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Alfons Balmann, Oliver Musshoff and Karin Larsén

DFG-Forschergruppe 986
Strukturwandel im Agrarsektor

Herausgeber:
DFG-Forschergruppe 986, Humboldt-Universität zu Berlin
Philippstr. 13, Haus 12A, D-10099 Berlin
http://www.agrar.hu-berlin.de/struktur/institute/wisola/fowisola/siag

Redaktion:
Tel.: +49 (30) 2093 6340, E-Mail: k.oertel@agrar.hu-berlin.de

Does vertical integration reduce investment reluctance in production chains? An agent-based real options approach

Kann vertikale Integration die Investitionszurückhaltung in Wertschöpfungsketten reduzieren? Ein agentenbasierter Realoptionsansatz

Alfons Balmann[1], Oliver Musshoff [2] and Karin Larsén[1]

[1] Leibniz Institute of Agricultural Development in Central and Eastern Europe (IAMO)

[2] Georg-August-Universität Göttingen, Department for Agricultural Economics and Rural Development

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Abstract

This paper uses an agent-based real options approach to analyze whether stronger vertical integration reduces investment reluctance in pork production. A competitive model in which firms identify optimal investment strategies by using genetic algorithms is developed. Two production systems are compared: a perfectly integrated system and a system in which firms produce either the intermediate product (piglets) or the final product (pork). Simulations show that the spot market solution and the perfectly integrated system lead to a very similar production dynamics even with limited information on production capacities. The results suggest that, from a pure real options perspective, spot markets are not significantly inferior to perfectly integrated supply chains.

Keywords: real options, supply chain, agent-based models, genetic algorithms

Zusammenfassung

In diesem Beitrag wird ein agentenbasierter Realoptionsansatz genutzt, um zu analysieren, ob durch vertikale Integration die Investitionszurückhaltung in die Schweinemast reduziert werden kann. In dem Modell werden zum einen Wettbewerbseffekte zwischen den Unternehmen berücksichtigt. Zum anderen bestimmen die Unternehmen ihre optimale Investitionsstrategie mit Hilfe eines genetischen Algorithmus. Es werden zwei Produktionssysteme verglichen: Ein perfekt integriertes System und ein System, in dem Unternehmen entweder das Zwischenprodukt (Ferkel) oder das Endprodukt (Mastschweine) erzeugen. Die Simulationen zeigen, dass die Spotmarktlösung und das perfekt integrierte System zu sehr ähnlichen Ergebnissen führen; und dies, trotzdem begrenzte Informationen bezüglich der Produktionskapazitäten berücksichtigt werden. Die Ergebnisse deuten darauf hin, dass – allein aus der Realoptionsperspektive – Spotmärkte den perfekt integrierten Systemen nicht unterlegen sind.

Schlüsselwörter: Realoptionen, Wertschöpfungsketten, Agentenmodellierung, genetische Algorithmen

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1. Introduction

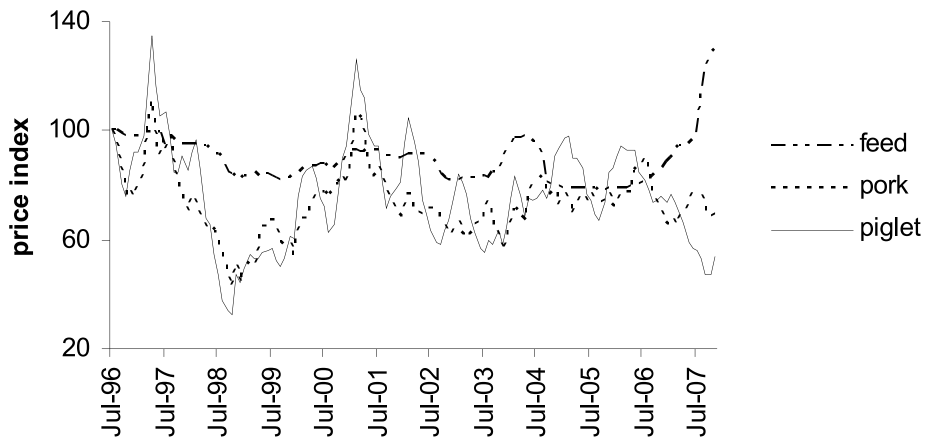
Modern pork production has become extremely capital and technology intensive. For German conditions, necessary investment outlays for asset and current capital for state-of-art facilities may be more than one million Euros in hog finishing respectively more than 500.000 Euros in piglet production in order to create one full-time job. Thus, for hog finishing activities the interest costs may be higher than the labour costs and it is reasonable to believe that investments in hog finishing are rather motivated by the search for attractive investment opportunities than by safeguarding the employment of a farmer. Also for piglet production, capital costs including depreciation are higher than labour costs. Moreover, such investments are irreversible and long-lasting with significant share of sunk cost. Accordingly, investment decisions in the pork chain demand for a sound investment analysis. This need seems to be even more important as returns for pork as well as for piglets are highly uncertain due to significant price fluctuations. Thus an investment analysis should not just account for the expected profitability but also for issues of uncertainty in order to cope with threads and chances. One approach which fulfils this demand is the real options approach.

According to the real options approach, irreversible investment decisions under uncertainty should consider the opportunity costs of deferring the investment decision in order to obtain improved information on the involved risks (Henry, 1974; McDonald and Siegel, 1986; Pindyck, 1991; Leahy, 1993). Numerous empirical applications illustrate these effects and show that price uncertainty creates investment reluctance beyond risk aversion. Examples related to agriculture can be found in, e.g., Hyde *et al*. (2003), Khanna *et al*. (2005), Price and Wetzstein (1999) and Purvis *et al*. (1995). Among these studies, several applications focus on pork production (Pietola and Wang, 2000; Odening *et al.*, 2005; 2007). However, Odening *et al.* (2005; 2007) show that the outcomes of real options applications respond very sensitive to assumptions about type and measurement of the underlying uncertainty. Accordingly, it is very important to have an adequate understanding of the underlying dynamics of e.g. prices.

In addition to the uncertainty on output markets, price uncertainty may arise along value chains in which intermediate products are often exchanged via spot markets. Then the market participants may face a double-sided price risk on the input as well as the output side. Depending on the transmission of price fluctuations of the final product, risk may be higher or lower. For instance, Pietola and Wang (2000) find that for the pork chain in Finland, prices for piglets and pork are not strongly correlated. By using a real options approach, the authors come to the conclusion that investment reluctance is higher in a pork chain in which farms are producing either piglets or hogs and trade piglets on a spot market than if farms would integrate piglet production and hog feeding to a combined production system.

For Germany, the coefficients of variation in hog and piglet prices are approximately 0.16 and 0.24 respectively.[1] The uncertainty in prices (including feed price) is illustrated graphically in Figure 1. Thus, specialized hog producers that buy piglets on the spot market are facing substantial price risk on both the input and output side. The same holds for piglet producers. The total variation in net return will depend on the correlation between input and output prices (were a lower correlation implies a greater total variation given the same variation in piglet and pork prices). In the case of German pork and piglet prices, the coefficient of correlation is high, around 80%. This may suggest that German hog producers that buy piglets on the spot market are not exposed to a substantially higher uncertainty in total net return compared to pig producers operating in closed production systems. However, Figure 1 also illustrates that piglet and pork prices are not always coherent. In particular, fluctuations of piglet prices quite often overshot the price change for pork. This may be related to 'bullwhip effects' within supply chains (Forrester, 1961). Accordingly, a shock on one side of a supply chain can cause amplifying shocks up-/downstream the chain. Hence, it seems important to relate investment decisions within a supply chain not only to the external uncertainty of the chain but also to consider how the different participants of the chain respond.

Figure 1. Variation in German piglet, hog and feed prices 1996-2008



Source: Own figure based on price data provided by the ZMP (Zentrale Markt- und Preisberichtstelle GmbH)

Based on these reflections, this paper takes the finding of Pietola and Wang (2000) as a starting point for analyzing whether stronger vertical integration along the production chain really reduces investment reluctance under uncertainty. As in Pietola and Wang (2000), two production systems are compared: Firstly, every firm can invest in a perfectly integrated system in which the intermediate and the final product are produced in equal amounts. Secondly, in an alternative production system, firms can either specialize in the intermediate product or in the final product. The intermediate product is traded on a spot market. As source

[1] Calculated using data for monthly prices over the time period 1996-2007.

of uncertainty, it is assumed that an iso-elastic demand curve for pork follows a random walk. For reasons of simplicity, all other variables including buildings, feed etc are assumed to be constant.

Within this setting, the subsectors and the spot market interaction are explicitly modelled. Instead of looking at the market at an aggregate level, we use a bottom-up approach by explicitly modelling the farms and their behaviour, as well as their interaction in an agent-based approach. In the discrete-time model, a number of agents represent identical farms which compete within their subsector and trade with another subsector. The farms identify optimal investment strategies for Monte Carlo simulations of demand changes for the final product, and can invest irreversibly into production assets (buildings) without knowing how the market environment will evolve in the future. Producers of the intermediate product and producers of the final product are assumed to be aware of the investment strategies and the production capacities of other producers, which is the rational expectation hypothesis. Moreover, piglet producers are assumed to know the actually existing production capacity of pork producers, but not the actual (dis-)investments. Every farm invests according to its individual investment trigger which is derived by linking Monte Carlo simulations of the agent-based model with a genetic algorithm (cf. Arifovic, 1994).

In contrast to the findings of Pietola and Wang (2000), our analysis shows that the closed system and spot market solutions both lead to very similar production dynamics. Differences in investment behaviour are only marginal, even in the case of inelastic demand respectively high price flexibility for the intermediate product. In accordance with real German pork and piglet prices, we identify a positive correlation between simulated pork and piglet prices. Moreover, we are able to identify under which parameter assumptions (concerning e.g. demand elasticities) patterns in simulated prices best describe patterns in real price data.

The outline of this paper is the following. First, a brief review of the literature dealing with modelling of price dynamics in pig production is provided. The model is thereafter described followed by the results. Summary and conclusions end the paper.

2. Modelling price dynamics in pig production – overview of literature

The modelling of stochastic outcomes such as volatility in net returns due to price uncertainty and/or uncertainty in other variables obviously is an important part of any application of the real options approach and the way this is modelled has an impact on the results. In option pricing theory, the assumption of geometric Brownian motion (GBM) for the development of the underlying has been widely applied as it is generally considered a reasonable approximation for stock price dynamics. An advantage of assuming GBM is that it allows to obtain analytical solutions.[2] However, the implications of assuming GBM are not necessarily plausible for the

[2] In the context of modeling volatility in pork production, GBM was applied by e.g. Pietola and Wang (2000).

case of revenues and costs or gross margins of a real investment (Odening *et al.*, 2005). Odening *et al.* (2005) compare GBM, arithmetic Brownian motion (ABM) and a mean-reverting process in an application of the real options approach to hog finishing using stochastic simulations. The authors find that the results are substantially affected by the type of stochastic process assumed. Moreover, Odening *et al.* (2007) discuss problems connected to using real world data for obtaining parameter estimates of the stochastic processes. Using simulation experiments, the authors show that applications of the GBM approach tend to generate considerably biased parameter estimates and investment conclusions.

Traditionally, studies of pork market dynamics, other than option pricing models, have used linear time-series models (e.g. Bessler and Kling, 1986; Kaylen, 1988). A commonly estimated model is the univariate autoregressive moving-average (ARMA) model. The main short-coming of this model is that it does not consider information about other potentially important variables. In order to overcome this problem, the vector autoregression (VAR) model has been suggested. But applications of this model are also connected with problems as they generally do not forecast well (as a result of over-parameterisation). Attempts to overcome this problem have been made and include exclusion of explanatory variables (e.g. Kaylen, 1988) and Bayesian estimation (an application of Bayesian estimation in a VAR for forecasting of the dynamics in the U.S. hog industry is provided in Bessler and Kling, 1986).

Moreover, Cobweb models have been considered to be useful for agricultural commodities such as hog production. The idea of these models is that cycles are a result of lagged responses to changes in prices and other variables (e.g. Ezekiel, 1938). A criticism against the Cobweb models is that they assume producers to be irrational in the sense that they do not respond in a countercyclical way in order to receive a larger than “normal” profit (e.g. Hayes and Schmitz, 1987; Chavas and Holt, 1991). A countercyclical behaviour would eventually smooth out the cycles. It has furthermore been questioned whether it is appropriate to model price and output dynamics using linear models (e.g. Stripes, 1995). Some authors have however incorporated non-linearities in the Cobweb model (e.g. Harlow, 1960).

Chavas and Holt (1991) and Stripes (1995) argue that a common mistake done by many authors modelling pork market dynamics is to assume that seemingly random disturbances are white noise while in reality such fluctuations may be a part of the non-linear dynamics of the system. Thus, it may be the case that unpredictable patterns are a result of deterministic, non-linear dynamics (often referred to as ‘chaotic’ systems). Chaotic systems can be characterized by non-linear state-equations that exhibit dynamic patterns which cannot be generated or reproduced by a system of linear state equations. Chavas and Holt (1991) analyze whether the pork business cycle may be characterized by a deterministic non-linear dynamic process. Although the statistical tests conducted by the authors support that the processes generating the pork cycle is characterized by non-linear dynamics, they stress that the evidence in favour of chaos is somewhat weak. Also Stripes (1995) perform statistical tests using pork price data that support the presence of non-linear dynamics and chaotic behaviour. Thus, the results of Chavas and Holt (1991) and Stripes (1995) suggest that the commonly used linear models may fail to capture economic dynamics in the pork industry and that chaos theory may be a useful tool to understand pork market dynamics.

As mentioned above, it has often been assumed that returns follow a GBM in applications of the real options approach in spite of the facts that this assumption may not be plausible and that there are problems with biased estimates when estimating the necessary parameters. In this application, where the interaction between agents is explicitly modelled in an agent-based setting, the price in each time period is determined endogenously as a response to uncertain demand and rational production response[3] (the model is described in the following section). In order to evaluate how well patterns in simulated prices correspond to patterns observed in real price data, coefficients calculated from real data and simulated data will be compared, too.

3. The Model

3.1 The investment problem

Consider a number of firms *N*, each repeatedly having the opportunity to invest in identical assets or a fraction thereof, i.e., the assets are perfectly divisible. Initially, no firm has previously invested. The asset stock of a firm n has a maximum size of 1 and can be used by the firm to produce up to $x_{t,n} \leq 1$ units of output per production period. Size, investment outlay and production are proportional, i.e., there are no economies of scale. If a firm invests for the first time, its maximum initial investment outlay $M_{t,n}^{\max}$ is I. The investment outlay $M_{t,n}$ is considered to be totally sunk after the investment is carried out. For every future period, we consider a geometrical decay of the asset. The asset's productivity declines to $(1-\lambda)$ of the previous period's output, i.e., we consider a depreciation rate λ such that $x_{t+\Delta t,n} = (1-\lambda)\cdot x_{t,n}$.[4] However, in every period, each firm can invest or reinvest in order to increase production or to regain a production capacity of up to one unit of output. The outlay $M_{t,n}$ then has a maximum amount $M_{t,n}^{\max}$ depending on the missing production capacity to one, i.e.,

(1) $$M_{t,n}^{\max} = \left[1-(1-\lambda)\cdot x_{t,n}\right]\cdot I$$

such that $x_{t+\Delta t,n}^{\max} = 1$. Each firm's investment decisions aim to maximize the expected net present value of future cash flows by choosing a specific investment trigger P_n^*, i.e., the goal of firm n can be formulated as:

3 It can be shown that the agent-based model and a direct price simulation lead to an identical price path.

4 The use of the decay parameter λ is from a market perspective analogous to the probabilistic approach presented in Dixit and Pindyck (1994, pp. 200). To understand this, simply consider that any firm *n* would consist of an infinite number of identical, infinitely small firms.

(2) $$\max_{P_n^*}\left\{\hat{\Pi}_n\left(P_n^*\right)=E\left[\sum_{t=0}^{\infty}\left(x_{t,n}\cdot\left(P_t-c\right)-M_{t,n}\left(x_{t,n},P_n^*,\nabla_{t,-n}\right)\right)\cdot\left(1+r\right)^{-t}\right]\right\}$$

with P_t as the output price in period t, c as the variable production costs per unit of output and period, r as the risk-free interest rate and $\nabla_{t,-n}$ denoting a certain market operator that captures demand developments which are assumed to be stochastic as well as dependent on the behaviour of the other firms.[5] Accordingly, we consider that the firms compete and interact on a market. To capture competition, the firms and their interaction are represented in an agent-based setting in which the firms are represented as agents that perceive their environment and respond to it individually and autonomously (Russel and Norvig, 1995).

The environment of a firm n comprises of two parts: the first is the behaviour of other firms, and the second is the demand for outputs, modelled in terms of a demand function. Total supply in period t is

(3) $$X_t^S=\sum_{n=1}^{N}x_{t,n}$$

and demand is

(4) $$X_t^D=\frac{\alpha_t}{\left(P_t\right)^{\eta}}$$

with the elasticity of demand η. For the identity of demand and supply, we get

(5) $$P_t=\left(\frac{\alpha_t}{X_t^D}\right)^{\frac{1}{\eta}}=\left(\frac{\alpha_t}{X_t^S}\right)^{\frac{1}{\eta}}$$

The demand parameter α_t is considered to follow a geometric Brownian motion. Assuming discrete time, this can be modelled as

(6) $$\alpha_t=\alpha_{t-\Delta t}\cdot\exp\left[\left(\mu-\frac{\sigma^2}{2}\right)\cdot\Delta t+\sigma\cdot\varepsilon_t\cdot\sqrt{\Delta t}\right]$$

with a volatility σ, a drift rate μ, a standard, normally distributed random number ε_t, and a time step length Δt. The expected value for α_t (given $\alpha_{t-\Delta t}$) equals $\hat{\alpha}_t=\alpha_{t-\Delta t}\cdot\exp\left(\mu\cdot\Delta t\right)$.

Firm n invests in period t if the expected price $\hat{P}_{t+\Delta t}$ is larger than or equal to the trigger price P_n^*. For the expected price $\hat{P}_{t+\Delta t}$ holds:

5 Note that equation (2) implicitly assumes either risk neutrality or that risks can be hedged perfectly.

(7) $$\hat{P}_{t+\Delta t} = \left(\frac{\hat{\alpha}_{t+\Delta t}}{\hat{X}_{t+\Delta t}} \right)^{\frac{1}{\eta}} \text{ with}$$

$$\hat{X}_{t+\Delta t} = \sum_{n=1}^{N} x_{t+\Delta t,n} \text{ and}$$

(8) $$x_{t+\Delta t,n} = \begin{cases} 1 & \text{if } n \text{ invests } M_{t,n}^{\max} \\ (1-\lambda) \cdot x_{t,n} + \frac{M_{t,n}}{I} & \text{if } n \text{ invests } 0 < M_{t,n} < M_{t,n}^{\max} \\ (1-\lambda) \cdot x_{t,n} & \text{if } n \text{ invests } M_{t,n} = 0 \end{cases}$$

The questions now are: Which firms invest? And how much do they invest? It is assumed that firms with lower trigger prices P_n^* have a stronger tendency to invest. Consequently, all firms can be sorted according to their trigger prices, starting with the lowest investment trigger, i.e., $P_n^* \le P_{n+1}^*$. The following propositions are posited:

Proposition 1: If firm n <u>does not invest</u> in t, then firm $n+1$ will also <u>not invest</u> in t, i.e., $M_{t,n} = 0 \Rightarrow M_{t,n+1} = 0$.

Proposition 2: If firm n <u>does invest</u> in t, then firm $n-1$ <u>will invest</u> $M_{t,n-1}^{\max}$ in t, i.e., $M_{t,n} > 0 \Rightarrow M_{t,n-1} = M_{t,n-1}^{\max} \Rightarrow x_{t+1,n-1} = 1$.

Proposition 3: In every period t, a marginal (or last) firm n_t^o exists which invests M_{t,n^o} such that the expected price for the next period is equal to the investment trigger of firm n_t^o, i.e., $P^{n^\circ *} = \hat{P}_{t+\Delta t}$ with $0 < M_{t,n^o} \le M_{t,n^o}^{\max}$ and $0 \le n_t^o \le N$.[6]

The investment of firm n_t^o can be computed according to

(9) $$P_{n^\circ}^* = \hat{P}_{t+\Delta t} = \left(\frac{\hat{\alpha}_{t+\Delta t}}{x_{n^\circ,t+\Delta t} + (n^\circ - 1) + (1-\lambda)^{\Delta t} \sum_{n=n^\circ+1}^{N} x_{t,n}} \right)^{\frac{1}{\eta}}$$

(10) $$\Leftrightarrow x_{n^\circ,t+\Delta t} = \frac{\hat{\alpha}_{t+\Delta t}}{\left(P_{n^\circ}^*\right)^{\eta}} - \left[(n^\circ - 1) + (1-\lambda)^{\Delta t} \sum_{n=n^\circ+1}^{N} x_{t,n} \right]$$

6 Notice, n_t^o is zero if there is no investor in period *t*.

$$(11) \Leftrightarrow \frac{M_{t,n^o}}{I} = \frac{\hat{\alpha}_{t+\Delta t}}{\left(P^*_{n^\circ}\right)^{\eta}} - (n^o_t - 1) - (1-\lambda)^{\Delta t} \sum_{n=n^o_t}^{N} x_{t,n}$$

Now, n^o_t can be identified by iteratively testing all firms for $P^*_{n^o_t} \leq \hat{P}^{n^o}_{t+\Delta t}$. The last firm with a positive investment is n^o_t.

Equation (11) is an equilibrium condition: All firms which fully invest and hence produce at maximum capacity have trigger prices which are less than or equal to the trigger price of firm $n^o + 1$, which is also equal to the expected price for $t + \Delta t$. All firms which do not invest have trigger prices which are higher than or equal to the expected price for $t + \Delta t$.

For a given set of trigger prices P^*, and arbitrary initializations of α_0, the expected profitability of each strategy

$$(12) \quad \hat{\Pi}_n\left(P^*_n\right) = E\left[\sum_{l=0}^{\infty}\left(x_{l\cdot\Delta t,n} \cdot \left(P_{l\cdot\Delta t} - c\right) - M_{l\cdot\Delta t,n}\left(x_{l\cdot\Delta t,n}, P^*_n, \nabla_{l\cdot\Delta t,-n}\right)\right) \cdot \left(1+r\right)^{-l\cdot\Delta t}\right]$$

can be simultaneously determined by a sufficiently high number of repeated stochastic simulations of the market. Due to the competitive environment and identical production technologies, the expected profitability of a rational strategy will fulfil the zero-profit condition given all other strategies are also rational.

Until this point, the model resembles a farm's investment problem for a closed system of pork production in which the intermediate product "piglets" and the final product "pork" are produced in appropriate amounts within a production unit, such that trading the intermediate product is not necessary. The investment costs I cover the costs for both production assets, i.e., $I = {}^{pi}I + {}^{ho}I$. The italic superscripts on the left side denote **pi**glet producers and **ho**g finishers, respectively.

What are the consequences of a spot market relationship between hog finishers and piglet producers for their investment triggers? It is straight forward that in such a system the production capacity of the hog finishers can be interpreted as a demand parameter of the piglet producers,[7] i.e.

[7] Principally, one could consider iso-elastic demand and that the market equilibrium for the piglet producers fulfils ${}^{pi}P_t = \left(\frac{{}^{pi}\alpha_t}{{}^{pi}X_t}\right)^{\frac{1}{{}^{pi}\eta}} = \left(\frac{{}^{ho}X_t}{{}^{pi}X_t}\right)^{\frac{1}{{}^{pi}\eta}}$ with ${}^{pi}\eta$ is the demand elasticity for piglets. But this would presume that there is a specific use for excess supply of piglets as well as the opportunity to increase the number of piglets if there is excess demand.

(13) $\quad {}^{ho}X_t = {}^{pi}\alpha_t$

Regarding the price formation for piglets we consider a logistic relationship with a maximum price for piglets ${}^{pi}P_t^{\max}$ to avoid that the expected gross margin of hog finishing is negative as well as that there is some minimum price for piglets ${}^{pi}P_t^{\min}$ considering non-negativity of gross margins for piglets. Considering iso-elastic demand for piglets, then the market equilibrium for the piglet producers fulfils

(14) $$ {}^{pi}P_t = \frac{{}^{pi}P_t^{\max}}{1 + e^{-S_t \cdot R_t}\left(\frac{{}^{pi}P_t^{\max}}{R_t} - 1\right)} \text{ with } R_t = \left(\frac{{}^{ho}X_t}{{}^{pi}X_t}\right)^{\frac{1}{{}^{pi}\eta}} \text{ and} $$

a normalization parameter $S_t = -\ln\left(\left(\frac{{}^{pi}P_t^{\max} \cdot {}^{pi}P^*}{{}^{ho}P_t \cdot {}^{ho}P^*} - 1\right) \cdot \left({}^{pi}P_t^{\max} - 1\right)^{-1}\right)$

The normalization parameter S_t ensures that in case of identity of hog finishing capacity and piglet capacity the piglet price is proportional to the relation of the pork and the piglet price triggers. R_t can be understood as a price response coefficient considering the relation of supply and demand for piglets including ${}^{pi}\eta$ representing a kind of "demand elasticity" for piglets.

Piglet producer n invests if the expected price for piglets ${}^{pi}\hat{P}_{t+\Delta t}$ is larger than or equal to their trigger price ${}^{pi}P_n^*$. Total production of piglets in the period $t + \Delta t$ is:

(15) $$ {}^{pi}x_{t+\Delta t}^{n^o} = \frac{{}^{pi}\alpha_t \hat{P}_t}{{}^{pi}P_n^*} - \sum_{{}^{pi}n=1}^{{}^{pi}n_t^o - 1} {}^{pi}x_{pi_n}^{Max} - {}^{pi}\lambda \sum_{{}^{pi}n=n^o+1}^{{}^{pi}N} {}^{pi}x_{t,n}^{pi} $$

where $\hat{P}_t = \left(\hat{P}_{t-\Delta t}\right)^{0.8}\left({}^{pi}P_t\right)^{0.2}$, i.e. an adaptive price expectation is used as a proxy.[8] Note that in contrast to the description above, the net return for hog finishers ${}^{ho}G_t$ must be adjusted by the piglet price and other variable costs in the hog finishing stage, ${}^{ho}c$.[9] Additionally, since finishers would not spend more money on piglets and other variable costs than the expected return for pork, the expected minimum net return is zero, i.e.,

8 This formation of expectations is a slight deviation of the rational expectations assumption. In an alternative setting of the model it was assumed that piglet producers were perfectly aware of the investment strategies of hog feeders and vice versa. This led to identical pork prices like the closed system und thus to identical investment triggers. Thus these adaptive expectations can be understood as boundedly rational behaviour.

9 Other variable costs include, for example, costs for feed. In an extension of the model, the consequences of a randomness as well as stochastic investment costs for piglet barns may be analyzed.

(16) $$ {}^{ho}G = \begin{cases} 0 & \text{if } {}^{pi}P_t + {}^{ho}c \geq {}^{ho}\hat{P}_t \\ \left(\frac{{}^{ho}\alpha_t}{{}^{ho}X_t}\right)^{\frac{1}{{}^{ho}\eta}} - {}^{pi}P_t - {}^{ho}c & \text{otherwise} \end{cases} $$

we consider that for hog finishers the following holds:

(17) $$ {}^{ho}X_t = \frac{{}^{ho}\alpha_t}{\left({}^{pi}P_t^*\right)^{{}^{ho}\eta}} $$

The remaining question is how to determine appropriate sets of trigger prices ${}^{ho}P_n^*$ and ${}^{pi}P_n^*$? To answer this, the multi-firm market models are combined with a genetic algorithm (GA), which is described in the following section.

3.2 The Genetic Algorithm and its implementation

Even though many variations of GA exist, there are some basic elements which all have in common (cf. Holland, 1975; Goldberg, 1989; Forrest, 1993; Mitchell, 1996).[10] The first task of a GA application is to specify a way of representing each possible solution or strategy as a string of genes located on one or more chromosomes. Since our problem is relatively simple, i.e., we are just searching for a single value (every strategy consists just of a certain trigger price), and we can assume a convex search space, we take the investment trigger as a real value and apply the GA operators to the nominal value of trigger price. The second task is to define a population of genomes to which the genetic operators, i.e., selection, crossover and mutation, can be applied. The population size is set equal to N, the number of firms (farms). This allows the direct mapping of the set of genomes to the various firms' strategies, i.e., every firm's trigger price in our model is represented by one genome from the genome population.

After random initialization, the genome population passes in every generation through the steps of fitness evaluation, selection, recombination (crossover) and mutation. The fitness value is directly derived from the strategy's average profitability for 1,000 to 5,000 repeated stochastic simulations of the market model. The selection procedure replaces the least profitable strategies with the most profitable ones. The higher the relative profitability, the higher is the probability for replication. For recombination or crossover, the geometric average of two parent genomes is calculated resulting in one offspring which replaces one parent. Mutation is implemented here by multiplying every solution by chance (with a small likelihood) with a random number within a closed range ([e.g., 0.95,1.05]. The mutation likelihood, as well as the range of the random number, may be chosen according to experience or according to the already obtained results. A flow diagram of this procedure can be found in the appendix.

[10] For other GA-applications to real options cf. Balmann *et al*. (2001).

In one particular point, our GA application deviates from the conventional use of GA for optimization problems. Here, the GA is not just used to solve a complex optimization problem in which the goodness of the solution respectively the problem at hand are directly related. In our case, the goodness of a solution rather depends on the alternative solutions generated by the GA, i.e., the genomes compete directly. Thus, we are applying the GA to a game theoretic setting and are searching not just for an optimal solution, but for an equilibrium solution, i.e., the Nash-equilibrium strategy.[11] Moreover, for the spot market model, the genome population for investment triggers piglet production and for hog feeding co-evolve, i.e., optimal triggers for piglets and hogs depend on each other.

3.3 The scenarios

In order to validate the agent-based model of multiple competing farms, it will first be shown that the agent-based approach leads for the standard case of a one-step production system, i.e., the closed breeding-finishing system, to the same dynamics as a direct simulation of the price dynamics that would likely be expected. For these reference experiments, it is assumed that output prices directly follow a regulated GBM, which is a standard assumption for competitive markets. This idea is based on the seminal finding of Leahy (1993) who showed that the market impacts of competition can be ignored in the way that myopic behaviour leads to adequate decisions if volatilities and the drift rate of the price process are estimated properly.[12] After validating the model representing a perfectly integrated system, the quantitative results of this system will be compared with those of the spot market interaction.

The calculations are based on an interest rate of $r = 6\%$. The depreciation rate, λ, is assumed to be 5% in the base scenario. The model is based on discrete time steps and a time step length of 0.25 is assumed. Thus, an investment cost of $I_{\lambda=5\%} = 36.0112$ implies a periodical fixed production cost of 1 per unit of output. The drift rate, μ, is assumed to be zero and the volatility, σ, is assumed to be either 5, 10 or 15%.[13] The total time span T simulated in every stochastic simulation is determined as 100 years. For later periods, the expected returns are set equal to the returns in year 100. The possible error can be assumed to be negligible since later returns are discounted by more than 99.7%.

Regarding production costs, it is assumed that the total production cost per piglet is 2.5 (which, multiplied by 20, corresponds to 50 € per piglet), of which 1.0 (20 €) is fixed costs (related to the annual irreversible investment cost) and 1.5 (30 €) is variable costs. The production costs for pork (per hog) are 3.5 (which multiplied by 20, corresponds to 70 € per hog), of which 1.0 (20 €) is fixed costs (related to the annual irreversible investment cost) and

[11] A number of publications during the past 15 years show that agent-based GA approaches function quite well for analysing strategic interactions. Examples and discussions are given, for instance in Arifovic (1994, 1996), Axelrod (1997), Dawid (1996), Dawid and Kopel (1998), Vriend (2000) and Chattoe (1998).

[12] For an analysis with particular regards to depreciation and demand elasticities cf. Odening *et al.* (2007).

[13] Remember, we model external markets shocks through demand shock.

2.5 (50 €) is variable costs, plus the cost of the piglet. These production costs correspond approximately to the cost structure of German pig production today.[14]

4. Results

4.1 Validation

Consider the existence of an equilibrium investment trigger P^* at which all firms invest and assume that in period $t-\Delta t$ firms have invested according to $\hat{P}_t = P^*$. From equations (5) and (6) we know that after the investment decisions are made, P_t purely depends on the relation of α_t and $\alpha_{t-\Delta t}$. Hence, the price in t will be

$$(18) \qquad P_t = P^* \cdot \exp\left[\left(\mu - \frac{\sigma^2}{2}\right) \cdot \Delta t + \sigma \cdot \varepsilon_t \cdot \sqrt{\Delta t}\right]$$

Consider now that the actual price in period t is $P_t \geq P^*$. Then the firms will respond and invest such that $\hat{P}_{t+\Delta t} = P^*$. For $P_t \leq P^*$, two cases have to be differentiated. If $P^* \geq P_t > (1-\lambda)^{\Delta t} \cdot P^*$ then some firms will reinvest, such that $\hat{P}_{t+\Delta t} = P^*$. Otherwise, if $P_t \leq (1-\lambda)^{\Delta t} \cdot P^*$ no firm will reinvest and $\hat{P}_{t+\Delta t} = P_t / (1-\lambda)^{\Delta t}$. With this knowledge and in accordance with equations (1) to (12) the price dynamics can be described as:

$$(19) \qquad P_t = \begin{cases} P^* \cdot \exp\left[\eta \cdot \left(-\frac{\sigma^2}{2} \cdot \Delta t + \sigma \cdot \varepsilon_t \cdot \sqrt{\Delta t}\right)\right] & \text{if } P_{t-\Delta t} \geq \exp[-\eta \cdot (\mu - \ln(1\text{-}\lambda) \cdot \Delta t)] \cdot P^* \\ P_{t-\Delta t} \cdot \exp\left[\eta \cdot \left(\left(\mu - \ln(1\text{-}\lambda) - \frac{\sigma^2}{2}\right) \cdot \Delta t + \sigma \cdot \varepsilon_t \cdot \sqrt{\Delta t}\right)\right] & \text{otherwise.} \end{cases}$$

Equation (19) represents the discrete time version of a so-called regulated Brownian motion, which permits the simulation of price dynamics directly, i.e., without the explicit representation of firms (Leahy, 1993; Odening *et al.* 2007). Moreover, (19) can be used to determine the equilibrium investment trigger P^*. Repeated stochastic simulations of equation (19) for various values of P^* should reveal that the zero-profit condition will only be fulfilled if P^* is equal to the equilibrium investment trigger. If P^* is higher, the dynamics should

[14] The figures are within the same range as those reported by the Bayerische Landesanstalt für Landwirtschaft (2008) and the Datensammlung für die Betriebsplanung und die Betriebswirtschaftliche Bewertung landwirtschaftlicher Produktionsverfahren im Land Brandenburg (2008).

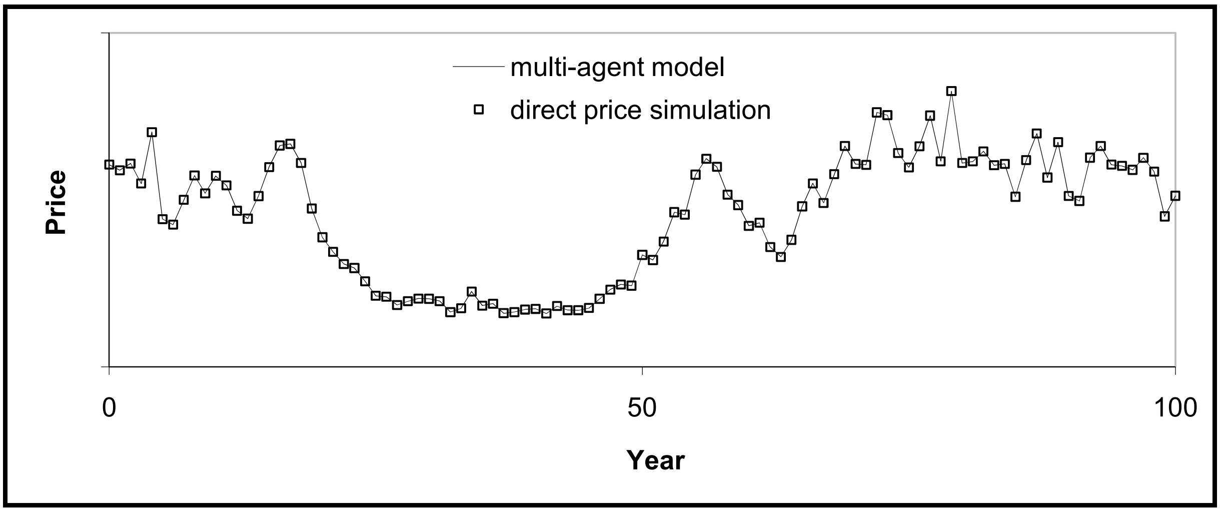
allow for profits. If P^* is smaller, this should imply losses. Accordingly, the equilibrium trigger price P^* can be determined by minimizing the square of the expected profits, i.e.,

$$(20) \qquad \min_{P^*}\left\{E^2\left[\left(P^*\right)\right]=E^2\left[\sum_{l=0}^{\infty}\left(x_{l\cdot\Delta t,n}\cdot\left(P_{l\cdot\Delta t}-c\right)-M_{l\cdot\Delta t,n}\left(x_{l\cdot\Delta t,n},P_n^*\right)\right)(1+r)^{-l\cdot\Delta t}\right]\right\}$$

with $P_0 = P^*$ and P_t follows equation (19).

Figure 2 shows that for identical trigger prices, P^*, and identical α_t, the agent-based model and the direct price simulation lead to an identical price path. Moreover, the direct price simulations lead to identical trigger prices. Hence, the direct price simulation validates the results of the agent-based approach.

Figure 2. Price dynamics in the agent-based model and in the direct price simulation (identical trigger prices for all genomes)



Source: Authors

4.2 Closed systems versus spot market interaction

Table 1 presents the trigger prices for investments under alternative assumptions concerning the parameter values for demand elasticities and volatility. For a given demand elasticity, the trigger prices for pork in the closed systems do not differ substantially from the trigger prices of the spot market solution. In general, the difference is below 0.1% of the trigger price respectively 0.5% of the difference between the trigger price and the total production cost.[15] Thus, our results suggest that from a pure real options perspective, a stronger vertical integration does not significantly increase investments. This result contradicts the empirically-based results of, e.g., Pietola and Wang (2000). This can, for example, be explained by our

[15] If we would consider that piglet and pork producers would be perfectly aware of the investment behaviour of each side, identical trigger prices for closed systems and market interaction would be achieved.

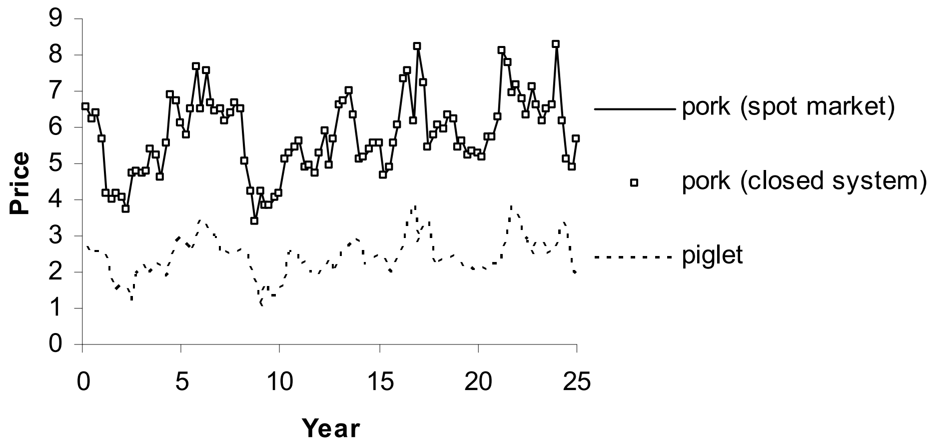
implicit assumption of rational expectations about the behaviour of market partners - with the exception of a small time lag. This, however, is not unrealistic considering that public statistics usually provides information about production capacities of piglet and pork producers. Moreover, capacity differences are usually reflected in market prices, which give signals to invest or disinvest in reasonable time. Our results furthermore suggest that vertical integration does not strongly influence production volume and welfare. This is shown by Figure 3. For given dynamics of demand for pork, the scenarios lead to very similar price paths.

Table 1. Trigger prices in closed systems and spot market solutions for different demand elaticities ($^{pi}\lambda={}^{ho}\lambda$=0.05, σ=5%, 10% and 15%)

	Closed system		Spot market			Relations		
	η	P^*	$^{ho}\eta={}^{pi}\eta$	$^{pi}P^*$	$^{ho}P^*$	$^{ho}P^*/C$	$P^*/{}^{ho}P^*$	$^{ho}X^*/X^*$
σ =5%	-2	6.037	-2	2.515	6.037	1.006	1.000	1.000
	-1	6.072	-1	2.530	6.073	1.012	1.000	1.000
	-½	6.140	-½	2.560	6.141	1.024	1.000	1.000
	-1/3	6.200	-1/3	2.583	6.205	1.034	1.001	1.000
	-1/6	6.338	-1/6	2.684	6.346	1.058	1.001	1.000
σ =10%	-2	6.188	-2	2.575	6.188	1.031	1.000	1.000
	-1	6.368	-1	2,653	6.369	1.062	1.000	1.000
	-½	6.677	-½	2.783	6.687	1.115	1.001	0.999
	-1/3	6.934	-1/3	2.891	6.943	1.157	1.001	1,000
	-1/6	7.325	-1/6	3.037	7.345	1.224	1.003	1.000
σ =15%	-2	6.430	-2	2.680	6.436	1.073	1.001	0.998
	-1	6.825	-1	2.836	6.829	1.138	1.001	0.999
	-½	7.459	-½	3.082	7.470	1.245	1.001	0.999
	-1/3	7.882	-1/3	3.220	7.910	1.318	1.004	0.999
	-1/6	8.297	-1/6	3.237	8.349	1.392	1.006	0.999

Source: Authors

Figure 3. Price paths as results from alternative scenarios (identical trigger prices, P^*, and demand parameters, a_t, for pork assumed, $^{pi}\lambda={}^{ho}\lambda$=0.05, $^{ho}\eta={}^{pi}\eta$=-1/2, and σ=10%)



Source: Authors

In accordance with real prices, the simulated hog and piglet prices in Figure 3 display substantial fluctuations. In Table 2, the coefficients of variation and the coefficient of correlation between simulated piglet and hog prices are presented for different assumptions concerning demand elasticity and volatility of the demand parameter (the same scenarios as in Table 1). These can be compared with coefficients of variation and correlation calculated from real data on piglet and hog prices in order to evaluate how well the simulated prices capture patterns observed in real price data, as well as to determine what ranges of parameter values that best describe patterns in real price data.[16] Since a time step length of 0.25 years is used in the simulations, the coefficients calculated from the simulated price data should be compared to the corresponding coefficients calculated from real quarterly price data (the second row in Table 3). In accordance with real price data, a high positive correlation between piglet and hog prices is observed in the simulated prices. For the simulations the correlation is even higher if a time lag of 0.25 years (i.e. 3 months) is used – while this is not true for real prices. This suggests that in reality piglet and pork prices are well integrated, that is piglet and pork producers are aware of what happens on the upstream respectively downstream the supply chain. Furthermore, the coefficient of variation is in all cases larger for the piglet price compared to the hog price, also this is consistent with real prices. The fluctuations in piglet prices in the simulated data arise because we assume there is not an exact adjustment of piglet production to the hog finishing capacities (this is implied by equation (14)). Table 3 shows that the scenarios (σ=5%, ${}^{ho}\eta={}^{pi}\eta$=-1/6), (σ=10%, ${}^{ho}\eta={}^{pi}\eta$=-1/2) and (σ=15%, ${}^{ho}\eta={}^{pi}\eta$=-1) gives coefficients that correspond quite well to the coefficients obtained from real data. Estimated demand elasticities for pork that can be found in the literature are often around -0.5. [17] Therefore, the assumptions of σ=10% and ${}^{ho}\eta={}^{pi}\eta$=-1/2 will be used in the following analysis.

In order to analyse the impact of the price flexibility on the spot market for piglets, demand elasticities for piglets have been varied. In Table 3, it is illustrated that the trigger prices are not affected substantially when varying the demand elasticity for piglets. Accordingly, the above presented findings can be considered as robust against assumptions regarding the definition of the piglet prices.

16 Information on real data for pork and piglets prices in Germany was obtained from the ZMP (Zentrale Markt- und Preisberichtstelle) for the time period 1996-2007.

17 Lusk *et al*. (2001) obtained an elasticity of demand for pork of -0.47 and Parcell (2001) reported demand elasticities of -0.24 and -0.49 for two different types of pork.

Table 2. Coefficients of variation and correlations in real price data and simulated prices (${}^{pi}\lambda={}^{ho}\lambda=0.05$)

		${}^{ho}\eta={}^{pi}\eta$	Coefficient of variation. piglet price	Coefficient of variation. hog price	Coefficient of correlation between ${}^{pi}P$ and ${}^{ho}P$	Coefficient of correlation between ${}^{pi}P$ and ${}^{ho}P$ lagged 3 months/one quarter
Real data (1996-2007)	Monthly	-	0.24	0.16	0.81	0.83
	Quarterly	-	0.23	0.16	0.83	0.72
Simulated data[†, ††]	σ=5%	-2	0.019	0.016	0.510	0.926
		-1	0.038	0.032	0.493	0.919
		-1/2	0.076	0.065	0.487	0.904
		-1/3	0.122	0.100	0.501	0.889
		-1/6	0.247	0.188	0.403	0.841
	σ=10%	-2	0.055	0.050	0.793	0.974
		-1	0.108	0.097	0.783	0.967
		-1/2	0.215	0.178	0.716	0.944
		-1/3	0.295	0.234	0.630	0.907
		-1/6	0.535	0.188	0.403	0.841
	σ=15%	-2	0.123	0.111	0.898	0.987
		-1	0.199	0.170	0.827	0.971
		-1/2	0.337	0.268	0.704	0.931
		-1/3	0.460	0.362	0.599	0.900
		-1/6	0.816	0.599	0.284	0.765

† The time step length used in the simulations is 0.25. Thus. the coefficients calculated from the simulated data should be compared with the coefficients obtained from quarterly real data.

†† The exact magnitudes of these coefficients depend on the stochastic demand parameter. α_t. Here. an average of 20 coefficients (representing 20 values of α_t) is presented.

Source: Authors

Table 3. Trigger prices in closed systems and spot market solutions for different demand elasticities for piglets (${}^{ho}\eta$=-1/2, ${}^{pi}\lambda={}^{ho}\lambda$=0.05 and σ=10%)

P^*	${}^{pi}\eta$	${}^{pi}P^*$	${}^{ho}P^*$
6.677	-2	2.776	6.687
	-1	2.778	6.687
	-1/2	2.783	6.687
	-1/3	2.806	6.688
	-1/6	2.871	6.694

Source: Authors

A variation of the useful lifetime of the breeding barns (represented by the depreciation rate) changes the price dynamics for piglets. This is illustrated in Table 4. However, variations of the depreciation rate of breeding barns do not affect the trigger price for finishing barns strongly. Higher depreciation rates for piglet breeding barns lower their trigger price as a consequence of the higher flexibility of piglet production. Vice versa, lower depreciation rates for piglet breeding barns lead to a higher volatility of the piglet prices and therefore to higher trigger prices.

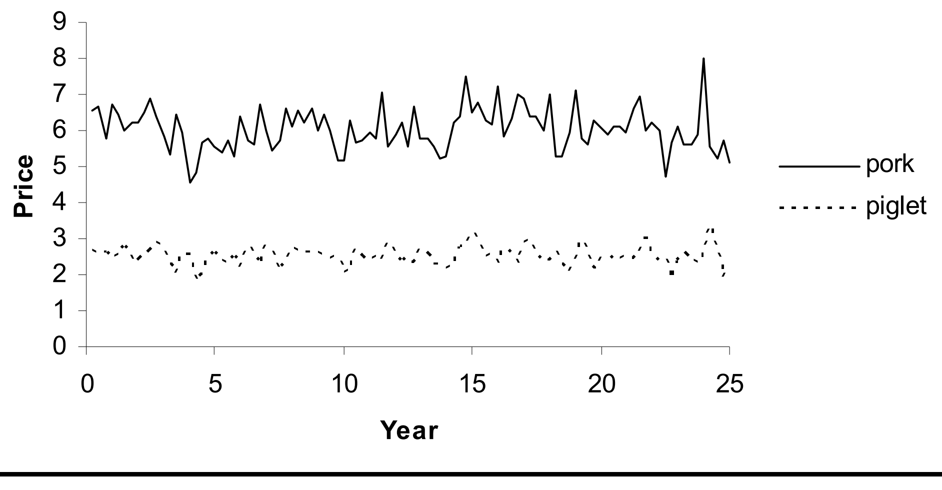
Table 4. Trigger prices depending on depreciation rates ($^{pi}\eta$=$^{ho}\eta$=-1/2, σ=10%)

Closed system		Spot market			
λ (in %)	P^*	$^{pi}\lambda$ (in %)	$^{ho}\lambda$ (in %)	$^{pi}P^*$	$^{ho}P^*$
		5%		2.783	6.687
5%	6.677	10%	5%	2.669	6.672
		20%		2.631	6.650
		5%		2.764	6.259
10%	6.245	10%	10%	2.604	6.251
		20%		2.545	6.246
		5%		2.769	6.058
20%	6.036	10%	20%	2.585	6.045
		20%		2.506	6.044

Source: Authors

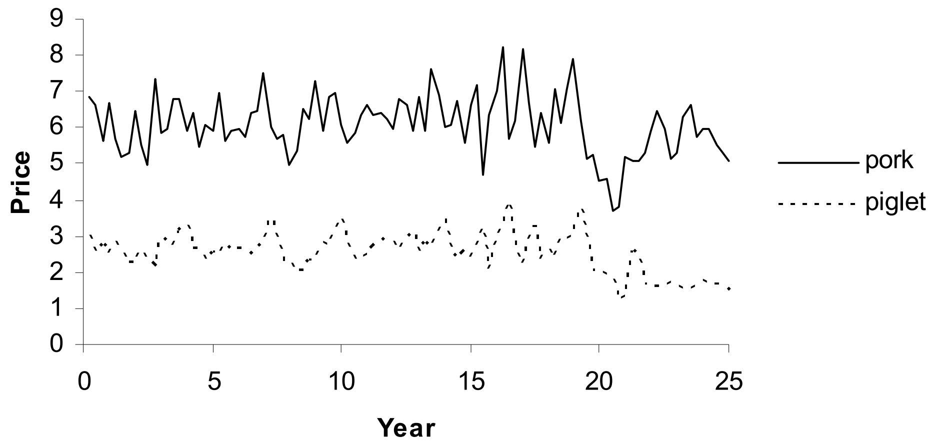
Figures 4 and 5 illustrate the dynamics of prices for hogs and piglets for different depreciation rates for breeding barns ($^{pi}\lambda$ = 20% and $^{pi}\lambda$ = 5% for $^{ho}\lambda$ = 10%). Note that if the depreciation rates for piglet and hog producers are equal, higher depreciation rates lead to lower trigger prices and vice versa. Higher depreciation is equivalent to higher flexibility of adjustment. That is to say, investments with high depreciation rates can be considered as less irreversible and thus also investment reluctance is lower. On the aggregate level, this means that production can relatively quickly respond to negative demand shocks. In Odening *et al.* (2007) it is shown that the depreciation rate corresponds to a positive drift rate for prices. In the case that depreciation rates differ within a supply chain, this allows in certain situations the sector with the higher depreciations rate to exploit the upstream (downstream) sector.

Figure 4. Price dynamics for $^{ho}\lambda$ = 10% and $^{pi}\lambda$ = 20% ($^{ho}\eta$=$^{pi}\eta$=-1/2, σ=10%)



Source: Authors

Figure 5. Price dynamics for $^{ho}\lambda$ = 10% and $^{pi}\lambda$ = 5% ($^{ho}\eta$=$^{pi}\eta$=-1/2, σ=10%)



Source: Authors

Although the experiments show that certain assumptions regarding elasticities and depreciation rates have an impact on investment triggers of the different production steps, our general result is that from a pure real options perspective, closed systems are hardly superior to market solutions.

5. Summary and conclusions

Participants along a production chain which exchange intermediate products on spot markets face price risks such as a certain transmission of price fluctuations of the final product. In a real options environment this uncertainty may cause investment reluctance on the different steps of the production chain. This paper analyses whether stronger vertical integration along the production chain reduces investment reluctance in pig production. Therefore, an agent-based competitive model of production chains was developed in which firms use optimal investment strategies identified by genetic algorithms. Two production systems were compared: As an example of a perfectly integrated system, it was considered that every firm can invest in closed systems in which the intermediate product (piglets) and the final product (pork) are produced in equal amounts. In an alternative production system, firms can either invest in the intermediate product or the final product. The intermediate product is traded on a spot market. Our simulations showed that the spot market solution and the closed system lead to practically the same production dynamics. The only precondition is that for the spot market system, producers of the intermediate product and producers of the final product have a good guess of the investment strategies and production capacities of other producers. This general finding is independent of different depreciation rates of the production steps, though the price dynamics for the intermediate product is strongly affected by the relation of depreciation rates on the different levels of the chain.

At first glance, our results may be intuitively surprising, but this is in accordance with several other surprising insights provided by the real options theory, for example, that myopic investors who ignore the impacts of competition behave efficiently (Leahy, 1993) or that real options theory does not justify price stabilization policies (Dixit and Pindyck, 1994).

The results in this study differ from the findings of Pietola and Wang (2000) who, using data from Finland, found that hog producers have an incentive to choose vertically coordinated or integrated production systems. However, these differences can be explained. Although both studies employ a real options approach, the methodological approach used in this paper is different from that of Pietola and Wang (2000) as we endogenise the price dynamics of the intermediate product by using an agent-based approach to solve the investment problem. Thus, the individual firms' behaviours are modelled explicitly (assuming rational behaviour) instead of looking at the market at an aggregate level. The simulated prices in our study display a high positive correlation between pork and piglet prices, which is also the case for real pork and piglet prices in Germany. This implies that the volatility in total net returns faced by specialized hog producers is lower than would be the case if the correlation was close to zero, given that same variation in hog and piglet prices.

In addition to a high positive correlation between pork and piglet prices, the coefficient of variation in the simulated prices was higher for piglets than for pork. Also this result is consistent with real German price data. Furthermore, for certain parameter values, the magnitude of these coefficients were close to those obtained from real data. This suggests that an agent-based approach were prices are endogenously determined can give a plausible picture of patterns observed in real prices. Thus, the well-recognized problems connected to an accurate estimation of price dynamics (discussed in section 2) can in this way be avoided.

Considering that in reality also futures markets for pork and piglets exist, supports our conclusions even more. However, it should also be noted that there are other factors that are not considered in this study which offer good reasons for vertically coordinated production system. In addition to the problem that actors on a spot market may face the risk of not being able to sell/buy piglets in times of excess/under supply, improved production results in vertically coordinated production systems (e.g. lower mortality rate and improved growth rates) are one example (Larsen *et al.*, 2007). Further important aspects are quality management issues and last but not least the very high capital intensity of modern piglet and pork production which increasingly demands for risk capital (Gray and Boehlje, 2005).

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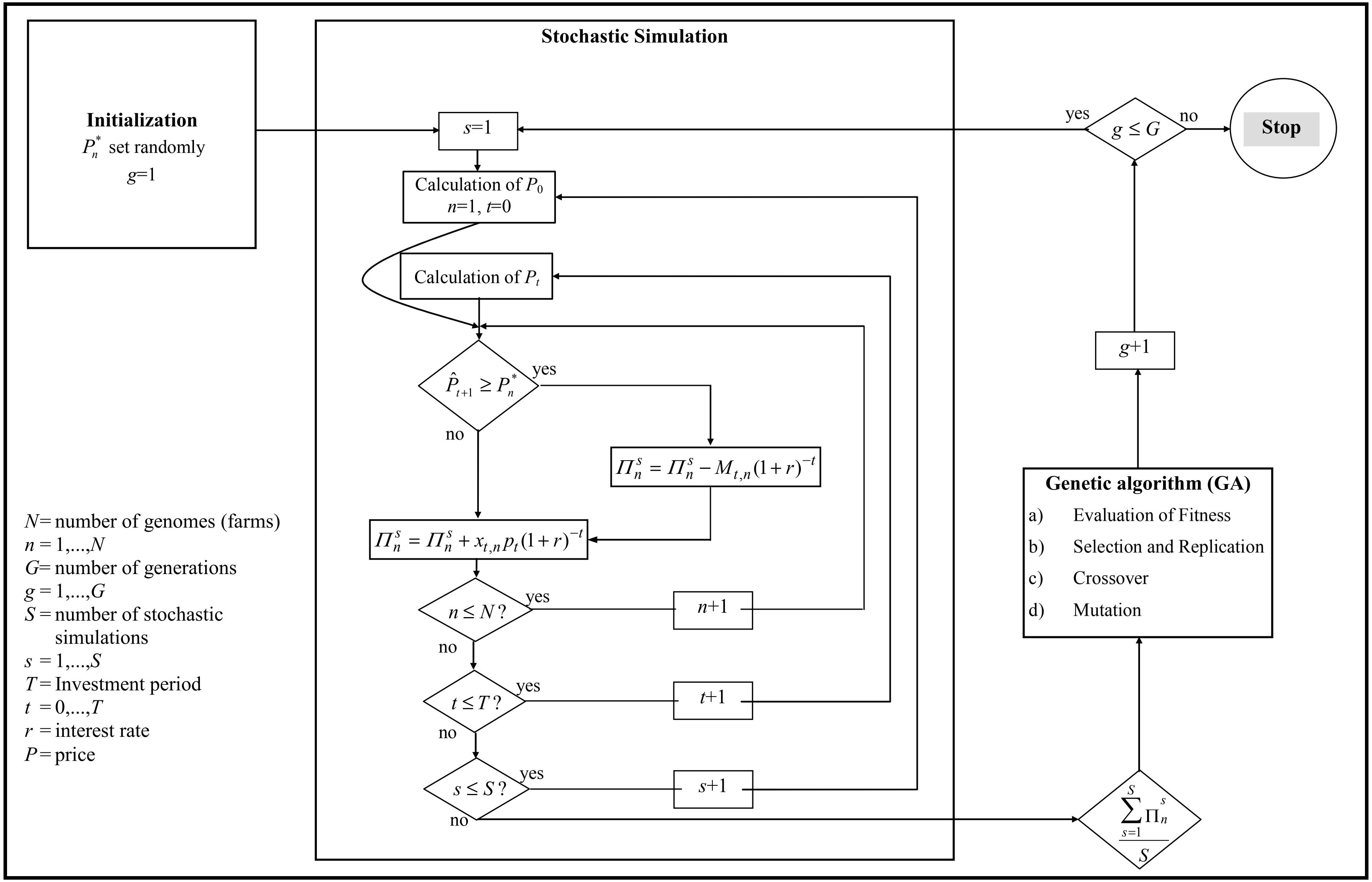
Appendix: Figure 6. Flow diagram of the agent-based simulation approach



Source: Authors

About the authors

Prof. Dr. Alfons Balmann is Director and Head of the department Structural Development of Farms and Rural Areas at the Leibniz Institute of Agricultural Development in Central and Eastern Europe (IAMO). His major research interests are structural change, agricultural policy analysis, investment theory and agent-based modeling.

Address:
Leibniz Institute of Agricultural Development in Central and Eastern Europe (IAMO)
Theodor-Lieser-Straße 2,
06120 Halle (Saale), Germany
phone: ++49(0)345 2928300
fax: ++49(0)345 2928399
e-mail: balmann@iamo.de

Prof. Dr. Oliver Mußhoff is Professor of Agricultural Economics at the Universitaet Goettingen. The main area of research interest is farm management. He has published various articles on investment, finance, and risk management.

Address:
Faculty of Agricultural Sciences, Department for Agricultural Economics and Rural Development, Georg-August-Universität Göttingen
Platz der Göttinger Sieben 5,
37073 Göttingen, Germany
phone: ++49(0)551-394842
fax: ++49(0)551-392030
e-mail: oliver.musshoff@agr.uni-goettingen.de

Dr. Karin Larsén is Senior Researcher at the Leibniz Institute of Agricultural Development in Central and Eastern Europe (IAMO), department of Structural Development of Farms and Rural Areas. Her main research interests include efficiency and productivity analysis, investment and finance and horizontal and vertical integration in the food supply chain.

Address:
Leibniz Institute of Agricultural Development in Central and Eastern Europe (IAMO)
Theodor-Lieser-Strasse 2,
06120 Halle (Saale), Germany
phone: ++49(0)345 2928134
fax: ++49(0)345 2928399
e-mail: larsen@iamo.de

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Editorial office

Dr. Astrid Häger *(Managing editor)*
e-mail: astrid.haeger@agrar.hu-berlin.de
phone: +49-30-2093.6062

Kerstin Oertel *(Layout)*
e-mail: k.oertel@agrar.hu-berlin.de
phone: +49-30-2093.6340

Humboldt-Universität zu Berlin
Landwirtschaftlich-Gärtnerische Fakultät
Department für Agrarökonomie
FG Agrarpolitik
Philippstr. 13, Haus 12A
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