, especially in the first rounds. The differences gradually diminished over the course of each experiment. This finding can be attributed to the scenario setting – in some scenarios, the difficulty was designed in such a way that both the computer agent and the participants were under permanent financial pressure. At the same time, the level of the rents paid approached the increasing economic land rent over time, reducing the scope of action for bids by the computer agents and the participants (see Fig. 5 and Table A2).

4.2. Regression analysis

According to the regressions presented in Table 2, participants were more successful than the computer agents in those experiments that seemed to be more challenging (scenarios three, six, seven, eight and nine; see Fig. 3). For these scenarios it was considered that the farms to be played suffered from relatively high variable costs (Farm 3) and that prices were uncertain. This finding was particularly strong when price development was not only uncertain, but also showed a declining trend after an initial rise (Price 3). Regarding the characteristics of the participants, we found in our regression that only the age of the participants and their knowledge of agricultural management (self-assessment) had a significantly positive impact on the performance.

4.3. Cluster analysis of participant performance

According to group-based trajectory clustering, the participants can be divided into four clusters. Fig. 6 shows the courses of the related estimated trajectories and Table A3 shows the distribution of clusters by scenarios. An overview of the cluster characteristics is given in Table 3 (for summary statistics see Table A4). The detailed results are presented in Table A5 in the Appendix.

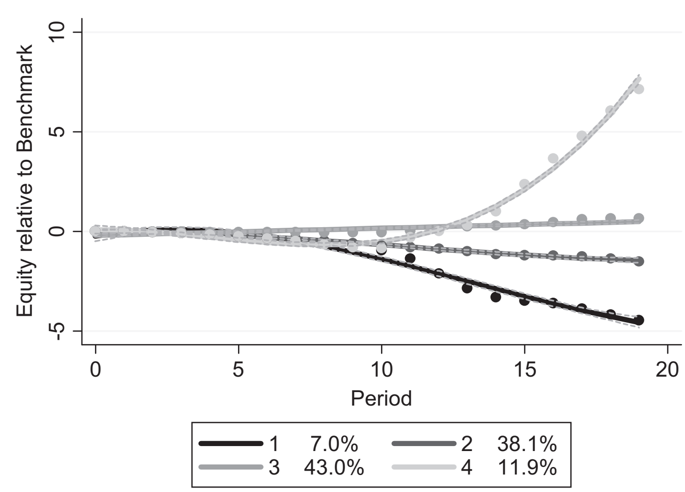


Fig. 6. Calculated trajectories based on the equity capital relative to the benchmark.

Table 3
Cluster characteristics.

Variable	Cluster 1		Cluster 2		Cluster 3		Cluster 4	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Initial farm size (ha)	991	420.86	1,020.64	407.91	758.52	261.92	1288.24	356.35
Initial equity capital (€1,000)	813.02	150.04	815.46	153.11	705.78	103.88	920.56	127.75
Production cost factor[a]	0.94	0.05	0.99	0.09	1.05	1.11	0.98	0.04
Av. equity capital (€1000)	439.79	1824.05	1377.92	1350.30	1149.34	1179.39	2723.19	1394.98
Final equity capital (€1,000)	−2584.32	2509.41	1040.44	2726.24	937.13	2357.27	4297.49	1491.21
Av. profit p.a. (€1000)	100.59	777.14	375.93	586.17	290.44	587.52	934.30	758.97
Final profit (€1000)	−460.86	279.45	135.57	718.19	134.89	889.23	696.71	449.55
Av. size (ha)	1014.90	975.20	1218.36	1147.19	911.27	852.56	2272.79	1356.47
Final size (ha)	0	0	1300.27	1519.69	934.58	1525.67	4177.35	1429.82
Av. revenue (€1000)	3082.56	1939.46	3555.01	2723.13	2711.58	2712.36	6571.81	4025.20
Gender (1 = female)	0.40	0.49	0.44	0.50	0.26	0.44	0.24	0.42
Age	24	2.10	25.49	2.89	26.24	3.46	27.65	3.78
Knowledge of farm management [b]	2.88	1.17	2.86	0.95	2.86	1.13	2.08	0.64
HLL (safe choices)	5.5	1.50	4.95	2.52	5.75	1.90	5.76	2.29
Risk (self-assessment)[c]	4.7	1.42	4.55	1.99	5.16	1.83	4.35	1.57
Maximising[d]	3.35	0.55	3.03	0.58	2.97	0.39	3.23	0.35
Rational[e]	3.78	0.54	3.85	0.57	4	0.47	4.01	0.30
Intuitive[e]	3.46	0.79	3.56	0.70	3.14	0.71	3.04	0.78
Dependent[e]	2.96	0.79	3.09	0.80	3.20	0.80	3.33	0.64
Avoidant[e]	2.44	0.94	2.62	1.10	2.68	0.85	2.92	0.96
Spontaneous[e]	2.98	0.77	2.93	0.84	2.81	0.87	2.88	0.66
Number of farms	10		55		61		17	

Note:
[a] factor multiplied by variable costs of the farm for each production activity.
[b] I have sound knowledge of agricultural management. - 1 = strongly agree, 2 = agree, 3 = neither agree nor disagree, 4 = disagree, and 5 = strongly disagree.
[c] 0 = highly risk tolerant, …, 10 = completely risk averse.
[d] 1 = strong satisficing behaviour, …, 5 = strong maximising behaviour.
[e] 1 = very low expression of the resp. characteristic, …, 5 = very high expression of the resp. characteristic.

In summary, the four clusters can be described as follows:

Cluster 1 – "The negligent gamblers"
The participants with the strongest ambitions (strongest maximising tendency) are in Cluster 1. Approximately 7% of the participants belonged to this group. Their decision-making style was intuitive and spontaneous. Additionally, they were the youngest participants and assessed themselves as having the lowest level of knowledge of agricultural management. These members may therefore be considered as less-experienced participants. Although they had relatively good starting conditions regarding farm size and level of variable costs (represented by the production cost factor), this cluster exhibited the most unfavourable development in relative equity compared to the benchmark results achieved by the respective computer agents: After a promising start, the participants often ended up with huge losses on average. The participants faced high price volatility in eight out of the ten experiments belonging to this cluster. Accordingly, the poor performance may be explained by a deficit in coping with uncertainty amongst the participants.
Cluster 2 – "Missed opportunities"
The starting conditions for the farms of Cluster 2 were also quite good. The farms in this cluster were initially rather large, their production cost factor was at an average level (that is, close to one), and the participants mainly experienced fairly stable price development. While the respective computerised benchmark farms were quite successful and faced little economic pressure on average, the participants performed less successfully in these experiments. The participants were evidently unable to exploit the opportunities offered. Some 38% of all participants fell into this category. The participants may be described as rather risk neutral and acting intuitively according to the post experimental survey. Interestingly, this group showed the highest share of female participants.
Cluster 3 – "The solid farm managers"
Cluster 3 mainly included experiments with rather challenging scenarios, where the farms were on the small side and their production costs relatively high (see Table A5). The respective benchmark farms exited farming or suffered bankruptcy in many of the scenarios shown. The participants were quite successful compared to the benchmark farms. Around 43% of the participants belonged to this group, which included participants who deliberately decided to quit (8% of the participants in Cluster 3) and successfully prevented or minimised losses as a result (see Table A6). The participants in Cluster 3 were slightly more risk averse in the Holt and Laury Lottery (higher number of safe choices) and according to their own self-assessment. They also had the lowest maximising tendency and therefore could be described as risk-averse satisficers.
Cluster 4 – "The successful path-breakers"
The participants with the most positive relative equity development were located in Cluster 4. They started with a relatively high initial farm size but were constantly confronted with challenging price developments (fluctuating, partly declining). These participants performed very well compared to their benchmark farms, as well as in absolute terms. As Table 3 shows, these participants developed large and financially well-equipped farms. Approximately 12% of the participants fell into this successful group. In contrast to the other clusters, the participants acted less intuitively and more rationally; they showed a higher maximisation tendency than Cluster 2 and Cluster 3. In addition, this cluster contained the oldest and possibly the most experienced participants. They also categorised themselves with the highest level of knowledge of agricultural management compared to other clusters. The participants' strategies in this group enabled them to leave the predetermined development paths and to open up new possibilities for successful farm management. These participants may be considered as more entrepreneurial, path breaking farmers.

5. Discussion

The results of Sections 4.1 and 4.2 support hypotheses 1, 2 and 3 as defined in Section 2.2. The participants deviated systematically in their strategies although on average, they were not more successful than the computerised benchmark farms. Key findings of the statistical analysis are:

- The participants focused more on growth through renting additional land than on investing in assets. As a result of this bias, they generated less added value on average.
- The participants performed more successfully than the computer agent in scenarios that were more challenging, that is, where farms encountered higher production costs than other farms and uncertain or even declining prices.
- Older and more educated participants tended to be more successful than the computer agent and other participants.

On average, the participants were not more successful than the optimising agents. However, the clustering confirmed the finding that the participants differed from the optimising benchmark farms in response to economic pressure and regarding certain individual characteristics such as age and knowledge in farm management. The clustering in Section 4.3 therefore further supports hypotheses of Section 2.2:

- In accordance with Hypothesis 3, the participants differed not only in behavioural patterns; there were evidently also clusters of behavioural patterns among the participants.
- In accordance with Hypothesis 4, the participants exhibited path breaking or path creating behaviour in some experiments by successfully developing and managing very ambitious growth strategies. Interestingly, this occurred most often in scenarios with mediocre or challenging starting conditions.
- In accordance with Hypothesis 5, the participants revealed more resilient behaviour than the computer agents in some 50% of the experiments. This especially occurred in more difficult situations through different types of strategy: successful survival in case of a crisis, successful exits, and successful growth.

The difference in behaviour and performance (i) between human participants and myopic optimising agents, and (ii) between different participants in participatory agent-based experiments on managing farms in a competitive environment can be further systematised: In contrast to optimising computer agents, the participants were on average more effective in avoiding losses but less successful in generating high profits and equity which is in accordance with prospect theory (Kahnemann and Tversky, 1979). The different strategies of computer agents and participants are also reflected in the investment and growth strategies revealed: Overall, participants tended to invest and produce less, but generally tended to rent more land and at higher prices, especially in the more challenging scenarios with volatile returns.

We also analysed the conditions in which participants were more successful than computer agents. As participants were more adept at avoiding losses, they should have been more successful in more challenging conditions, like those which exist for farms with comparative disadvantages and uncertain, partly declining price developments. Under these conditions, the participants performed substantially better than the computer agents. Alternatively, this result may be interpreted as rational but myopic profit-maximising computer agents struggling with uncertainty and pressure. That is, this phenomenon may hint towards a weakness of the computer agents in AgriPoliS and FarmAgriPoliS rather than towards a strength of the participants. The current decision algorithms in FarmAgriPoliS and AgriPoliS may be poor in coping with specific strategic issues. For instance, myopic optimisation may cause investments and land rentals in unfavourable situations, as may be the case if returns are deteriorating due to falling prices or increasing competitive pressure.

At the same time, the performance of the participants substantially differed. A cluster analysis revealed heterogeneity in behaviour amongst the participants. We identified four distinct experimental outcome clusters. Three clusters that included some 88% of the experiments corresponded with the prospect theory – that is, the participants were more successful at avoiding losses than at exploiting opportunities. However, approximately 12% of the participants succeeded in leaving predetermined development paths. In these experiments, the participants managed strong growth and performed substantially more successfully than computer agents and other participants. Interestingly, these participants faced relatively difficult scenarios with challenging price developments (fluctuating or even declining) and average cost structures. These very successful path breakers do not fit into prospect theory and characterise rather entrepreneurial actors. Both groups – loss avoiders according to prospect theory, and path breakers – relate to different interpretations of resilience. The "solid farm managers" in particular represent the ability to withstand disturbances and the capacity to maintain function and state (Folke, 2006; Holling, 1973) whereas the "successful path breakers" represent the ability to adapt successfully to new opportunities resulting from environmental changes (Walker and Salt, 2012).

Within the "solid farm managers" group, we further identified farmers that managed successful farm exits by developing an exit plan. However, this behaviour and its relative success also suggests considering resilience in agricultural structural change as not just preventing exits, but also in considering planned exits as entrepreneurial decisions in an adaptive and specific response to environmental and situational conditions and shocks. Planned exits may be motivated by minimising losses from devaluation and deterioration in fixed assets, human capital, or the well-being of the people involved. More than half of the conscious farm exits in the experiments were successful exits in this regard. Taking these farm exits into account, some 55% of the participants' responses in the experiments belong to the clusters including the "solid farm managers" and "successful path-breakers." That is, a considerable number of participants revealed more resilient behaviour than computer agents.

At this point, it seems appropriate to cite Kahnemann and Tversky (1979) once more: "… we feel that the present analysis falls far too short of a fully adequate account of these complex phenomena" (p. 286). A future challenge will be to use these findings to make behavioural assumptions more realistic in models such as AgriPoliS. Moreover, the experiments revealed that the age of the participants and their (self-assessed) knowledge of agricultural management had a strong positive impact on a participant's performance, a finding that warrants repeating the experiments with well-educated and experienced farmers. Such experiments may reveal further weaknesses in the decision algorithms in AgriPoliS and FarmAgriPoliS regarding strategic decisions.

6. Conclusions

Considering the complexity of structural change in agriculture, the first lesson to be learnt from our analysis is that not just models of structural change should be able to reproduce key phenomena of the complex reality but also that the cognitive capacities of actors within the models should be able to cope in their decisions with complexity. However, our experiments indicate that not all actors will have similar cognitive capacities. Thus, the heterogeneity of farms and their performance may not just be attributed to starting conditions and more or less lucky conditions but also to the farmer themself. Most likely this applies to reality as well as to complex decisions within models.

A second lesson to be learnt relates to the understanding of resilience. It is not sufficient to consider resilient agricultural systems as merely having robust farms. As resilience concepts argue that resilience can also be based on the agents' and system's ability to adapt, it seems to be important to consider the adaptiveness and transformability of farms as indicators of resilient structures. This becomes even more relevant if the ability of an agricultural system to fulfil its societal functions is the main concern of, e.g., policy makers. Under such conditions, policies are misleading if they do not value the potential societal benefits of change. Concerning societal functions such as production of food and other agricultural products and the generation of farm income, key policy questions must balance whether farmers who do not have promising prospects are provided with adequate tools and incentives to recognise their options with farmers who have prospects are potentially able to recognise and eventually exploit promising strategies. This is at least true in the absence of negative externalities.

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Appendix

Table A1
Student's *T*-test for selected financial indicators (period 19).

	Scen.	Obs.	Bench- mark	Mean participants	Std. err.	Std. dev.	$Pr(T < t)$	$Pr(\|T\| > \|t\|)$	$Pr(T > t)$
Equity capital (€1000)	1	15	2,843	1,733	270	1,045	0.0005***	0.0011**	0.9995
	2	20	2,484	1,430	293	1,312	0.0010**	0.0019**	0.999
	3	15	−1,099	−387	669	2,589	0.8476	0.3048	0.1524
	4	18	6,084	4,239	491	2,084	0.0008***	0.0016**	0.9992
	5	8	6,271	5,587	448	1,267	0.0852	0.1703	0.9148
	6	24	−2,723	1,053	887	4,343	0.9999	0.0003***	0.0001***
	7	20	−490	−533	117	523	0.3592	0.7184	0.6408
	8	11	−822	−303	114	378	0.9995	0.0010**	0.0005***
	9	13	−1,174	−714	222	801	0.9698	0.0605*	0.0302*
Liquidity (€1000)	1	15	1,295	449	182	703	0.0002***	0.0004***	0.9998
	2	20	893	107	212	947	0.0007***	0.0015**	0.9993
	3	15	−2,021	−1,629	571	2,213	0.7481	0.5039	0.2519
	4	18	2,712	1,707	322	1,367	0.0031**	0.0062**	0.9969
	5	8	1,674	2,020	309	873	0.8505	0.2990	0.1495
	6	24	−4,895	−1,305	722	3,535	1.0000	0.0000***	0.0000***
	7	20	−745	−850	103	461	0.1606	0.3212	0.8394
	8	11	−1,235	−685	105	349	0.9998	0.0004***	0.0002***
	9	13	−1,641	−1,193	234	844	0.9602	0.0796*	0.0398*
Profit (€1000)	1	15	842	214	146	566	0.0004***	0.0007***	0.9996
	2	20	359	111	90	403	0.0064**	0.0127*	0.9936
	3	15	−441	−104	149	577	1.0000	0.0000***	0.0000***
	4	18	1,915	1,142	233	987	0.0000***	0.0000***	1.0000
	5	8	1,719	1,350	213	602	0.0000***	0.0000***	1.0000
	6	24	−1,005	−84	216	1,056	1.0000	0.0000***	0.0000***
	7	20	−116	−138	9	38	1.0000	0.0000***	0.0000***
	8	11	−177	−143	12	39	1.0000	0.0000***	0.0000***
	9	13	−216	−192	20	73	1.0000	0.0000***	0.0000***
ESU[a]	1	15	2,638	1,726	291	1,129	0.0037**	0.0074**	0.9963
	2	20	1,953	1,590	189	845	0.0349*	0.0698*	0.9651
	3	15	500	1,104	295	1,141	0.9701	0.0598*	0.0299*
	4	18	6,055	4,245	440	1,866	0.0004***	0.0007***	0.9996
	5	8	6,327	5,002	575	1,627	0.0273*	0.0547	0.9727
	6	24	1,401	2,590	451	2,208	0.9927	0.0147*	0.0073**
	7	20	0	226	44	196	1.0000	0.0001***	0.0000***
	8	11	255	220	30	98	0.1333	0.2666	0.8667
	9	13	115	291	61	218	0.9934	0.0133*	0.0066**
Farm size(ha)	1	15	2,160	1,531	247	957	0.0117	0.0234	0.9883
	2	20	1,085	954	157	701	0.2059	0.4117	0.7941
	3	15	0	823	351	1,360	0.9828	0.0345*	0.0172*
	4	18	4,940	3,578	414	1,756	0.0022**	0.0043**	0.9978
	5	8	3,490	3,084	386	1,092	0.1642	0.3284	0.8358
	6	24	0	2,626	503	2,462	1.0000	0.0000***	0.0000***
	7	20	0	23	23	104	0.8351	0.3299	0.1649
	8	11	0	3	3	11	0.8296	0.3409	0.1704
	9	13	0	112	76	274	0.9164	0.1673	0.0836

(*continued on next page*)

Table A1 (*continued*)

	Scen.	Obs.	Bench- mark	Mean participants	Std. err.	Std. dev.	Pr($T < t$)	Pr($\|T\| > \|t\|$)	Pr($T > t$)
Rented arable land(ha)	1	15	509	639	24	91	1.000	0.000***	0.000***
	2	20	718	783	19	85	0.999	0.003**	0.001**
	3	15	503	579	42	162	0.955	0.091	0.045*
	4	18	467	481	19	79	0.762	0.476	0.238
	5	8	597	585	13	36	0.192	0.385	0.808
	6	24	40	407	41	203	1.000	0.000***	0.000***
	7	20	683	689	21	96	0.603	0.794	0.397
	8	11	870	758	49	162	0.022*	0.045*	0.978
	9	13	748	575	39	142	0.000***	0.001**	1.000
Rented grassland(ha)	1	15	637	658	26	102	0.778	0.443	0.222
	2	20	819	808	28	127	0.359	0.718	0.641
	3	15	478	557	52	201	0.924	0.152	0.076
	4	18	423	415	28	117	0.387	0.774	0.613
	5	8	643	652	45	127	0.575	0.850	0.425
	6	24	13	202	35	170	1.000	0.000***	0.000***
	7	20	494	664	33	148	1.000	0.000***	0.000***
	8	11	759	755	82	272	0.481	0.961	0.519
	9	13	495	529	68	247	0.684	0.632	0.316
Revenue (€1000)	1	15	6,627	4,449	726	2,810	0.005**	0.009**	0.995
	2	20	4,961	4,152	442	1,976	0.042*	0.083	0.959
	3	15	1,724	3,460	817	3,164	0.974	0.052	0.026*
	4	18	15,322	10,639	1,019	4,324	0.000***	0.000***	0.999
	5	8	15,833	12,309	1,386	3,919	0.019*	0.039*	0.981
	6	24	4,310	7,711	1,221	5,979	0.995	0.011*	0.005**
	7	20	0	775	113	506	1.000	0.000***	0.000***
	8	11	688	687	69	229	0.495	0.990	0.505
	9	13	413	1,013	174	627	0.998	0.005**	0.002**
Revenue cumulated (€1000)	1	15	71,173	56,651	4,931	19,098	0.005**	0.011*	0.995
	2	20	64,029	57,339	3,331	14,896	0.029*	0.059	0.971
	3	15	58,203	60,399	5,898	22,844	0.642	0.715	0.358
	4	18	157,291	123,104	7,919	31,674	0.000***	0.000***	0.999
	5	8	163,224	144,209	12,128	34,302	0.081	0.161	0.919
	6	24	122,599	120,005	8,449	41,393	0.381	0.762	0.619
	7	20	18,326	24,040	1,295	5,934	0.999	0.000***	0.000***
	8	11	20,613	24,723	1,286	4,266	0.995	0.009**	0.005**
	9	13	19,637	29,543	1,915	6,905	0.999	0.000***	0.000***

Note: significance level: *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

[a] 1 ESU = €1200 standard gross margin.

Table A2

Ratio between rental prices and economic land rent.

		Period																				
Scen.		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	Mean
1	Particip.	0.25	0.22	0.22	0.24	0.24	0.25	0.40	0.42	0.44	0.47	0.50	0.57	0.59	0.61	0.63	0.66	0.67	0.71	0.74	0.70	0.48
	Bench.	0.25	0.21	0.17	0.16	0.16	0.16	0.42	0.40	0.41	0.42	0.45	0.52	0.51	0.53	0.56	0.57	0.55	0.58	0.60	0.59	0.41
2	Particip.	0.25	0.23	0.22	0.24	0.29	0.29	0.25	0.30	0.35	0.42	0.33	0.56	0.66	0.48	0.65	0.64	0.86	0.91	0.65	0.81	0.47
	Bench.	0.25	0.20	0.16	0.15	0.19	0.18	0.14	0.28	0.31	0.37	0.28	0.50	0.59	0.42	0.60	0.59	0.80	0.82	0.58	0.73	0.41
3	Particip.	0.25	0.25	0.29	0.24	0.17	0.15	0.16	0.17	0.19	0.28	0.54	2.77	1.47	1.02	1.16	1.39	0.80	0.81	0.55	0.74	0.67
	Bench.	0.25	0.21	0.23	0.18	0.11	0.10	0.13	0.14	0.19	0.30	0.59	3.30	1.57	1.04	1.30	1.87					0.72
4	Particip.	0.11	0.12	0.13	0.13	0.17	0.20	0.28	0.29	0.37	0.39	0.44	0.48	0.49	0.53	0.53	0.54	0.56	0.58	0.58	0.59	0.38
	Bench.	0.11	0.11	0.08	0.07	0.10	0.14	0.24	0.24	0.33	0.33	0.38	0.42	0.44	0.48	0.49	0.50	0.53	0.55	0.55	0.56	0.33
5	Particip.	0.10	0.10	0.08	0.08	0.12	0.14	0.22	0.21	0.25	0.32	0.27	0.42	0.46	0.36	0.49	0.50	0.67	0.66	0.50	0.59	0.33
	Bench.	0.10	0.10	0.07	0.06	0.06	0.06	0.19	0.20	0.24	0.31	0.25	0.40	0.45	0.32	0.47	0.48	0.68	0.65	0.48	0.57	0.31
6	Particip.	0.10	0.10	0.09	0.09	0.08	0.08	0.12	0.12	0.12	0.24	0.45	2.17	1.23	1.08	1.39	1.03	0.77	0.76	0.62	0.81	0.57
	Bench.	0.10	0.09	0.07	0.05	0.04	0.03	0.09	0.09	0.09	0.25	0.43	2.67	1.32	1.23	2.02						0.57
7	Particip.	0.71	0.43	0.44	0.41	0.42	0.50	0.56	0.63	0.68	0.89	1.01	1.45	1.69	1.94	2.52	2.63	2.73	4.26	2.04		1.36
	Bench.	0.71	0.39	0.35	0.31	0.31	0.31	0.37	0.41	0.43	0.72	0.87	1.56	1.78	2.16	2.70	3.03	3.91				1.20
8	Particip.	0.69	0.40	0.39	0.40	0.43	0.58	0.46	0.31	0.45	1.03	0.67			1.44	5.95	2.52					1.12
	Bench.	0.69	0.34	0.31	0.29	0.29	0.43	0.37	0.24	0.31	1.28	0.78										0.49
9	Particip.	0.67	0.38	0.40	0.35	0.27	0.28	0.25	0.25	0.22	0.28	0.88			1.88	2.14	1.80	1.37	1.44	1.12	3.16	0.95
	Bench.	0.67	0.34	0.30	0.25	0.20	0.20	0.18	0.18	0.14	0.17	1.03										0.33

Table A3
Distribution of clusters by scenarios.

Scenario	Cluster				Total
	1	2	3	4	
1		10	5		15
2	3	8	9		20
3	3	3	5	4	15
4	2	11	3		16
5		6	2		8
6	2	7	2	13	24
7		8	13		31
8		1	10		11
9		1	12		13
Total	10	55	61	17	143

Table A4
Summary statistics.

Variable	Obs	Mean	Std. dev.	Min	Max
Initial farm size (ha)	143	938.57	386.21	665.00	1,480.00
Production cost factor	143	1.01	0.10	0.90	1.15
Equity capital (€1000)	2,859	1,374.82	1,433.72	−7,503.74	8,343.65
Liquidity (€1000)	2,859	187.28	939.21	−9,473.73	4,477.03
Profit p.a. (€1000)	2,859	386.62	659.55	−3,326.60	3,735.63
ESU	2,859	1,312.24	1,268.07	−157.61	7,501.99
Size (ha)	2,859	1,198.59	1,062.31	0.00	6,360.00
Rented arable land (ha)	2,859	376.16	226.36	56.00	1,329.23
Rented grassland (ha)	2,859	332.96	253.45	0.00	1,204.02
Revenue cumulated (€1000)	2,859	3,521.11	3,093.72	156.22	19,015.30
Gender (1 = female)	143	0.34	0.47	0.00	1.00
Age	143	25.96	3.32	20.00	36.00
Knowledge of farm management[a]	105	2.77	1.04	1.00	5.00
HLL (safe choices)	143	5.43	2.21	0.00	10.00
Risk (self-assessment)[b]	143	4.80	1.87	2.00	9.00
Maximising	143	3.05	0.49	1.77	4.31
Rational	143	3.93	0.51	2.50	5.00
Intuitive	143	3.31	0.75	1.60	4.80
Dependent	143	3.16	0.78	1.00	5.00
Avoidant	143	2.67	0.97	1.00	4.80
Spontaneous	143	2.88	0.83	1.00	5.00

Note:
[a] I have solid knowledge of agricultural management. - 1 = strongly agree, 2 = agree, 3 = neither agree nor disagree, 4 = disagree, and 5 = strongly disagree.
[b] 0 = highly risk-tolerant, ..., 10 = completely risk-averse.

Table A5
Mean deviation between clusters (adjusted *p*-values of pairwise comparison).

Variable		Cluster		
	Cluster	1	2	3
Scenario***	2	.57 (1.000)		
	3	**2.25** **(0.041)**	**1.68** **(0.002)**	
	4	1.79 (0.381)	1.22 (0.417)	−0.46 (1.000)
Initial farm size*** (ha)	2	29.64 (1.000)		
	3	−232.48 (0.309)	**−262.11** **(0.000)**	
	4	297.235 (0.200)	**267.60** **(0.037)**	**529.71** **(0.000)**

(*continued on next page*)

Table A5 (*continued*)

Variable	Cluster	Cluster 1	2	3
Initial equity capital*** (€1000)	2	2.44 (1.000)		
	3	−107.24 (0.105)	**−109.68 (0.000)**	
	4	107.54 (0.246)	**105.10 (0.026)**	**214.779 (0.000)**
Production cost factor***	2	.049 (0.831)		
	3	**.115 (0.004)**	**.066 (0.002)**	
	4	.036 (1.000)	−0.013 (1.000)	**−0.078 (0.020)**
Av. equity capital*** (€1000)	2	**938.14 (0.000)**		
	3	**709.55 (0.000)**	**−228.59 (0.013)**	
	4	**2283.40 (0.000)**	**1345.26 (0.000)**	**1573.85 (0.000)**
Av. profit p.a.*** (€1000)	2	**275.34 (0.000)**		
	3	**189.84 (0.000)**	**−85.50 (0.006)**	
	4	**833.71 (0.000)**	**558.37 (0.000)**	**643.87 (0.000)**
Av. size*** (ha)	2	**203.46 (0.041)**		
	3	−103.63 (0.987)	**−307.09 (0.000)**	
	4	**1257.89 (0.000)**	**1054.44 (0.000)**	**1361.53 (0.000)**
Av. revenue*** (€1000)	2	472.45 (0.190)		
	3	−370.98 (0.535)	**−843.43 (0.000)**	
	4	**3489.25 (0.000)**	**3016.80 (0.000)**	**3860.23 (0.000)**
Gender*** (1 = female)	2	.036 (1.000)		
	3	**−0.137 (0.001)**	**−0.174 (0.000)**	
	4	**−0.165 (0.000)**	**−0.201 (0.000)**	−0.027 (1.000)
Age***	2	**1.49 (0.000)**		
	3	**2.24 (0.000)**	**.75 (0.000)**	
	4	**3.65 (0.000)**	**2.15 (0.000)**	**1.45 (0.000)**
Knowledge of farm management***	2	−0.014 (1.000)		
	3	−0.018 (1.000)	−0.003 (1.000)	
	4	**−0.792 (0.000)**	**−0.777 (0.000)**	**.774 (0.000)**
HLL***	2	**−0.55 (0.006)**		
	3	.25 (0.771)	**.81 (0.000)**	
	4	.26 (1.000)	**.82 (0.000)**	.01 (1.000)
Risk***	2	−0.15 (1.000)		
	3	**.46 (0.006)**	**.62 (0.000)**	
	4	−0.35 (0.207)	−0.19 (0.552)	**−0.81 (0.000)**
Maximising***	2	**−0.31 (0.000)**		
	3	**−0.38 (0.000)**	**−0.06 (0.010)**	
	4	**−0.12 (0.043)**	**.20 (0.000)**	**.26 (0.000)**

(*continued on next page*)

Table A5 (*continued*)

Variable	Cluster	Cluster 1	2	3
Rational***	2	.08 (0.230)		
	3	**.23** **(0.000)**	**.15** **(0.000)**	
	4	**.24** **(0.000)**	**.16** **(0.000)**	.01 (1.000)
Intuitive***	2	.10 (0.494)		
	3	**−0.32** **(0.000)**	**−0.42** **(0.000)**	
	4	**−0.42** **(0.000)**	**−0.52** **(0.000)**	**−0.11** **(0.103)**
Dependent***	2	.13 (0.172)		
	3	**.24** **(0.000)**	**.11** **(0.005)**	
	4	**.37** **(0.000)**	**.24** **(0.000)**	**−0.13** **(0.038)**
Avoidant***	2	.18 (0.101)		
	3	**.24** **(0.006)**	.06 (0.656)	
	4	**.48** **(0.000)**	**.30** **(0.000)**	**.23** **(0.000)**
Spontaneous**	2	−0.04 (1.000)		
	3	−0.17 (0.050)	**−0.12** **(0.002)**	
	4	−0.09 (1.000)	−0.05 (1.000)	.07 (0.854)

Note: Prob. > *F*: * < 0.05; ** < 0.01; *** < 0.001.

Table A6
Deliberate farm exits by cluster.

ID	Cluster	Scenario	Equity capital (€1000)[a] Participant	Benchmark	Difference
22-01-15-3	2	1	739.79	2843.39	−2103.60
20-05-15-2	2	2	−369.58	2484.32	−2853.90
27-08-14-1	2	3	−1102.41	−1098.92	−3.49
29-01-15-1	2	4	379.95	6,084.24	−5704.29
22-01-15-1	2	4	−606.16	6084.24	−6690.40
27-08-14-4	2	7	−184.43	−490.36	305.93
19-05-15-3	2	7	−267.25	−490.36	223.11
20-05-15-6	2	7	−317.57	−490.36	172.79
19-05-15-2	2	7	−883.38	−490.36	−393.02
Mean			−290.11	1,603.98	−1894.10
19-05-15-4	3	7	161.62	−490.36	651.98
20-05-15-1	3	7	307.58	−490.36	797.94
22-01-15-3	3	7	335.80	−490.36	826.15
22-04-15-1	3	8	−79.07	−822.28	743.21
27-08-14-1	3	8	133.62	−822.28	955.90
Mean			171.91	−623.12	795.04

Note:
[a] Equity capital at the end of experiment.

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