What drives the German hog price cycle?
Diagnostic modelling of a nonlinear dynamic system

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Abstract

We investigated causal factors driving German hog-price dynamics with an innovative 'diagnostic' modeling approach. Hog-price cycles are conventionally attributed to randomly-generated behavior best modeled stochastically—most recently as randomly-shifting sinusoidal oscillations. Alternatively, we applied nonlinear time series analysis to empirically reconstruct a deterministic hog-price attractor from observed hog prices. Hog prices cycle aperiodically along this attractor as time evolves. The empirically diagnosed attractor indicates that causal factors driving the German hog-price cycle are endogenous to the hog industry itself. We next formulated a structural (explanatory) model of the pork industry to synthesize the empirical hog-price attractor and to determine causal factors generating it. Model simulations demonstrate that low price elasticity of demand contributes to aperiodic price cycling – a well know result – and further reveal two other important causal factors: the irreversibility of investment (caused by high specificity of technology), and the liquidity-driven investment behavior of German farmers.

Keywords: hog, cycle, nonlinear dynamics, chaos, phase space reconstruction

1. Introduction

Past work investigating the persistent hog-price cycle has resulted in substantial disagreement over underlying causes. Early work attributed the phenomenon to naïve producer behavior characterized by linear-cobweb price adjustments (cf. Hanau, 1928, Ezekiel, 1938, Harlow 1960, Waugh 1964, Buchholz 1982). More recent studies proposed that persistent fluctuations are driven by nonlinear chaotic price dynamics. Statistical tests by Chavas and Holt (1991) (using quarterly US data) and Holzer and Precht (1993) (using weekly German data) failed to reject the hypothesis of nonlinear price dynamics. Streips (1995) verified the results in Chavas and Holt (1991) for monthly data, and further reconstructed a chaotic attractor composed of non-repeating aperiodic price cycles. Holt and Craig (2006) employed regime switching models to provide evidence of nonlinearity, regime dependent behavior, and structural change over an almost 100-year study period. A recent contribution by Parker and Shonkwiler (2013) returned to a linear representation of hog-cycle dynamics. They modeled the hog cycle in Germany as a randomly-shifting sinusoidal oscillation with time varying amplitudes. They hypothesized that producer inability to predict future prices due to stochastic influences is responsible for persistent cycling.

We employ a 'diagnostic' modeling approach to determine causal factors driving the German hog-price cycle. We apply nonlinear time series analysis to diagnose the presence of deterministic nonlinear dynamics in observed hog-price data. The presence of nonlinear dynamics provides evidence that the hog-price cycle is endogenous to the hog industry itself (Chavas and Holt, 1993), and not driven principally by random supply/demand shocks (Aadland, 2004) or a randomly perturbed sinusoidal cycle (Parker and Shonkwiler, 2013). It also provides information that can be used, along with knowledge of the structure and technology of the pork industry, to formulate a structural (explanatory) model capable of simulating, and identifying causal factors driving, empirically-diagnosed hog-price dynamics.

2. Characteristics of the hog cycle in Germany

The graph of the German hog-price cycle is shown in Figure 1. It is based on average producer prices for slaughtered pigs of quality E to P, in € per kg carcass weight, for the state of North Rhine-Westphalia, Germany.[1] The record comprises the period from January 1990 to

[1] The data were officially recorded and provided by the "Landesamt für Natur, Umwelt und Verbraucherschutz NRW".

December 2011 for a total of 1144 observations. Hog prices exhibit the well-known cycles superimposed by irregular disturbances. Furthermore, the average price level decreases during the first decade and increases slightly thereafter. This pattern is mainly caused by the change of the Common Agricultural Policy (CAP) of the European Union, starting with the McSharry reform in 1992. The CAP reform liberalized commodity markets by reducing the price support (i.e. intervention prices). This led to a strong decrease of grain prices during the nineties and the early years of the new century. Consequently, hog prices followed declining feed prices leaving the farmers' margins largely unchanged. The increase in average hog price in the latter part of the record is observed for most agricultural commodities.

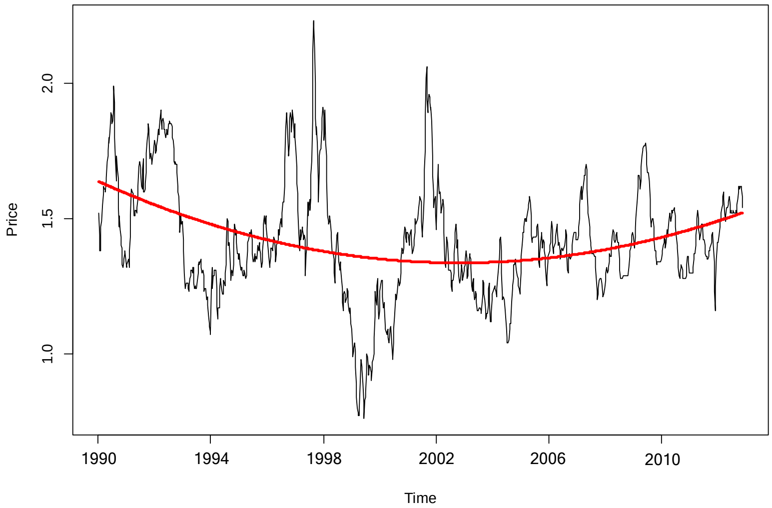


Figure 1: Time series of hog prices and estimated trend

In the studies of the USA, the hog cycle is normally represented by the hog to corn price ratio. This implies that the decision makers value the slaughter pigs in quantities of corn. This might have been a valid assumption in the past, but it is highly questionable for the present circumstances, at least under European conditions. With today's commonly used technology, significantly more than half of the total cost are fixed cost associated with the provision of the durable assets. For the past two decades, we found hardly any hog-to-feed price ratio for which the preferable choice would have been to leave capacities idle. Thus, short term production decisions are primarily driven by past investments, and are largely independent from current feed prices. Furthermore, farmers as well as feed suppliers can choose between different components. Consequently, the volatility of feeding cost will always be less than the volatility of a single feedstuff. Finally, changes of feedstuff prices will be encoded in the hog prices as far as there is a causality. Our empirical results to follow provide evidence for such causality.

For these reasons, we contend that representing the hog cycle by a hog-to-feed price ratio biases the analysis by mixing two phenomena with totally different origins: the hog price cycle on one hand and the volatility of barley prices on the other.[2] Increased barley price volatility is a recent phenomenon due to CAP reforms, whereas the hog cycle has existed for a long time caused by factors requiring further analysis. We focus our analysis on slaughter hog prices. Given nonlinear dynamic industry structure, slaughter-hog-price dynamics encode patterns of feedstuff prices.

[2] For example, Parker and Shonkwiler (2013) conclude that – contrary to the USA – the hog cycle in Germany is becoming more volatile. This however contradicts the pattern of slaughter pig prices that exhibits a slightly decreasing volatility in the most recent years (Figure 1).

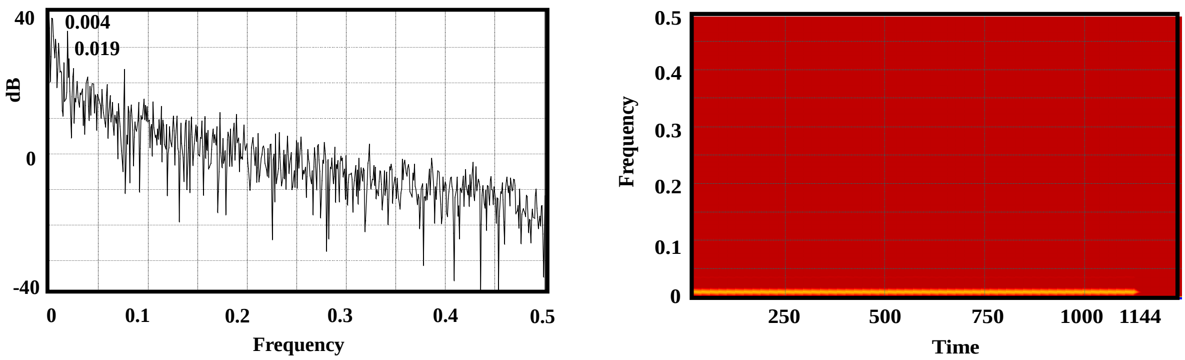
3. Nonlinear time series analysis

Hog-price cycles are characterized by nonrepeating oscillations with different periods (i.e., ‘aperiodic’ cycles). Deterministic nonlinear dynamic systems generate nonrepeating aperiodic ‘chaotic’ cycles endogenously. Chaotic dynamics are characterized by ‘sensitivity to initial conditions’ in which close neighboring trajectories at a given point in time exponentially diverge as time evolves. Accurate long-term predictions of chaotic systems are unachievable. Despite exponential divergence, chaotic trajectories converge toward a bounded, spatially-organized, and low-dimensional geometric structure (‘strange attractor’) upon which they orbit irregularly (Kaplan and Glass, 1995; Williams, 1997; Schreiber, 1999). Chavas and Holt (1993) modeled a chaotic dairy-market strange attractor (Chavas and Holt, 1993). We apply nonlinear time series analysis to search for the presence of a hog-price strange attractor in the observed German hog-price record.

3.1 Signal analysis

Fourier Spectrum Analysis identified dominant peak frequencies in the hog-price record at 0.004 Hz (a 260-week or 5-year oscillation period) and 0.019 Hz (a 52-week or annual oscillation period) (Figure 2a).

Continuous Wavelet Analysis verified stationary power at the low frequency 5-year oscillation as required by subsequent analysis (Figure 2b).[3]



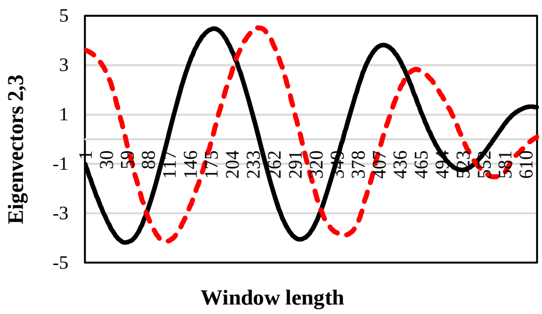
a. The Fourier frequency spectrum **b. Continuous wavelet time-frequency spectrum**

Figure 2: Spectral analysis

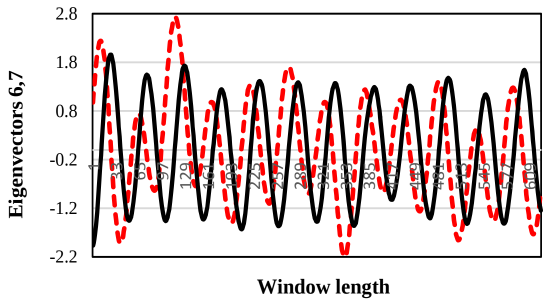
We applied Singular Spectrum Analysis (*SSA*) (Elsner, 2010; Vautard; 1999; Ghil, 2002; Golyandina, 2001) to reconstruct the hog-price record into the sum of structured (trend and oscillations) and unstructured-residual components.[4] The hog-price record was filtered of noise by deleting the unstructured-residual component from the reconstruction. The filtered record was used to search for an empirical hog-price attractor. *SSA* commenced by embedding the hog-price record, *P(t)*, into a ‘trajectory matrix’, *X*, whose columns are $K = N - L + 1$ single-period lagged vectors of *P(t)*, *N* is record length, and *L* is ‘window length’ restricted by $2 \le L \le N/2$ and conventionally selected proportional to the dominant spectral peak in the Fourier spectrum (Hassani, 2007). Accordingly, the window length was set at $L = 520$, which allows for 10 repetitions of the annual oscillation period. ‘Singular value decomposition’ decomposed the trajectory matrix into the sum of ‘empirical orthogonal functions’ (*EOF*),

[3] AutoSignal 1.7 (© SeaSolve Software Inc., 1999-2003) was used for Fourier spectral analysis and Continuous Wavelet Analysis.
[4] R-package Rssa was used for Singular Spectrum Analysis

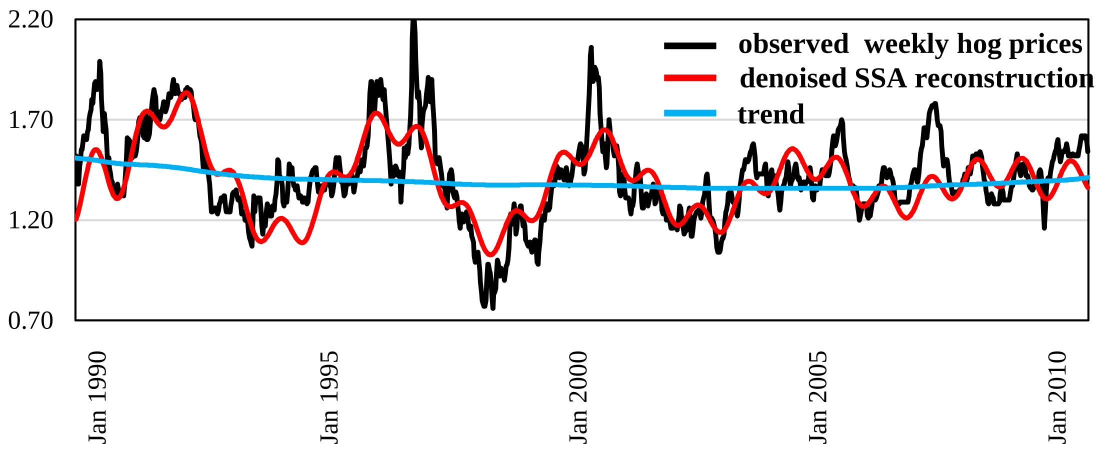
$X = \sum_{i=1}^{r} EOF_i$, where $EOF_i = \sqrt{\lambda_i} EV_i PC_i^T$, r = *rank X*, and eigenvalues λ_i, eigenvectors (EV_i), and principal components (PC_i) are drawn from the eigensystem of the covariance matrix, XX^T. Next, the *EOFs* were arranged in rank order according to magnitude of their respective singular values, $(\sqrt{\lambda_i})$, and then grouped to form the basis for trend, oscillatory, and unstructured-noise components. The initial *EOF* typically forms the basis for the trend component. Subsequent consecutive *EOF* pairs whose eigenvectors oscillate with identical frequency in phase quadrature are grouped to form the basis of harmonic oscillations. The eigenvectors associated with *EOFs* 2,3 and 6,7 exhibit the 5-year and annual oscillations detected by the Fourier spectrum, respectively (Figure 3a,b). Finally, 'diagonal averaging' of grouped *EOF* matrices converts them to vector time series' of corresponding trend, oscillatory, and unstructured-residual components (Golyandina, 2001). The isolated trend component and the composite *SSA*-reconstruction filtered of the unstructured-residual component are graphed against the observed hog-price record in Figure 3c. Compelling evidence for the quality of the filtered *SSA*-reconstruction is that its trend and oscillatory components account for 99% of the variation in the observed record.[5]



a. **Eigenvectors associated with 5-year oscillation**



b. Eigenvectors associated with annual oscillation



b. Reconstructed SSA components

Figure 3: Singular Spectrum Analysis

3.2 Phase Space Reconstruction

We applied 'Phase Space Reconstruction' techniques (Kaplan and Glass, 1995; Williams, 1997; Takens, 1980) to detect whether long-term system dynamics governing hog-price dy-

[5] Singular values measure the partial variance explained by their respective *EOFs*.

namics evolve along an attractor. Given nonlinear dynamic structure, reconstructing real-world system dynamics from the single *SSA*-filtered hog-price record is possible because interactions among system variables are embedded in the record of each variable (Kot, 1988; Sugihara et al., 2012). Everything depends on everything else, or as explained by the naturalist John Muir (1911), *"[w]hen we try to pick something up by itself, we find it hitched to everything else in the universe."* (Muir, 1911)

The 'time-delay' embedding method of phase space reconstruction (Takens, 1980) represents the multidimensionality of the real-world dynamic systems governing hog-price dynamics by segmenting the de-trended[6] and filtered hog-price record, $P_f(t)$, into a sequence of delay coordinate vectors: $P_f(t-d), P_f(t-2d), ..., P_f(t-(m-1)d)$ where 'd' is the 'embedding delay' and 'm' is the 'embedding dimension' (i.e., the number of delayed coordinate vectors). The embedding delay was selected as the delay for which the mutual information function reaches its first minimum (d = 20 weeks) (Williams, 1997). The embedding dimension was selected as the dimension for which the percentage of 'false nearest neighbors' falls below a prescribed tolerance (m = 4) (Williams, 1997). [7] If $m \geq 2n+1$, the reconstructed attractor shares these key topological properties with a reconstruction in any coordinate system, where n is the dimension of the real-world attractor (Takens, 1980). Since n is unobserved, in practice, $m \geq n$ is generally considered adequate to reconstruct true system dynamics (Small and Tse, 2002).

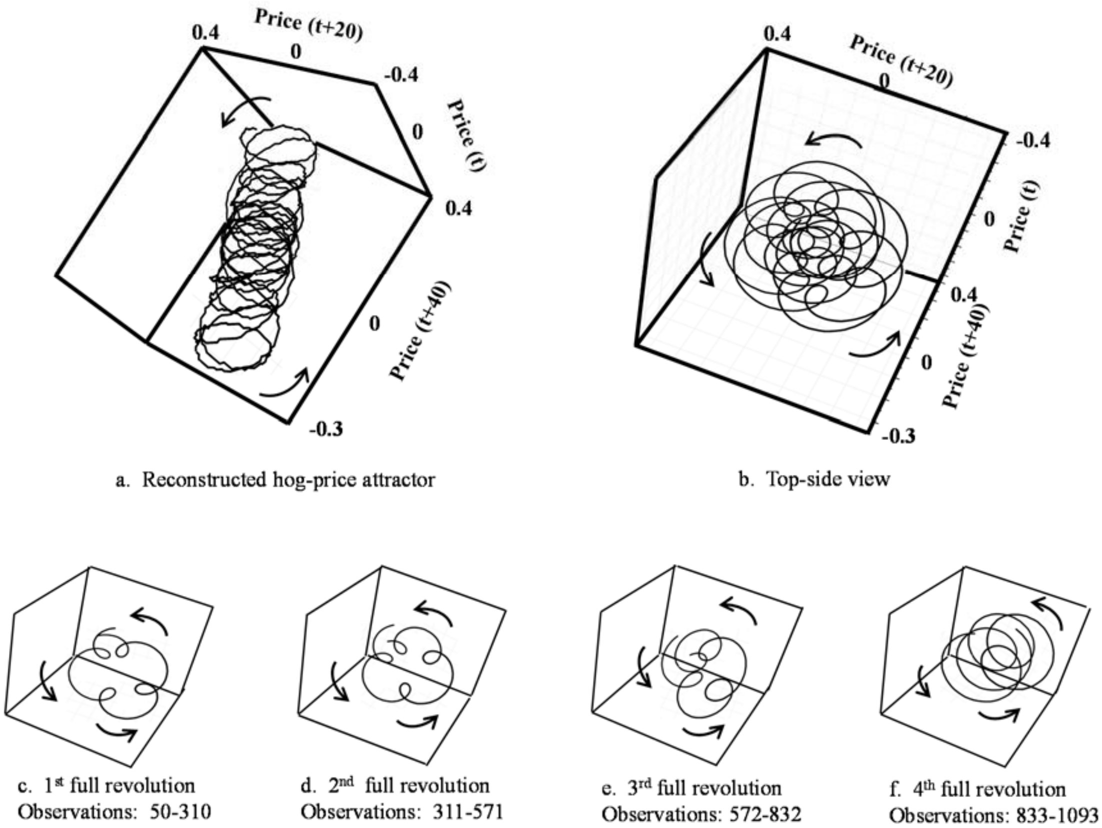


Figure 4: Anatomy of Empirical Hog-Price Attractor

[6] During the period under consideration, there were no abrupt technological or structural changes that would have caused structural breaks. Thus, the de-trended price series can be viewed as being generated under a relatively constant economic environment.

[7] R-package 'tseriesChaos' was used for computing the embedding delay and the embedding dimension.

3.3 Surrogate Data Analysis

We applied surrogate data analysis to test whether apparent structure detected in the empirically reconstructed hog-price attractor is more likely the figment of a mimicking stochastic process. The empirical attractor's topological properties were compared statistically with those taken from phase space reconstructed from randomized surrogate vectors (Small and Tse, 2002; Theiler et al., 1992, Small and Tse, 2003).

Surrogate vectors are designed to destroy intertemporal patterns in the SSA-filtered record while preserving various statistical properties. We generated two conventional types of surrogate vectors: AAFT (amplitude-adjusted Fourier transform) surrogates and PPS (pseudo phase space) surrogates. AAFT surrogates are generated as static monotonic nonlinear transformations of linearly filtered noise. They preserve both the probability distribution and power spectrum of the SSA-filtered data (Theiler et al., 1992). PPS surrogates test for the presence of a noisy limit cycle by preserving periodic trends in the SSA-filtered data while destroying chaotic structures (Small and Tse, 2003).[8]

Surrogate data testing proceeds by measuring topological properties associated with the phase space reconstructed from each surrogate vector. The mean from the distribution of each measure for the set of surrogate vectors is tested for significant difference from the corresponding empirical measure. Statistically insignificant differences indicate that detected empirical structure is more likely attributed to stochastic behavior.

We formulated a two-tailed test rejecting the null hypothesis of insignificant difference when mean surrogate topological properties are significantly above or below their empirical counterparts. Rejection occurs for the set of critical significance levels α_c satisfying:

$$\alpha_c \geq 2\left(1-\Phi\left|t\right|\right)$$

where the right-hand side of the inequality is the *p*-value for a two-tailed test (Minitab), $\Phi\left|t\right|$ is the CDF for the *t*-statistic with *N-1* degrees of freedom, and $\left| \; \right|$ is absolute value. The null hypotheses of insignificant difference were rejected for both correlation dimension and Lyapunov exponent with computed *p*-values effectively zero. Consequently, we rejected the hypothesis that the structure detected in the empirical hog-price attractor is due to mimicking random behavior.

4. A nonlinear dynamic model of the hog industry

The information revealed by nonlinear time series analysis guides our modeling of the German hog industry. The empirical hog-price attractor has an embedding dimension of 4, indicating that a minimum of 4 state variables is necessary to capture the essential system dynamics. Since the purpose of our model is to capture these dynamics, we do not attempt to formulate a detailed simulation model. The computed Lyapunov exponent supports the hypothesis of divergent, possibly chaotic behavior. If the system is represented in continuous[9] time, at least three differential equations are necessary to generate chaotic behavior. The empirical attractor is composed of two major cycles. The 5-year cycle could represent an investment pattern, and the annual cycle the short term adjustment of production. Both are linked to the price of slaughter hogs.

[8] We follow methods outlined in Kaplan and Glass (1995) and Small and Tse (2002) to write R-code generating AAFT and PPS surrogate vectors, respectively.

[9] The system will be modeled in continuous time since all actors are assumed to make their decisions independently at arbitrary points in time. This leads to a continuous time representation of the aggregated flows incorporated in the model. Contrary, a discrete time model would imply that all actions are synchronized as to take place at the discrete time steps of the model which, in our case, would be an unrealistic assumption.

We propose the following fifth order system of differential equations:

$$\dot{P} = f_p(D, S, P)$$
$$\dddot{S} = f_s(P, S, C)$$
$$\dot{C} = f_c(P, C) \tag{1}$$

The system is composed of three dynamic processes: price adjustment, adjustment of the quantity of supply resulting from production decisions, and adjustment of the production capacities through investments. There are three state variables: production capacities (*C*), actual production or supply (*S*), and hog prices (*P*); along with time lags constituting additional (intermediate) states. The first equation describes the price adjustment process in which price change $\dot{P}$ depends on demand (*D*), supply (*S*) and the current price (*P*). The notation $\dddot{S}$ indicates a third order differential equation that determines supply adjustment. This equation, to be specified later, models the production decisions based on the marginal cost function, and likewise considers the delay caused by the time period necessary to complete the production process. Production decisions in the short run are constrained by available production capacities; in the long run these may be expanded through investments. This process is modeled by the third equation, where the rate of change of production capacities $\dot{C}$ depends on product price (*P*) and current resources (*C*). Given the third order plus two first order differential equations, the above equations comprise a fifth order system.

Operationalizing the model requires specification of the above equations. We begin with the price adjustment. Assuming a trial and error process, the rate of price change can be viewed as dependent on the difference between demand and supply, i.e. (*D* – *S*). This implies that the actors on the market have crude information on actual prices and trade volumes. This information is available for the German hog market from weekly magazines and the internet. The simplest functional form is a linear relationship, i.e. $\dot{P} = a\,(D - S)$, $a > 0$. Assuming that large surpluses of either demand or supply speed up the adjustment process, a more adequate formulation is

$$\dot{P} = a\,(D - S)^3 \;, \quad a > 0 \tag{2}$$

Alternatively, we may postulate that the *relative* rate of price change equals the right hand side expression of the above formula:

$$\frac{\dot{P}}{P} = a\,(D - S)^3$$

or

$$\dot{P} = a\,(D - S)^3\, P \;, \quad a > 0 \tag{3}$$

This constitutes an additional feedback loop in the model. We use equation (3) in the model. Figure 5 depicts the dependence of the marginal price change $\dot{P}$ on the difference between demand and supply (*D* – *S*) and the price level *P* respectively, according to equation (3).

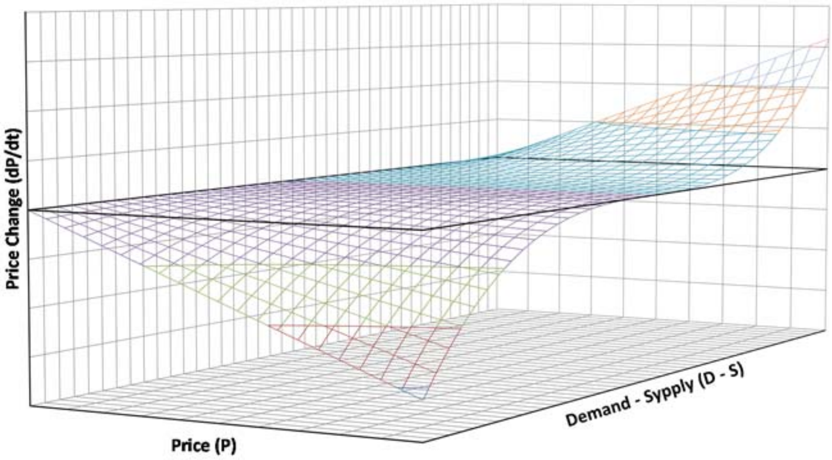


Figure 5: Price Change as a Function of Demand and Supply

Demand (D) is modeled with an isoelastic demand function:

$$D = b\,P^{-c}\,,\quad c > 0 \tag{4}$$

where c represents the price elasticity of demand and b is a scale factor.

The process of supply adjustment is represented by the third order differential equation $\dddot{S}$ in (1). It can be separated into two components representing (a) the production decisions and (b) the time lag that occurs between the decision to start a production process and its completion. The production decision is based on the marginal cost function of the average production unit and the number of production units currently in service:

$$S_p = C\,g\,P^{\,d}\quad,\quad g,d > 0 \tag{5}$$

S_p represents "planned" supply according to the actual decisions, and $g\,P^{\,d}$ represents the marginal cost function. An exponent $d < 1$ indicates economies of scale while $d > 1$ marks diseconomies of scale. If $d = 1$ no scale effects occur.

The production time lag is modeled via an *exponentially distributed delay* which is generally defined by the system of first order differential equations

$$\dot{r}_i = \frac{k}{DEL}\left(r_{i-1} - r_i\right),\quad i = 1,2,\ldots,k$$

with

$$r_0 = S_p$$

$$r_k = S \tag{6}$$

where k marks the order of the delay (in our case k=3), and DEL denotes the average delay time (the production period plus the reaction time of the decision makers).

The adjustment of production capacities follows the differential equation

$$\dot{C} = w\left(1 - \frac{C}{v\,P}\right)C - \frac{C}{l}\,,\qquad w,v,l > 0 \tag{7}$$

The first term represents investments and the second measures the reduction of production facilities due to wear and tear. The parameter l measures the service life of the production facilities. The investment term assumes that the adjustment of production capacities follows a logistic growth process for the case of constant product price *P*. The term *v P* marks the upper limit of this process, and can be interpreted as a “target size” of the sector proportional to *P*. A falling market price *P* can cause disinvestments if the term inside the brackets becomes negative as current capacities *C* exceed *v P*. This negates sunk cost effects that are important in the German hog sector due to the high specificity of the facilities. To allow for irreversibility due to sunk costs, the following formulation was used in the model:

$$\dot{C} = Max\left[w\left(1-\frac{C}{v\,P}\right)C, 0\right]-\frac{C}{l}, \qquad w,v,l>0 \tag{8}$$

where the *Max*[·] operator ensures that investments are always positive or zero, and capacities can decline only through deterioration.

Large investments often cause high financial leverage that inhibit investments for a period of financial consolidation. This can be factored into equation (8) by introducing a (discrete) time lag:

$$\dot{C} = Max\left[w\left(1-\frac{C(t-T)}{v\,P}\right)C, 0\right]-\frac{C}{l}, \qquad w,v,l>0 \tag{9}$$

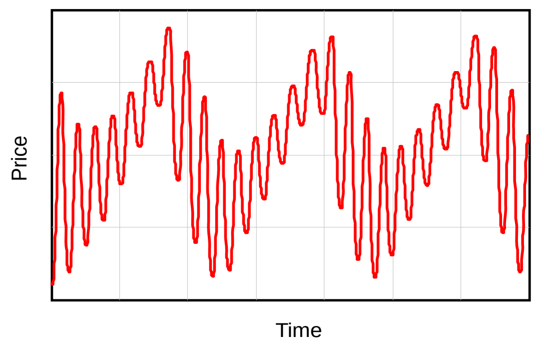
The expression *C*(*t*–*T*) represents production capacities lagged by *T* time units. This formulation is equivalent to the introduction of a maturation delay in logistic population models and may cause a periodicity if the time lag is significant.

5. Model results

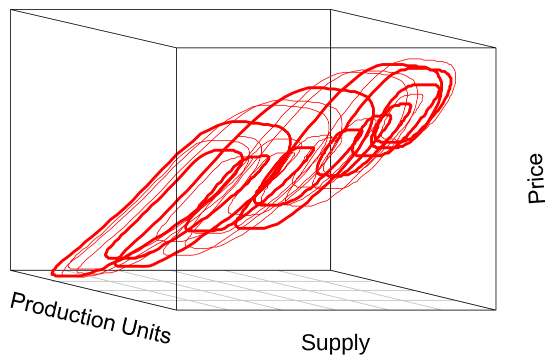
The model was implemented in © *Vensim* and solved using a 4th order *Runge-Kutta* integrator. It was simulated over a period of 50 years. Following our empirical results, the base run set the production delay *DEL* to 1 year and the time lag *T* for financial consolidation after large investments to 5 years. The service life of the facilities (*l*) was assumed to be 15 years on average. No scale effects were considered (i.e. *d*=1). The demand elasticity was set to 0.25. Other parameters were normalized to generate a hypothetical equilibrium price of roughly 1.4 €/kg.

The simulation results are depicted in Figure 6. The price series generated by the base run of the model (part a. of Figure 6) exhibits aperiodic cyclical behavior consistent with the observed hog-price record. Part b. of the figure portrays the trajectory of the primary state variables of the model, i.e. price, supply and production, in three-dimensional space and thus illustrates the attractor of the system. The graph reveals noticeable similarities with the reconstructed attractor depicted in Figure 4. Reconstructing phase space from the simulated price series results in an embedded dimension of 4 and a time lag of 20, and thus reveals largely the same results as obtained in the reconstruction for the original time series. This indicates that our model exhibits the same dynamic behavior as found for the real world system, and therefore provides a means to identify important determinants for the persistent hog cycle.

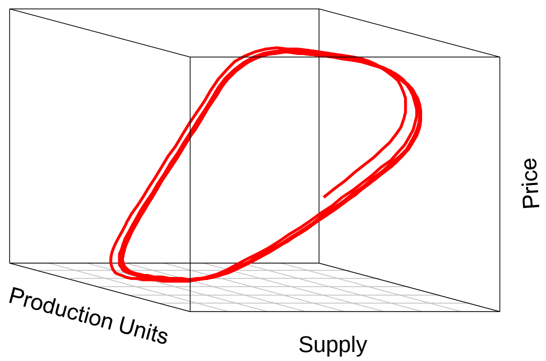
Since the model is completely deterministic, the revealed market instability is endogenous and the aperiodic cycling emerges without external shocks. The dynamic properties of the system are due to the inherent nonlinearities along with the built in time lags. The nonlinearities refer primarily to (1) the price adjustment process, (2) the irreversibility of investments due to sunk cost and (3) the logistic type adjustment of production capacities. Together with the periodicity of investments induced by the financial consolidation time lag, these factors result in the dynamic response displayed in the upper part of Figure 6.



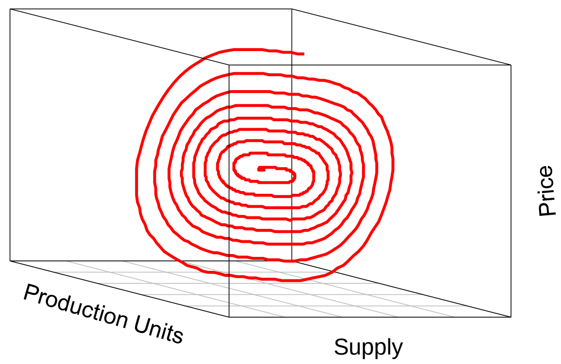
a. Time response of the base run



b. Simulated attractor in 3D space



c. Omitting the investment time lag causes a Limit cycle



d. Increased price elasticity of demand (c=0.55) leads to a stable equilibrium

Figure 6: Simulation results

With appropriate parameter changes, the model can generate quite different types of dynamic behavior as seen from the trajectories depicted in the lower part of Figure 6. If the financial consolidation time lag is omitted, the simulated attractor is converted into a *Limit Cycle*. Regardless of the starting point, all trajectories converge on one orbit (part c. of Figure 6). This behavior is caused by the combination of low demand elasticity and the irreversibility of investments. It holds over a fairly wide range of parameters. Only increased price elasticity of demand changes system dynamics to a *Point Attractor* (part d. Figure 6). In the absence of external shocks, the system approaches a stable equilibrium. However, this is unrealistic because low demand elasticity for food is characteristic for all industrialized countries where only a small portion of income is spent for food.

6. Conclusions

We applied a diagnostic modeling approach to investigate causal factors driving the persistent German hog-price cycle. Nonlinear time series analysis reconstructed an empirical hog-price attractor governing the aperiodic cycling of hog prices over time. Our empirical results indicate that causal factors driving the hog-price cycle are endogenous to the industry, and therefore can be investigated informatively by formulating a structural industry model. We drew from empirically diagnosed industry dynamics, and knowledge of industry structure and technology, to formulate a model that successfully simulated the dynamic complexity of the real-world hog-price cycle.

The model provided important insights into the origin of the hog cycle in Germany. Besides the low price elasticity of demand, which is a well-known determinant of market cycles, the model revealed two more important influence factors. One is the irreversibility of investments caused by the high specificity of the technology. Along with low demand elasticity, this leads to permanent fluctuations in form of a *Limit Cycle*. Another important factor is periodicity of investments induced by a time lag forcing a period of financial consolidation after a big investment. This is consistent with the investment behavior of German farmers which is often liquidity driven. It also reflects restrictions on the debt ratio imposed by the capital market. Adding this factor to the model converted the *Limit Cycle* into a *Torus* like attractor.

These results have several practical implications. First, valid medium and longer term price forecasts (i.e. beyond a few weeks) are precluded by the nature of the attractor. By the same token, policy measures aimed at price stabilization (i.e. buffer stock policies) are likely to fail. Accepting that in industrialized countries demand elasticity can hardly be influenced, the remaining starting points for altering the system behavior are (1) the technology and (2) the investment and financing behavior. First, a more flexible technology (e.g. multi-purpose instead of highly specialized facilities) involving less sunk cost would enable a flexible response to changing market conditions, thus lessening the degree of irreversibility of investments. Regarding the second aspect, utilizing alternative ways of financing which focus on equity capital (provided by external investors) rather than bank loans, would help smoothing the investment cycles.

The methodology presented in this paper goes beyond conventional time series modelling – including state of the art methods of price volatility analysis (e.g. GARCH-approaches) – as it not only aims at reconstructing the *time pattern* of the series, but seeks to identify *causal factors* driving the system dynamics. To this end, a *structural model* serves as analytical tool, the design and development of which is guided by the empirically-diagnosed dynamic properties of the system (i.e. the nature of the attractor) along with existing knowledge about the industry. The diagnostic part of the approach is primarily based on 'Phase Space Reconstruction' techniques. However, these techniques fail revealing a clear picture if the investigated time series contains notable (colored) noise, as is the case for most economic time series. 'Singular Spectrum Analysis (SSA)' was therefore applied first, and turned out to be a useful method for constructing a noise-free series for the further analysis that still incorporates the essential system dynamics.

The presented diagnostic modeling approach is applicable to a wide range of problems focusing on the analysis of systems driven by nonlinear dynamics. These systems are often characterized by chaotic attractors whose essential properties can be empirically diagnosed as described, and applied to formulate theory-based models able to simulate the complexity of real-world dynamics.

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