

Appel, Franziska; Balmann, Alfons

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ORIGINAL ARTICLE

Predator or prey? Effects of farm growth on neighbouring farms

Franziska Appel  | Alfons Balmann

Leibniz Institute of Agricultural
Development in Transition Economies,
Halle, Germany

Correspondence

Franziska Appel, Leibniz Institute of
Agricultural Development in Transition
Economies, Halle, Germany.
Email: appel@iamo.de

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Abstract

We provide explorative insights on how farms which manage strong and successful growth affect farms in their neighbourhoods through spatial competition for land. The study is based on an exploratory analysis of repeated framed experiments within the business game FarmAgriPoliS (Appel & Balmann, *Ecological Complexity*, 40, 2019). In particular, we analyse the spatial influences of different behavioural clusters of farm managers. Our analysis finds that farms which manage strong growth substantially affect the development of farms in a spatial neighbourhood of some 10 km. Although the influence on the neighbourhood decreases with distance, the functional correlations of farm growth as well as exits are neither linear nor exponential, but eventually rather wave-like. We further discuss the spatial interdependence of farms and the related overlaps of the predator–prey phenomenon with the phenomena of farms' path dependency and agricultural structural change. We conclude that along with farmers' strategies and their abilities, the characteristics of their neighbours and the distances between neighbouring farms also determine who is 'predator' and who is 'prey'.

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KEYWORDS

agent-based participatory experiments, behavioural experiments, business management game, farm growth, farm size, Germany, path dependency, spatial interaction, structural change

JEL CLASSIFICATION

C15; C99; D22; Q12; Q15; Q24

1 | INTRODUCTION

Structural change in the agricultural sector is controversial. One key policy issue is the changing number of farms, usually a decline through farm exits. Within this context, farm exits have a social dimension because they are often driven by farms' low profitability and breaks in their family tradition (see, e.g., Suess-Reyes & Fuetsch, 2016). Otherwise, structural change can be seen as a source of growth. Surviving and growing farms are likely to be more efficient and competitive (Breustedt & Glauben, 2007; Buchenrieder et al., 2007; Paul et al., 2004; Weersink et al., 1990). In addition, and from a historical perspective, the process of structural change in agriculture releases labour, to be used by other sectors and to contribute to industrial countries' general economic growth (cf. Boulding, 1944). In recent years, labour scarcity due to certain demographic trends in rural areas in Europe, such as declining birth rates after the boomer generation and outmigration, have become further drivers of structural change (Pitson et al., 2020).

Given the immobility of land and the fixed (and thus limited) amount of land in a specific region, changes in farm numbers and sizes in terms of average land endowment have to be seen as a reciprocal process resulting from spatial competition for land. We elaborate on the spatial and dynamic nature of such land market competition. Therefore, we study the extent to which farms can be affected positively or negatively by farm structural changes in their neighbourhood. Of particular interest is the question of how very fast-growing farms may affect their neighbours and—directly or indirectly—even the neighbours' neighbours. By using simulated and experimental data based on framed experiments with the business game FarmAgriPoliS (Appel & Balmann, 2019), we identify a spatial and dynamic predator–prey character of land market competition.

This research is motivated by the fact that in recent years, land distribution and access to land has become an issue. For example, in eastern German agriculture, the term 'land grabbing' has been used to describe phenomena such as land concentration towards large(r) farms (Bunkus & Theesfeld, 2018). In former socialist European countries, including the eastern part of Germany, a number of farms emerged which now farm several thousand hectares.¹ Moreover, holding structures appeared which farm areas of tens of thousands of hectares in the eastern part of Germany, Czech Republic, Slovakia, Romania or Bulgaria, and in Ukraine and Russia, reaching several hundred thousand hectares.² Subsequently, van der Ploeg et al. (2015) even concluded that 'the ongoing trend of (generic) land concentration is just as problematic as land grabbing'. These developments have raised concerns that family-based farming, in particular, may be affected negatively (Ciaian & Swinnen, 2006; Curtiss et al., 2020; Langenberg & Theuvsen, 2016). Though many of the large farms and enterprises in central and eastern Europe

¹According to the EU Farm Structure Survey 2020, some 15% of German farmland belongs to farms larger than 1000 hectares (DESTATIS, 2021).

²According to a communiqué from the German federal government to the Bundestag, four agricultural holdings existed in 2019 which each received EU CAP payments for more than 10,000 hectares (Bundestag, 2020). According to latifundist.com, in Ukraine, some 13 agroholdings each farmed more than 100,000 hectares in 2021 (Latifundist, 2022).

inherited their size from predecessors under socialism or through mergers and acquisitions (Ostapchuk et al., 2021a, 2021b), Graubner et al. (2021) found evidence for Ukraine that large agroholdings may exercise local land-market power by paying higher land prices and thus deterring entry for smaller farms.

However, competition for land is not just a matter of farm sizes but also of the dynamics of farm structural change. Based on Cochrane's (1958) concept of the technology treadmill, Levins and Cochrane (1996) argued that farmers who are early adopters of new, more efficient technologies are especially likely to drive up land prices and force other farms either to adopt the technologies without substantial benefits or to exit farming. This latter group may eventually benefit as landowners renting out or by selling their land to the remaining farmers. In such a context, competition for land can be seen as a predator–prey relationship between various actors (Lotka, 1910), as has already been discussed in other economic contexts (e.g., Goodwin, 1967). The Lotka–Volterra model describes the evolution of two dependent species, where the population of one species (prey) depends negatively on the population size of the other species (predator) but evolves positively in the absence of predators. The development of the predator population, in contrast, depends positively on the development of the prey population and decreases in the absence of the prey. Moreover, competition arises among predators given a limited prey population. In line with Levins and Cochrane (1996), larger farms—which eventually benefit from economies of size and adoption of new technologies—may be considered potential predators. If such farms have very strong growth ambitions regarding acreage, they may inhibit smaller farms' development or reduce their chances to survive.

Of particular interest for the investigation of potential predator–prey relationships in land markets may be regions with heterogeneous farm structures. In such regions, many small farms (potential prey) exist next to a smaller number of larger farms (potential predators). Such heterogeneous farm structures exist in the former socialist European countries, including, for example, the eastern part of Germany. Here, the largest 20% of farms hold approximately 80% of the land (DESTATIS, 2021, own calculations). This ratio of 80 to 20 conforms to the Pareto principle (80/20 rule; Pareto, 1964), as does the EU farm structure (European Commission, 2021).

Beyond the general economic and social dimensions of land concentration, the political dimension of structural change in agriculture may be driven by specific dynamic characteristics of structural change. Many agricultural policies are motivated by the argument that agricultural structures in general and farms in particular need to be protected. For instance, the German agricultural land sales regulation is titled 'Law on measures to improve the agricultural structure and safeguarding the agricultural and forestry businesses' (GrdstVG 1961). Accordingly, agricultural structures and farms are considered a kind of asset. A justification of this argument can be derived from the limited mobility of factors such as land and assets (e.g., stables for livestock), which impede fast structural adjustments (Balmann, 1995; Chavas, 2001). Moreover, the transition process of many formerly socialist countries showed a long period of decline and only a very slow recovery of agricultural production (Swinnen & Vranken, 2010). From a systems perspective, the inertia and difficulty to adjust and recover may be explained by path dependency. A general definition of path dependency is that historical events affect the future development of a system—that is, history matters (cf. Arthur, 1989; Cowan & Gunby, 1996; David, 1985; North, 1990; Pierson, 2000; Schreyögg et al., 2003). A path-dependent dynamic system often has multiple absorbing states with self-reinforcing mechanisms to which it can lock in. This means multiple equilibria or even persistent disequilibria may exist. Path dependency implies unpredictability of the future evolution of the system at some points in time; at other points in time, the system will display hardly any change at all, which includes irreversibility (Arthur, 1989). Path dependence has been identified as a major phenomenon that explains why technologically inefficient agricultural structures persist (Balmann, 1997; Latacz-Lohmann et al., 2001; Theuvsen, 2004).

Path dependency and agricultural structural change are related to the spatial interdependence of farms and the associated predator–prey phenomenon. A farm's development is not just influenced by its own actions, but also by interactions with other actors on the land market. This market is highly local due to the inherent immobility of agricultural land (Balmann, 1997; Happe et al., 2006). According to Cotteleer et al. (2008), farms in the Netherlands mainly buy land within a 6.7-km radius. In the German state of Brandenburg, Plogmann et al. (2020) found that 90% of newly acquired operated land (through buying or renting) is within a radius of 11.8 km around the farmstead (cf. Balmann et al., 2021). Thus, in a European context, where there is hardly any additional land available to be cultivated, farms can only increase their acreage if other farms in their neighbourhood decrease in size or exit. Therefore, the actions of a specific farm are likely to influence the development perspectives of neighbouring farms not just temporarily, but often in long-lasting and irreversible ways.

However, very few studies on agricultural structural change address neighbouring farms' spatial interdependencies. Storm et al. (2015) showed empirically that ignoring spatial interdependencies between farms leads to a substantial overestimation of the effects of direct payments to farms on farm survival. Saint-Cyr et al. (2019) identified various correlations between neighbouring farms regarding size and exits from farming. Moreover, they showed that the consideration of these correlations yields different results than pooled estimations. One reason for the small number of empirical studies considering these interdependencies may be the limited availability of data, for example, of exact locations of farms and fields and the related economic data, as well as appropriate counterfactuals. Within the EU, the Integrated Administration and Control System (IACS) provides spatial data. However, economic data on efficiency and profitability in relation to spatial data, for instance, is hardly extant or available. For instance, the EU's Farm Accountancy Data Network (FADN) only provides samples with limited spatial coverage.

An alternative to empirical approaches can be provided by simulated data generated with dynamical and spatially explicit agent-based models such as AgriPoliS (Agricultural Policy Simulator; Happe et al., 2006). One advantage of simulated data is that alternative scenarios allow for the analysis of counterfactual developments. Participatory agent-based models are a specific form of agent-based model. These models involve people, such as farmers and other stakeholders, or students, either as agents in their models; or as translators of the outcomes of simplified role-playing models into computerised agent-based models (cf. Barreteau et al., 2001). Another alternative is framed experimentation using business games such as FarmAgriPoliS. FarmAgriPoliS is based on AgriPoliS, and allows people to behave as agents in the AgriPoliS model, deciding on farm exit or continuation, investments and land rentals (Appel et al., 2018).

Appel and Balmann (2019) conducted experiments with a number of students who they asked to manage pre-specified farms for selected scenarios within FarmAgriPoliS. They found that on average, human participants were no more successful than non-human agents. However, a surprisingly large share (12%) were able to manage impressively strong and successful farm growth. This growth can be seen as a case of pathbreaking—that is, these participants managed to overcome the limitations of the usual path-dependent structural change.

Although Appel and Balmann (2019) identified some insights into conditions under which people can exhibit successful strategies, they did not tackle the question of the consequences of extremely successful growth strategies on their neighbours. The generated dataset, with a total of 143 experiments for nine scenarios plus nine reference simulations with the regular AgriPoliS model, allows not only analysis of managed farms' development, but also generates data for the spatial and dynamical mapping and analysis of the explicit development of all surrounding farms. With this paper, we provide insights on how the pathbreaking farms

affected their neighbouring farms. This allows us to identify how these neighbours are affected (positively or negatively), and thus provide insights into the spatial and dynamic predator–prey nature of land-market competition. Thereby, we aim to provide explorative insights which add to the scarce empirical literature on spatial interdependence (e.g., Saint-Cyr et al., 2019; Storm et al., 2015) and may stimulate the development of hypotheses for further empirical and theoretical research.

The next section is focused on the theoretical concept of path dependence and the methodological concept of conducting behavioural experiments in FarmAgriPoliS based on the spatially explicit agent-based AgriPoliS model. Section 3 describes the analytical approaches we applied to the behavioural experiments conducted by Appel and Balmann (2019). The results of our analysis are presented in Section 4, while Section 5 provides discussion and Section 6 concludes.

2 | THEORETICAL AND METHODOLOGICAL BACKGROUND

2.1 | Path dependence

The concept of path dependency (cf. Arthur, 1989; Cowan & Gunby, 1996; David, 1985; North, 1990; Pierson, 2000; Schreyögg et al., 2003) attempts to explain why similar systems may develop very differently. Balmann (1995) argued that agricultural structures are path dependent, so that certain feedback mechanisms lead to a lock-in at a quasi-stable state that may be inefficient and prevent the system from transitioning towards a more efficient state, even in the longer term. In the agricultural sector, such feedback mechanisms may result from sunk costs of assets, frictions on the land market and policies supporting current farms' incomes (Balmann, 1995). That is, today's agricultural structures are shaped by history, which affects 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) referred to the role of sunk costs of assets and human capital. Sydow et al. (2005) provided a more general overview and classification of reasons why path dependencies emerge. These include economies of scale and scope, direct and indirect network externalities, learning, expectations, expectations of expectations, and coordination and complementarity effects. Economies of scale and scope as well as direct and indirect network externalities may be classified as technological reasons, whereas the remainder may be classified as institutional (Sydow et al., 2005). Applications of path dependence in organisational theory recognise the roles of cognitive processes and socio-emotional aspects. Accordingly, mental models have to be seen as causes of self-reinforcement of a social system's existing states. Ignorance of innovations and deadlocked ways of thinking can be reasons for permanent path dependency in agriculture. Eckert and Bell (2005) discovered that farmers reject advice and feedback from experts if the advice is not in accordance with their own mental models about their agricultural systems. The consequence is that some innovations are not even contemplated, and mental models are simultaneously and repeatedly confirmed.

If path dependencies are potentially related to the inefficiency of a state, the question arises whether and under what circumstances a change towards a more efficient path is possible. Garud and Karnøe (2001) developed the concepts of 'path creation' and 'path-breaking'. If path dependence is an unintended macro result of intended micro-behaviours, pathbreaking as a mindful deviation may be an option to overcome a path dependence (Meyer & Schubert, 2005; Schreyögg et al., 2003; Stack & Gartland, 2003). Path creation further emphasises the role of entrepreneurs and how they can intentionally create desirable new paths.

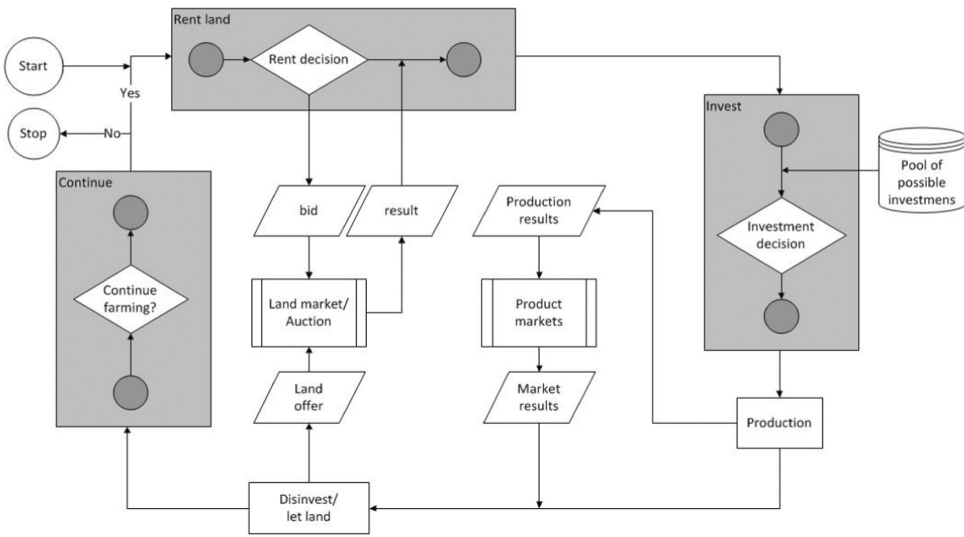


FIGURE 1 Flowchart of one period in AgriPoliS or FarmAgriPoliS. *Source:* Appel et al. (2018) based on Balmann (1995).

2.2 | AgriPoliS and FarmAgriPoliS³

FarmAgriPoliS is an experimental platform that uses the agent-based AgriPoliS model as a software-based environment for behavioural experiments or as a business management game. AgriPoliS is a spatially explicit and dynamic agent-based model that simulates farms, regional farm populations and structures, markets and other aspects of agricultural production (Happe, 2004; Happe et al., 2006; Kellermann et al., 2008; Sahrbacher et al., 2014). A participant is assumed to manage a farm and competes in a modelled agricultural region with other computer-simulated farms (agents) that derive their decisions from mixed-integer short-term profit maximisation (Appel et al., 2018).

Experiments with FarmAgriPoliS typically run 20 periods (equivalent to 20 simulated years) and focus on strategic decisions with long-term implications for the farm's development. Strategic decisions include decisions on farm exit or continuation, investments in durable and capital-intensive assets such as buildings and machinery, and bidding strategies for land rentals. The participants can access information on how a computer agent would decide. This provides a default for rental bids and investments; however, participants can deviate from the default suggestions. Short-term decisions such as planning annual production are considered non-strategic and are made by computer program using mixed-integer optimisation. The grey boxes in Figure 1 highlight the situations in which a participant has to decide.

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 an existing farm does not currently rent or own) via a repeated auction. In the auction process, every farm is asked to calculate a bid for a plot. The computer-simulated farms each bid a specific proportion (e.g., 80%) of their expected marginal revenue for this additional plot. The model automatically considers transportation costs that are assumed proportional to the distance between the plot and farm. The farm with the highest bid receives the plot and is able

³Appel et al. (2018) give a more detailed description of FarmAgriPoliS and is the basis of this section.

to use it for a specific contract length (Kellermann et al., 2008, p. 28 et seq.). In every simulated year, the iterative auction procedure continues as long as land is available. Farms that quit voluntarily are also considered in the model. They may quit due to the high opportunity cost of continuing, or they may be forced to quit due to illiquidity during the experiments. In the subsequent periods, exiting farms continue to receive income for the production factors they own. This means they receive the rent that the leaseholders pay for their own land, wages for off-farm working family members in the case of a family farm, and interest for their liquid capital. Closed farms bear the costs of depreciation as well as the interest costs of existing assets and debts (cf. Kellermann et al., 2008, p. 44).

2.3 | Region

For the experiments, the model environment is 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. Many of the farms are specialised arable farms or large mixed farms with livestock production. They are organised as family farms, corporate farms or cooperatives. A total of 1070 farms operate in the region, with an average size of 256 hectares (StaLa, 2016). Farm sizes are heterogeneous, ranging from small part-time farms with only a few hectares each to corporate farms with more than 1000 hectares each. Most farms have high shares of loan capital and rented land. Larger farms mostly use hired labour only. Ostermeyer (2015) provided a detailed description of how the Altmark region is implemented in AgriPoliS. For FarmAgriPoliS, a portion (approx. One-fifth) of the Altmark is simulated to reduce computation time and to avoid longer waiting times for participants during the experiments. However, the sub-region is large enough to represent the specific characteristics of the entire region and to consider relevant neighbourhood effects.

2.4 | Scenarios

Appel and Balmann (2019) defined nine scenarios for behavioural experiments designed to study participants' decision-making in a competitive agricultural context with (partly) uncertain environmental conditions. The scenarios differ in terms of the farm types (different sizes and individual production cost levels) as well as the milk price development. The resulting scenarios are presented in Table 1.

2.5 | Data collection

The participants in Appel and Balmann's (2019) experiments were students recruited from three German universities in 2014 and 2015. A total of 49 students participated. The participants studied agriculture and related subjects (80%) at Humboldt Universität zu Berlin (20%), Martin Luther University Halle-Wittenberg (53%), or Georg August University of Göttingen (27%). The participants were on average 25 years old ($SD = 3.45$), 35% were female, 63% already had a bachelor's degree, and 63% had some practical experience in agriculture. The participants were randomly assigned to scenarios, and each participant had to play up to three scenarios. In total, data sets of 144 experiments⁴ were used for our analysis. Every scenario was

⁴One data set was removed as an outlier in the cluster analysis by Appel and Balmann (2019). That is why we use the dataset of 143 experiments in this paper.

TABLE 1 Scenarios

Scenario	Milk price (trend) ^a	Farm	Production cost factor ^d	Size	Number of experiments ^e
1	Price 0 (constant)	Farm 1 ^b	Good (0.9)	Medium (665 ha)	14
2	Price 1 (fluctuating)				19
3	Price 2 (failed expectation)				14
4	Price 0 (constant)	Farm 2 ^c	Normal (1)	Large (1480 ha)	15
5	Price 1 (fluctuating)				7
6	Price 2 (failed expectation)				23
7	Price 0 (constant)	Farm 3 ^b	Poor (1.15)	Medium (665 ha)	30
8	Price 1 (fluctuating)				10
9	Price 2 (failed expectation)				12

Source: Appel and Balmann (2019).

^a'Failed expectations' means that an initially high milk price is followed by rather low milk prices.

^bMixed farm with an initial 580 ha of arable land and 85 ha of grassland, already equipped with the capacity for 70 dairy cows, 40 heifers and 710 sows.

^cMixed farm with an initial 1225 ha of arable land and 255 ha of grassland, already equipped with the capacity for 190 dairy cows and 76 heifers.

^dFactor multiplied with the variable costs of the farm for each production activity.

^eNumber of occurrences of each scenario under consideration.

also simulated by replacing the respective participant with 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.

During the experimental session, data on the decisions of every participant and various indicators, such as farm investments, land rentals, farm sizes, financial results and rents paid, were logged for the participants' farms as well as all other computer farms. The exact locations of all farms in the model regions were known. In addition, a post-experimental questionnaire was used to collect data on the participants' personal backgrounds (age, gender, educational level, etc.) and their perceptions of the experiments. Additionally, the questionnaire applied methods for identifying decision-making styles (GDSM; cf. Scott & Bruce, 1995; Mann et al., 1997), distinguishing satisfying and maximising behaviour (cf. Schwartz et al., 2002), and measuring risk attitudes (Ewald et al., 2012; Holt & Laury, 2002).

2.6 | Behavioural experiments with FarmAgriPoliS

With AgriPoliS and FarmAgriPoliS, Appel and Balmann (2019) used a combination of agent-based simulations and behavioural experiments that provided opportunities to study decision behaviours in a spatially explicit context.

The experiments show significant differences in the behaviour of human participants and computer agents in coping with the challenges of managing a farm in a complex competitive environment. A cluster analysis identified four distinct experimental outcome clusters, which can be described as Cluster 1—'negligent gamblers', Cluster 2—'missed opportunities', Cluster 3—'solid farm managers', and Cluster 4—'successful pathbreakers' (Appel & Balmann, 2019). While some 88% of the experiments (Clusters 1 to 3) corresponded with prospect theory (cf.

TABLE 2 Number of active farms (including participant) and their average farm sizes in the region (on average over the respective experiments)

Period	Indicator	All experiments	Benchmark	Experiments with participants of cluster 1	Benchmark	Experiments with participants of cluster 4	Benchmark
0	Number of farms	63.00	63.00	63.00	63.00	63.00	63.00
	Av. farm size (ha)	257.38	257.38	257.38	257.38	257.38	257.38
9	Number of farms	53.56	53.45	53.70	54.00	56.18	56.06
	Av. farm size (ha)	302.75	303.34	301.96	300.28	288.64	289.25
19	Number of farms	21.82	21.52	20.30	20.40	16.65***	13.35
	Av. farm size (ha)	743.23	753.38	798.77	794.85	974.05***	1214.34

Note: Significance level: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; Cluster 1 refers to 'negligent gamblers' and Cluster 4 refers to 'successful pathbreakers'.

Kahnemann & Tversky, 1979)—that is, the participants were more successful in avoiding losses than in exploiting opportunities—in approximately 12% of the experiments, the participants succeeded in departing from previous development paths (Cluster 4).

The participants in Appel and Balmann's (2019) study had larger than average farms, with an initial farm size of 665 hectares or 1480 hectares depending on the scenario (average initial farm size = 257.38 ha; see Tables 1 and 2). Besides large initial farm size, Clusters 1 and 4 consisted of participants with above-average growth ambitions (Table A1; Cluster 1 = 991 ha; Cluster 4 = 1288.24 ha, maximising behaviour) and therefore could be considered potential predators.

Clusters 1 and 4 differed in experience and knowledge. Cluster 4 contained the oldest and possibly the most experienced participants, who also categorised themselves as having the highest level of knowledge of agricultural management. These participants performed very well compared to their benchmark farms as well as in absolute terms, and developed large and financially well-equipped farms (Table A1). These participants can be considered 'successful pathbreakers', or in biological terms, successful predators.

Despite having comparable growth ambitions, participants of Cluster 1 were the youngest and assessed themselves as having the least knowledge of agricultural management. After a promising start and substantial growth, the participants often ended up with huge losses on average. Appel and Balmann (2019) therefore referred to them as 'negligent gamblers'.

3 | DATA ANALYSIS

To assess the regional and spatial effects of specific behavioural patterns, we analysed these experimental data focusing on the question of how large and ambitious farms affect the development of farms in their neighbourhoods, as well as whether evidence of the presence of a predator–prey relationship exists. We also analysed whether these effects are distributed uniformly over the entire neighbourhood or whether the effects depend on the distances to the farms that the participants managed and therefore on the spatial distribution of the farms.

3.1 | Regional development

Our analysis compares the regional developments of the behavioural experiments with the benchmark simulations. These benchmark simulations are standard AgriPoliS simulations of identical scenarios and initialisations of the model region, where the participants' respective farms are governed by the standard AgriPoliS optimisation routines. From a spatial perspective, the model region was programmed as a torus with a maximum possible distance of some 9 km. The scenarios (see Table 1) in Appel and Balmann's (2019) work used two farm sizes, which led to two initial distributions of farms (Figure A1). In scenarios 1 to 3 and 7 to 9, the participants initially operated a farm with an identical initial size of 665 hectares. In scenarios 4 to 6, the participants operate a farm with 1480 hectares initially (see Table 1).

For the analysis of structural effects, we analyse the development of the number of farms and average farm sizes in the region, as well as the aggregated added value of agricultural production as an indicator of the region's economic development.

3.2 | Structural equation modelling

In a next step, the influence of the participants on the other farms is captured more precisely and statistically substantiated. As the complex multilayer panel structure of the experimental data is a challenge for econometric methods, the analysis in this section is based on structural equation

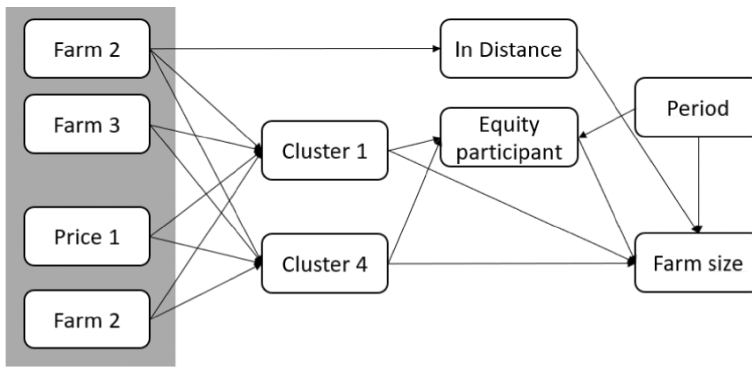


FIGURE 2 Structural equation model of the neighbourhood effects on farms' size (relative to benchmark). Variables used as a proxy for the scenario are marked grey; Cluster 1 refers to 'negligent gamblers' and Cluster 4 refers to 'successful pathbreakers'.

modelling⁵ (SEM; Kline, 2011). The previous findings of Appel and Balmann (2019) on success determinants, combined with the above findings on spatial interactions, are incorporated into this structure: The scenarios influence the participant's behaviour while success depends on the participant's cluster membership ('successful pathbreakers' [Cluster 4] or 'negligent gamblers' [Cluster 1]), which, in turn, impacts neighbouring farms through spatial interaction.

As Figure 2 shows, the scenarios are considered by including the proxy variables of Farm 2, Farm 3, Price 1 and Price 2 (cf. Table 1). In addition, because scenarios 4 to 6 (corresponding to Farm 2, cf. Table 1; Figure A1) have different spatial initialisations, Farm 2 also affects the distance between a model farm and the farm that the participant runs. Furthermore, we account for the participants' equity capital and whether they belong to the behavioural cluster of 'successful pathbreakers' (Cluster 4) or of 'negligent gamblers' (Cluster 1).

It can be assumed that the influence of the participants' farm development on the other farms' development is not equally distributed over the entire region; rather, it decreases with increasing distance. In FarmAgriPoliS, the coordinates of the farmstead and therefore the distance to the participant's farmstead as well as all other farmsteads and fields is recorded for each farm. As in gravity models of trade (cf. Isard, 1954; Tinbergen, 1962), we use the logarithmic distance to account for the spatial interaction.

The graphic structure of these influencing factors is constructed by using the SEM Builder from Stata. Figure 2 provides a visual impression of the structural design of the model. The SEM is run repeatedly for equity capital, sizes and rental prices of farms in the model region. Subsequently, maximum likelihood estimation is used to estimate the structural model (path analysis).

As shown in Figure 2, the behaviour of the participants (belonging to a behavioural cluster) can affect the resulting farm size via two paths: the equity of the participant (i.e., the participant's success), and directly via Cluster 1 or Cluster 4. In this way, we want to analyse further influences, such as a different investment strategy. Further details on the specification of the variables are given in the appendix (Table A2).

3.3 | Spatial analysis

In addition to the SEM, we used a graphical analysis to examine the influence of the distance between the participants and neighbouring farms in greater detail. For this purpose,

⁵Because no latent variables are considered, it is specifically a path analysis.

the farms are ordered on the figures' x -axes according to their distances to the participants' farms, which are assigned the coordinate origins. The distance-dependent relative spatial effects on the farms' equity capital, sizes and rental prices are quantified for the different clusters compared with the state in the benchmark situation with an identical initialisation (see Equation 1 exemplary for equity capital). As a divisor, we use the initial equity, size and rental price of the respective farm. Subsequently, a kernel-weighted local polynomial regression (Epanechnikov, 1969) is used to calculate the smoothed graphs for all participants: 'negligent gamblers' (Cluster 1) and 'successful pathbreakers' (Cluster 4).

$$\text{relativeEquity}_{\text{Farm}=j}^{\text{Period}=i} = \frac{\left(\text{Equity}_{\text{Farm}=j}^{\text{Period}=i} - \text{Equity}_{\text{Farm}=j}^{\text{Period}=i}_{\text{Benchmark}} \right)}{\text{Equity}_{\text{Benchmark}}^{\text{Period}=0}} \quad (1)$$

with $i = 0-19$ and $j = 0-62$.

4 | RESULTS

4.1 | Regional development

The analysis of regional development is focused particularly on those experiments which belong to the clusters 'negligent gamblers' (Cluster 1) and 'successful pathbreakers' (Cluster 4), which are of particular interest due to their size and growth ambitions. Table 2 shows the number of active farms and average farm sizes in relation to the benchmark (i.e., the respective AgriPoliS simulations without a human participant). Active farms are those farms which in the respective periods are active in agriculture and have not quit farming due to the high opportunity cost of continuing or due to being forced out as a result of illiquidity. The number of farms and the farm sizes for all experiments on average evolve similarly to the benchmark situation; this especially applies to experiments with the participants of Cluster 1 ('negligent gamblers'). However, in the experiments with the participants of Cluster 4 ('successful pathbreakers'), more farms stay active in agriculture than in the benchmark situation. These farms are accordingly smaller on average.

Figure 3 plots the farm sizes of the 'negligent gamblers' (Cluster 1) and the 'successful pathbreakers' (Cluster 4) against the average farm size of other farms in the region. The average farm size of the 'successful pathbreakers' (Cluster 4) increases over time, whereas the average farm size of the 'negligent gamblers' (Cluster 1) decreases from period 11 to zero in period 16.

According to Figure 4, the aggregated regional added value is slightly below the benchmark level at the beginning but approaches the benchmark level over time. Although the added values of experiments with participants in Cluster 1 ('negligent gamblers') and Cluster 4 ('successful pathbreakers') decrease even more strongly under the benchmark level for the first 14 periods, 'successful pathbreakers' (Cluster 4) outperform the benchmark simulations in the longer run with an approximately 250 euro/hectare higher added value than in the benchmark situation. Meanwhile, experiments with 'negligent gamblers' (Cluster 1) come close to the average and therefore also to the benchmark situation.

4.2 | Structural equation modelling

The SEM analysis (Table 4) shows that the participants' relative equity capital has a negative impact on the relative sizes and equity capital of neighbouring farms, and a positive effect on the relative rental prices for arable land and grassland. Thus, the better a participant is

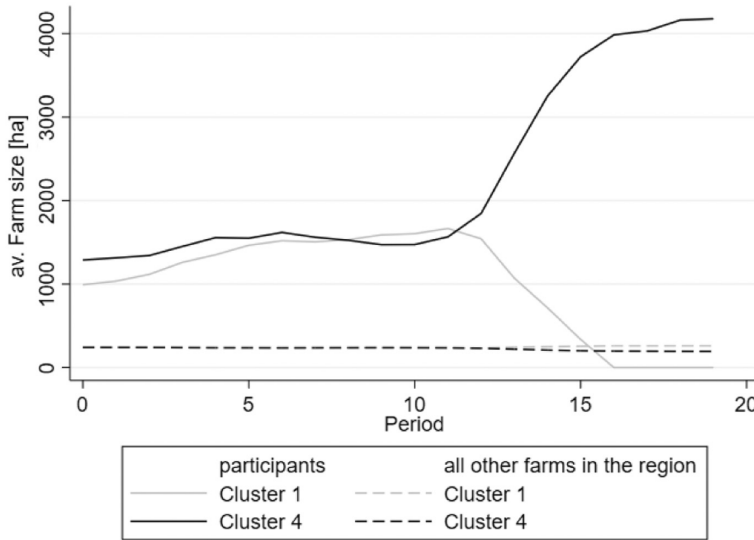


FIGURE 3 Farm sizes of ‘negligent gamblers’ (cluster 1) and ‘successful pathbreakers’ (cluster 4) farms against the average size of other farms in the region (on average over the respective experiments)

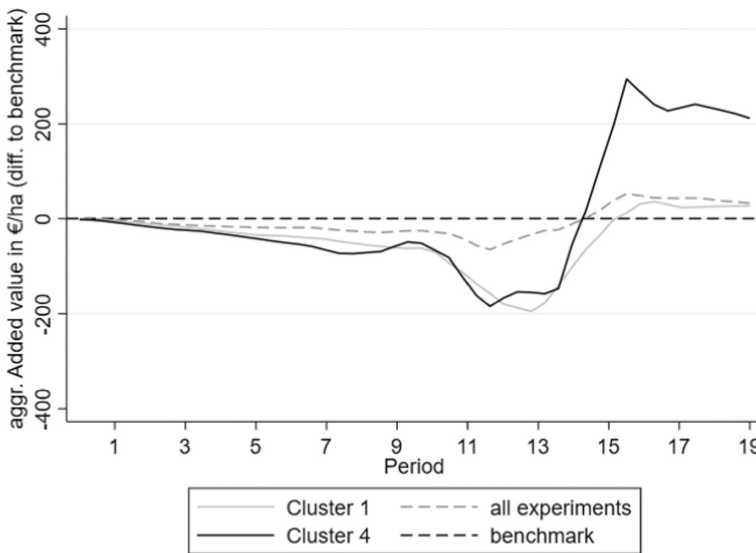


FIGURE 4 Development of aggregated added value in the region (difference to benchmark). ‘all experiments’ refers to experiments with all participants including all four clusters; Cluster 1 refers to ‘negligent gamblers’ and Cluster 4 refers to ‘successful pathbreakers’.

performing, the poorer and smaller the neighbouring farms are in terms of equity capital and farm sizes, and the higher the rental prices they pay.

Additionally, the distance to the participant's farm has an influence on all of the considered variables, although no consistent pattern seems to exist. For equity capital and rental prices, this effect is negative, and for farm size, it is positive. We further explore the spatial effects below (next section).

Categorising as one of the two behavioural clusters is considered via two paths (Figure 2): once via the relative equity capital of the participant (see Table 3) and once directly via Cluster

TABLE 3 SEM results for structure of the model

	Coef.	Robust std. err.
Equity capital participant ^a		
CLUSTER1	-1.418***	0.139
CLUSTER4	1.291***	0.150
Period	0.000	0.016
Const.	-0.238*	0.121
Cluster 1		
Farm 2	0.075***	0.000
_cons	3.075***	0.000
Cluster 1		
Farm 2	-0.041	0.062
Farm 3	-0.116**	0.041
Price 1	0.020	0.048
Price 2	0.046	0.053
Const.	0.098**	0.036
Cluster 4		
Farm 2	0.133*	0.062
Farm 3	-0.076	0.044
Price 1	0.004	0.019
Price 2	0.295***	0.056
_cons	-0.010	0.034
var(e.Equity capital participant ^a)	1.389	0.175
var(e.ln Distance)	0.188	0.001
var(e.Cluster 1)	0.062	0.016
var(e.Cluster 4)	0.072	0.010

Notes: 177,320 observations. Standard error adjusted for 49 clusters.

Significance level: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. The coefficients in bold reach a certain significance level.

Cluster 1 refers to 'negligent gamblers' and Cluster 4 refers to 'successful pathbreakers'.

^aRelative to benchmark.

1 ('negligent gamblers') and Cluster 4 ('successful pathbreakers'). The behavioural clusters have an impact through both paths. Cluster 4 ('successful pathbreakers') has a strong positive impact on the equity capital of the participant (Table 3), and via the direct path (Table 4). There is also a negative impact on the equity capital and rental prices for the arable land of neighbouring farms. Cluster 1 ('negligent gamblers') has a strong negative impact on the equity capital of the participant (Table 3), and via the direct path (Table 4). There is also a negative impact on the relative sizes of neighbouring farms.

The time variable 'Period' has a negative influence on the farm size and a positive influence on rental prices, which means that the size of the farms in the neighbourhood decreases over time while the rental prices increase.

4.3 | Spatial analysis

The spatial effect of a participant's behaviour on the final equity capital of neighbouring farms (Figure 5) depends on the distance and cluster. For this purpose, the Y-axis shows the relative deviation from the benchmark situation in terms of equity development (cf. Equation 1).

TABLE 4 SEM results for estimated measures

	Coef.	Robust std. err.
Equity capital ^a		
Equity capital participant ^a	-0.005**	0.002
ln Distance	-0.020***	0.003
CLUSTER1	-0.013	0.008
CLUSTER4	-0.019***	0.004
Period	0.000	0.000
Const.	0.061***	0.010
var(e.Equity capital ^a)	0.055	0.000
Farm size ^a		
Equity capital participant ^a	-0.101***	0.012
ln Distance	0.040**	0.014
Cluster1	-0.128***	0.032
Cluster4	-0.052	0.028
Period	-0.010***	0.001
Const.	-0.092*	0.042
var(e.Farm size)	1.499	0.005
Rental price arable land ^a		
Equity capital participant ^a	0.055***	0.008
ln Distance	-0.033*	0.015
CLUSTER1	0.022	0.022
CLUSTER4	-0.105***	0.032
Period	0.010***	0.002
Const.	0.060	0.045
var(e.Rental price arable land ^a)	1.891	0.047
Rental price grassland ^a		
Equity capital participant ^a	0.108***	0.023
ln Distance	-0.112*	0.051
Cluster1	0.013	0.058
Cluster4	-0.010	0.052
Period	0.009**	0.004
Const.	0.347*	0.153
var(e.Rental price grassland ^a)	5.163	0.797

Notes: 177,320 observations. Standard error adjusted for 49 clusters.

Significance level: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. The coefficients in bold reach a certain significance level.

Cluster 1 refers to 'negligent gamblers' and Cluster 4 refers to 'successful pathbreakers'.

^aRelative to benchmark.

Depicted as a function of the distance, it follows a wave. Considering all experiments, participants in general have a negative influence on the equity development of the farms in their immediate vicinity, while they have a positive effect on the equity development of farms that are somewhat further away (around 2.5 km). The overall influence of the participants decreases significantly at greater distances and is hardly detectable beyond 4 km. Cluster 1's 'negligent gamblers' tend to have a positive effect on farms in their neighbourhoods, with farms at a distance of some 2 and 3.5 km showing the largest positive development of their equity compared to the benchmark situation (+17%). The equity development of more distant farms from about

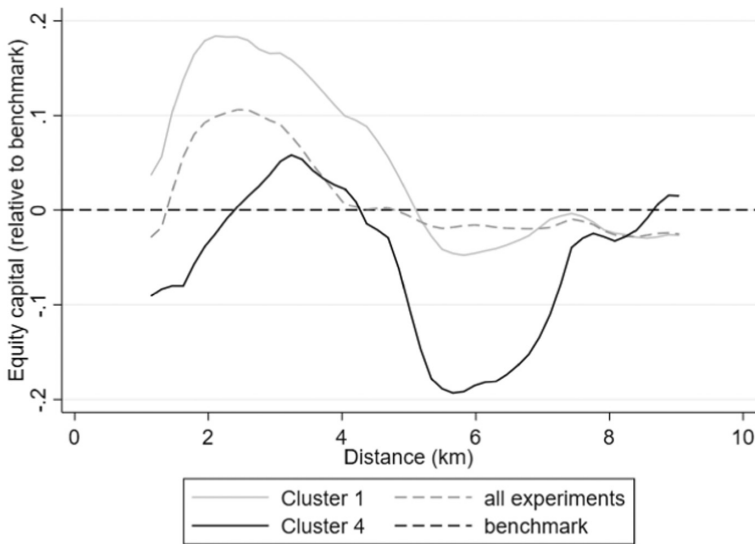


FIGURE 5 Distance-dependent spatial distribution of equity capital at the end of the experiment (relative to the benchmark; excluding the participant). Kernel-weighted local polynomial smoothing (Epanechnikov, 1969); ‘all experiments’ refers to experiments with all participants including all four clusters; Cluster 1 refers to ‘negligent gamblers’ and Cluster 4 refers to ‘successful pathbreakers’

5 km upwards, however, is hardly or only slightly negatively affected. In accordance with the SEM results, Cluster 4’s ‘successful pathbreakers’ have a significant negative influence on the equity development of their neighbouring farms. However, this influence is not evenly distributed across the whole region. For example, farms in around 3.5 km distance show a 5% higher equity development than in the benchmark situation. Farms at a further distance (around 5.5 km) are affected by a significantly more negative equity development. With an equity development of 17% below the benchmark level, the negative impact is even more pronounced than in the farms in the immediate vicinity. At a distance of 9 km and farther away, the farms’ relative equity capital is again slightly above the average.

A wave-like distance effect on the relative farm sizes can also be observed (Figure 6). In general, the participants’ direct neighbours are smaller than they are in the benchmark. With increasing distance, the effect of the ‘negligent gamblers’ (Cluster 1) on the farm sizes of neighbouring farms decreases. But there are areas (3–4 km and from 8 km) where the farms are slightly larger than in the benchmark situation. The effect of ‘successful pathbreakers’ (Cluster 4) on farm sizes of neighbouring farms are more remarkable: Although in general the farms in the neighbourhood have much lower relative farm sizes compared with the average of all experiments, at approximately 3.5 km and at 8.5 km the farm sizes are above the benchmark level. This means that the amplitude of the ‘wave’ is significantly larger compared to the average of all experiments and the ‘negligent gamblers’ (Cluster 1).

Cluster 4’s ‘successful pathbreakers’ also have strong positive effects on the levels of rental prices in their neighbourhoods (see Figure 7). Within a radius of some 3 km, the resulting increases in rental prices are twice as strong as they are in the benchmark. Although these effects are widely diminished for a greater distance from the participant’s farm, rental prices remain above the benchmark level. In total, the participants have positive effects on rental prices in their neighbourhoods, although these effects are smaller compared with Cluster 4 (‘successful pathbreakers’). For Cluster 1 (‘negligent gamblers’), only in the small range of around 4.5 km are the rental prices below the benchmark level. Here, too, the effects seem to be wave-like, with positive peaks at approximately 2.5 and 7 km.

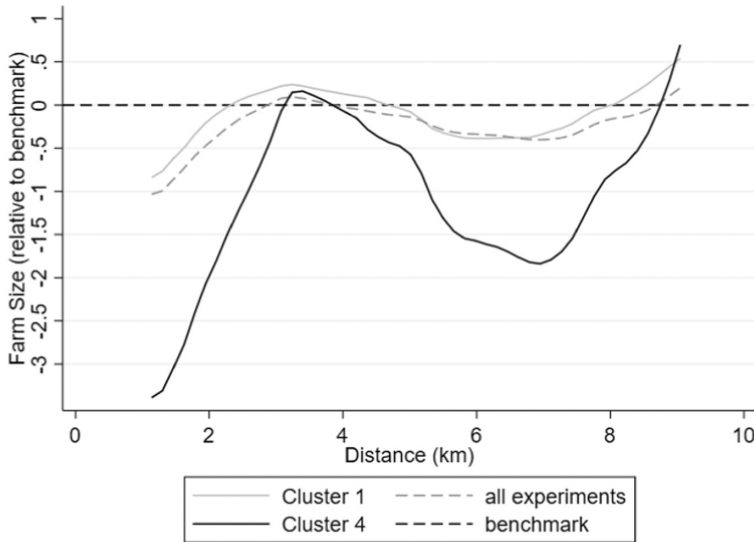


FIGURE 6 Distance-dependent spatial distribution of farm sizes at end of experiment (relative to benchmark, excluding the participant). Kernel-weighted local polynomial smoothing (Epanechnikov, 1969); ‘all experiments’ refers to experiments with all participants including all four clusters; Cluster 1 refers to ‘negligent gamblers’ and Cluster 4 refers to ‘successful pathbreakers’.

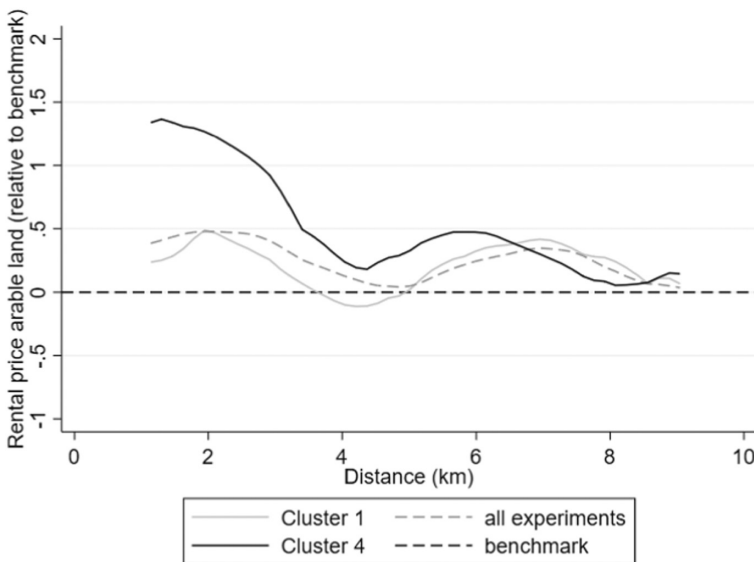


FIGURE 7 Distance-dependent spatial distribution of rental prices for arable land at the end of experiment (relative to benchmark, excluding the participant). *Note:* Kernel-weighted local polynomial smoothing (Epanechnikov, 1969); ‘all experiments’ refers to experiments with all participants including all four clusters; Cluster 1 refers to ‘negligent gamblers’ and Cluster 4 refers to ‘successful pathbreakers’.

5 | DISCUSSION

We present an exploratory analysis of experiments that Appel and Balmann (2019) performed with students, in which one person competed against several computer agents in the spatial agent-based dynamic models of AgriPoliS and FarmAgriPoliS. Appel and

Balmann (2019) chose this setting to study the difference between human behaviour and computer agents. Our study of farm-to-farm interactions are focused on the spatial interactions via the land rental market. Other aspects of farm-to-farm interactions, such as technology transfer, knowledge transfer and collaborations, are not included. Moreover, in FarmAgriPoliS, strategic aspects are limited to investments, lease decisions, and the closing (exit) of farms. Other strategic aspects of farm management are not considered, and agents were not able to communicate on cooperation or collaboration. Furthermore, the participants were aware that they were competing against computer agents that followed specific routines of short-term profit maximisation. Even though they were unlikely to be able to predict the behaviour of the competing computer agents and the dynamics created via their interactions and emergent processes, one can assume an information advantage on the participants' side.

An advantage of Appel and Balmann's (2019) methodological setting compared with potential empirical data is that a replicable computational benchmark exists for the regional development of all experiment runs.⁶ This benchmark indicates how the farms and the entire region would have developed had the optimising computer agents made all of the decisions. Appel and Balmann (2019) noted that some participants deviated significantly in their behaviour from that of the computer agents. In Appel and Balmann's (2019) work, 19% of the participants were particularly remarkable—either because they are very successful (12% 'successful pathbreakers') or because they gambled away great opportunities (7% 'negligent gamblers').

Our results reveal that large, fast-growing farms with high profitability and a higher maximisation tendency (cf. 2.2, 4.2 and Table A1) have negative effects on the sizes and profitability (in terms of final equity) of other farms in their neighbourhood, and they lead to higher land rental prices (see Table 4). Such successful farms may be interpreted as 'predator' farms that tend to restrict the prospective developments of other farms in the region, partly by driving up rental prices. Our results are therefore in line with the fundamental predator–prey relationship (Goodwin, 1967; Lotka, 1910), the observed land concentration towards large(r) farms (e.g., Bunkus & Theesfeld, 2018), and the land price effects of innovative farms (Graubner et al., 2021; Levins & Cochrane, 1996).

Appel and Balmann (2019) found further behavioural effects in their analysis, including differences in the participants' investment behaviour, such as a stronger focus on the land market with higher bids and a focus on long-term strategies instead of short-term optimisation. If the participants had a stronger focus on long-term strategies than the computer agents did, they opted out of pursuing short-term gains to be strategically better off in the future. This strategy is reflected in the generated value added, which may be lower than the benchmark in the beginning but rises above it later (Figure 4). In addition, in the SEM analysis, we found that participants' influence went beyond their own economic performance, that is, equity capital. In the case of Cluster 4, this initially led to lower rental prices for the arable land that neighbouring farms paid (Table 3). However, these 'successful pathbreakers' (Cluster 4) do not only have direct negative impacts on rental prices (coef. -0.105 , Table 3). Through their increasing equity capital (1.291), they have indirect positive effects on the levels of rental prices (0.055, Table 3). Over time, this led to a situation where the fewer neighbouring farms that succeeded in the land market had to pay rental prices that were well above the benchmark by the end of the experiment. According to the SEM analysis, the effects of 'negligent gamblers' (Cluster 1) are in the same direction as the 'successful pathbreakers' (Table 3). Appel and Balmann (2019) showed that the participants of Cluster 1 had a similar maximisation tendency and were very

⁶The lack of a counterfactual in reality could be overcome empirically by comparing different regions. However, due to spatial heterogeneity, numbers of observations may be very limited.

similar to the 'successful pathbreakers' (Cluster 4) in the initial periods of the experiments. However, members of Cluster 1 lacked reflection and experience, which causes risky growth and subsequent failure. Over time, the participants of Cluster 1 lost influence as a result of their failure and exited. Therefore, their overall results are generally smaller and closer to the benchmark situation.

We have additionally been able to show that these effects are not uniformly distributed in the modelled region. The chance of being able to rent land and to be economically successful depends, to a certain extent, on the farm's distance to fast-growing farms. The regional interdependences between farms—whether positive or negative—can be assumed stronger the closer a farm is located to fast-growing large farms. Our analysis (Figures 5–7) indicates that the spatial effect does not follow a linear or exponential form but rather follows a wave-like distribution. Direct competition with a successful pathbreaking participant will limit the development opportunities or even profitability of immediate neighbours. However, the reduced competitiveness of farms in the direct vicinity provides additional development opportunities for farms at greater distances. In other words, what influences immediate neighbours negatively can be positive for a neighbour's neighbours, and vice versa.

Furthermore, the spatial interdependence and the related predator–prey phenomenon overlap with the phenomenon of the path dependency of farms and agricultural structural change. A farm's development is not influenced just by its interactions with other actors in the land market, which is highly local due to the inherent immobility of agricultural land. Rather, history and irreversibility also influence a farm's development (Balmann, 1997; Happe et al., 2006). Therefore, the actions of a specific farm are likely to influence the development perspectives of neighbouring farms not just temporarily but often in a long-lasting and irreversible way. The effects of 'negligent gamblers' (Cluster 1), which initially grow but fail in the longer run, are long lasting and still noticeable even if the farms have long since exited. On the other hand, 'successful pathbreakers' (Cluster 4), which outcompete other potentially successful farms and inhibit their growth, may indirectly allow more smaller farms to survive. Although 'successful pathbreakers' may negatively affect the average incomes of neighbouring farms, the entire region's aggregated added income is above the benchmark level, which indicates that heterogeneous growth is not necessarily negative for total welfare. Based on the model assumptions of the adaptations of AgriPoliS and FarmAgripolis, the sources of these welfare increases can be seen in increases in scale efficiency, allocative efficiency and technological efficiency. Other potential welfare effects of pathbreakers through, for example, technological change and technological spillovers (Case, 1992; Harrington & Reinsel, 1995; Holloway et al., 2002; Mzoughi, 2011), are not considered in the model.

6 | CONCLUSIONS

We provide an explorative analysis of the neighbourhood effects of fast and successfully growing farms, as well as failing farms, on the basis of the behavioural simulation experiments by Appel and Balmann (2019) with students. In particular, we analysed the spatial influences of the different types of behaviour of farm managers. Accordingly, the behaviour of farm managers influences not only the development of their own farms but also the development of farms in the neighbourhood. These effects can be far reaching. Specifically, successful pathbreakers which establish very large farms can have strong effects over many kilometres.

Further supporting the recent literature on farms' spatial interdependence (Saint-Cyr et al., 2019; Storm et al., 2015), we conclude that the overall effects of neighbouring farms are ambiguous and that it is necessary to take greater account of the actual spatial distribution of effects on other farm sizes, exits, profitability and rental prices. Although the influence of neighbouring farms tends to decrease with growing distance, the functional correlation of

farm growth and exits is neither linear nor exponential. Rather, it is wave-like. Without further spatial distinction, it is not possible to conclude whether farms in a region are pure competitors or if they influence one another positively. Saint-Cyr et al. (2019) found significant positive and negative correlations between neighbouring farms with regard to size and the probability of remaining in farming due to the neighbouring farms' sizes. In addition to Saint-Cyr et al. (2019), who, due to data availability, had to consider all farms whose farmsteads were located in the same municipality as neighbours, Storm et al. (2015) explicitly considered spatial dependencies between the farms. However, due to data limitations, the age of the farm holder was their only available farm attribute variable. Using FarmAgriPoliS, we were able to consider spatial dependencies and include further characteristics of the farm managers and their behaviour. We found that the correlation between neighbouring farms further depends on the specific distance and the characteristics of the evolution of (particularly larger) farms (e.g., continuous or failing growth). Farmers' strategies and abilities, together with the farms' distances, determine who is the 'predator' and who is the 'prey'.

Because this study is based on laboratory experiments instead of actual empirical data, only limited conclusions can be drawn about the economic and political implications. Specifically, we only considered the behaviour of one human actor at a time, whereas all other entities were computer agents with myopic optimisation based on mixed-integer programming. Therefore, we could not address the strategic interactions of several farmers who explicitly observed or considered the potential responses of their neighbours. Nevertheless, this study offers indications of phenomena and interdependencies that may be verified via empirical studies in the future. In addition to empirical studies, it may be worth considering experimental or machine-learning-based methodological approaches to study strategic spatial interactions and their resulting impacts.

Despite these uncertainties and need for further research, our analyses and findings indicate that competition for land and land markets are highly complex processes with several emergent properties. These complexities and emergent properties imply that political interventions into land markets, such as regulations of land prices or restrictions on maximum farm sizes, are likely to have numerous unintended effects. For instance, restricting the competitiveness of a fast-growing farm on the land market may not just be seen as support for its competing neighbours but also as a potential restriction on the future development prospects of the neighbours' neighbours. This potential for unintended effects as well as of win-lose outcomes among the group of intended beneficiaries of regulations should be considered when assessing regulations of land markets. Moreover, these emergent properties, unintended effects and win-lose outcomes may provide an explanation for puzzling political phenomena such as the fact that farmers who ask for land market regulations often oppose concrete regulation proposals (Balmann, 2020)—possibly because they are afraid of facing unintended negative effects.

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ORCID

Franziska Appel  <https://orcid.org/0000-0002-6049-4511>

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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