Explaining the German hog price cycle: A nonlinear dynamics approach

Ernst Berg[1] and Ray Huffaker[2]

[1]Institute of Food and Resource Economics, University of Bonn, Germany

[2] Corresponding author, Department of Agricultural and Biological Engineering, University of Florida, USA, 281 Frazier Rogers Hall, Gainesville, FL 32611-0570, USA, (352)392-1864 Ext. 281 (phone), (352)392-4092 (FAX)

rhuffaker@ufl.edu

Abstract

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

JEL Classification: C02, C32, D22, Q02, Q11

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 [1-5]. More recent studies proposed that persistent fluctuations are driven by nonlinear chaotic price dynamics. Statistical tests by Chavas and Holt (1991) [6] (using quarterly US data) and Holzer and Precht (1993) [7] (using weekly German data) failed to reject the hypothesis of nonlinear price dynamics. Streips (1995) [8] verified the results in Chavas and Holt (1991) [6] for monthly data, and further reconstructed a chaotic attractor composed of non-repeating aperiodic price cycles. Holt and Craig (2006) [9] 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) [10] 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 an innovative '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 [11], and not driven principally by random supply/demand shocks [12] or a randomly perturbed sinusoidal cycle [10]. 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 Fig. 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 December 2011 for a total of 1144 observations. Hog prices

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

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

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. Diagnostic modeling approach

The diagnostic modeling approach we propose is depicted in Fig. 2. The leftward column analyzes the empirical time sires data, and the rightward column utilizes these findings—along with knowledge about the industry structure and important characteristics of the technology—to develop a structural model as an explanatory tool.

Nonlinear time series analysis (NLTS) is used to diagnose system dynamics from a single observed time series (leftward column). NLTS works best when the time series is filtered of noise characteristic of economic time series data. Some noise may be due to observation or measurement errors most effectively treated as white noise that can be eliminated with linear filters. However, substantial variability in observed data—commonly attributed to random noise—may instead be due to complex deterministic dynamics resulting from nonlinear feedback interactions among system components. NLTS tests for the presence of low-dimensional nonlinear system dynamics in observed data. If observed data test positive for these dynamics, modelers have reason to expect that low-dimension mechanistic dynamic models may be capable of explaining highly-variable and apparently-random empirical behavior.

NLTS results can be used—along with knowledge about the hog industry—to design a model capable of simulating structural dynamics reconstructed from observed data (rightward column) [13]. This provides a valuable empirical test of model design. Moreover, the model can be used to explore factors that may be responsible for empirically-diagnosed dynamics.

Figure 2

4. Nonlinear time series analysis (NLTS)

The German hog-price record observed in Fig. 1 is characterized by non-repeating oscillations with different periods (i.e., 'aperiodic' cycles). Deterministic nonlinear dynamic systems can generate these (potentially 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 [14-16]. We apply NLTS to search for the presence of a strange attractor in the observed German hog-price record.

The NLTS literature clearly teaches that an attractor can be empirically reconstructed from small and noisy data sets, but “one gives up the ambition of reconstructing the very fine structure of the attractor including complex folding and fractal patterns…” ([17], p. 268). One is limited to reconstructing the ‘skeleton’ of a real-world attractor [18]. Consequently, we restrict our objective to detecting and reconstructing the ‘skeleton’ of a strange attractor that can guide model design. [3] We do not attempt to empirically prove the existence of chaotic market dynamics with limited data.

4.1 Signal processing

Singular Spectrum Analysis (SSA) is a data-adaptive signal processing approach that can accommodate highly anharmonic oscillations—that is, periodic oscillations that are not usually sinusoidal [17-20]. SSA separates signal (S) from noise (N) in observed data without losing dynamic structure. We apply it to reconstruct the German hog-price record as the sum of trend and oscillation components (S) and an unstructured-residual (N) component.

The first task in S/N separation is to identify dominant peak frequencies of hog-price cycles in the record. Fourier Spectrum Analysis identifies dominant peak frequencies at 0.004 Hz (a 260-week or 5-year oscillation period) and 0.019 Hz (a 52-week or annual oscillation period) (Fig. 3a). Continuous Wavelet Analysis verifies stationary power at the low frequency 5-year oscillation as required by subsequent analysis (Fig. 3b).[4]

Figure 3

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 [21]. Accordingly, the window length was set at *L* = 520, which allows for 10 repetitions of the annual (52 month)

[3] NLTS may fail to reconstruct a real-world attractor for several reasons including: 1) System dynamics are not governed by a low-dimensional attractor; 2) Noisy or limited data prevent an existing attractor from being detected; or 3) Observed data do not lie on an attractor (Williams, 1997).

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

oscillation period. A *singular value decomposition* decomposes trajectory matrix *X* into the sum of 'empirical orthogonal functions' (*EOF*), $X = \sum_{i=1}^{r} EOF_i$, 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, $\left(\sqrt{\lambda_i}\right)$, 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 oscillations. The eigenvectors associated with *EOF* pairs 2,3 and 6,7 exhibit the 5-year and annual oscillations detected by the Fourier spectrum, respectively (Fig. 4a,b). Finally, 'diagonal averaging' of grouped *EOF* matrices converts them to vector time series' of corresponding trend, oscillatory, and unstructured-residual components [20]. The isolated trend component and the composite *SSA*-reconstruction filtered of the unstructured-residual component are graphed against the observed hog-price record in Fig. 4c. Compelling evidence for the strength of the signal in the SSA-reconstruction is that it accounts for 99% of the variation in the observed hog-price record.[5]

Figure 4

4.2 Phase Space Reconstruction

We applied *Phase Space Reconstruction* [14, 15, 22] to detect whether long-term system dynamics governing German hog-price dynamics evolve along a low-dimensional nonlinear 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 [23, 24]. 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."* [25]

The 'time-delay' embedding method of phase space reconstruction [22] represents the multidimensionality of the real-world dynamic systems governing hog-price dynamics by segmenting the de-

[5] Eigenvalues measure the partial variance explained by their respective *EOFs*. The sum of all eigenvalues measures the total variance in the record (Ghil *et al*., 2002).

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 is conventionally selected as the delay for which the mutual information function reaches its first minimum (*d* = 20 weeks) [15]. The embedding dimension is conventionally selected as the dimension for which the percentage of 'false nearest neighbors' falls below a prescribed tolerance (*m* = 4) [15]. [7] If $m \geq 2n+1$, the reconstructed attractor shares key topological properties with a reconstruction in any coordinate system, where *n* is the dimension of the real-world attractor [22]. Since *n* is unobserved, in practice, $m \geq n$ is generally considered adequate to reconstruct true system dynamics [26].

The scatterplot of the delay coordinate vectors depicts a trajectory in reconstructed phase space representing a sampling or 'skeleton' of the real-world attractor [17, 18]. The empirical attractor for the filtered hog-price record is projected into 3-space in Fig. 5a. It is a torus-type attractor composed of nonrepeating 5-year and annual oscillations. The top view of the empirical hog-price attractor is shown in Fig. 5b. The sampled trajectory makes four full 5-year revolutions around the attractor depicted in Figs. 5c-f.

Figure 5

The empirical hog-price attractor was characterized by key topological properties used to identify chaotic nonlinear dynamics including the 'correlation dimension' and the 'Lyapunov exponent' [14, 16]. The correlation dimension measures the attractor's geometric dimension, and thus indicates the minimum number of variables required to model real-world phase space [14, 16]. It was calculated to be 2.94. The Lyapunov exponent measures the average rate at which initially close points on the attractor exponentially diverge or converge, and thus indicates sensitivity to initial conditions. [8] It was calculated to be 0.03. Strange attractors are characterized by low-dimensional fractal correlation dimensions and positive Lyapunov exponents. While both measures are

[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.

[8] R-package 'tseriesChaos' was used for computing the correlation dimension, and Lyapunov exponent.

consistent with the presence of a strange hog-price attractor, they do not prove its existence given their unreliability when computed from short and noisy data [16]. Following conventional empirical practice, we use the computed correlation dimension in the analysis to follow [26-28].

3.3 Surrogate Data Analysis

Surrogate Data Analysis is conventionally applied to test whether apparent structure detected in an empirically reconstructed attractor is more likely the figment of a mimicking stochastic process. An empirical attractor's topological properties are compared statistically with those taken from phase space reconstructed from randomized surrogate vectors [26-28].

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 [27]. *PPS* surrogates test for the presence of a noisy limit cycle by preserving periodic trends in the SSA-filtered data while destroying chaotic structures [28].[9]

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:

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

[9] 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.

where the right-hand side of the inequality is the *p*-value for a two-tailed test [29], $\Phi|t|$ is the CDF for the *t*-statistic with *N-1* degrees of freedom, and $|\ |$ is absolute value. The null hypothesis of insignificant difference was rejected for the correlation dimension with a computed *p*-value effectively zero. Consequently, we rejected the hypothesis that the structure detected in the empirical hog-price attractor is due to mimicking random behavior.

5. 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 *m = 4*, indicating that a minimum of four 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[10] 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. We propose the following fifth order system of differential equations:

$$\begin{aligned}\dot{P} &= \mathrm{f}_p(D,S,P)\\ \dddot{S} &= \mathrm{f}_S(P,S,C)\\ \dot{C} &= \mathrm{f}_C(P,C)\end{aligned} \tag{1}$$

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

[10] 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.

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. $\dot{P} = a\left(D-S\right), \quad a>0$. Assuming that large surpluses of either demand or supply speed up the adjustment process, a more adequate formulation is:

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

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

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

or

$$\dot{P} = a\left(D-S\right)^3 P \ , \quad a>0 \qquad (3)$$

This constitutes an additional feedback loop in the model. We use equation (3) in the model. Fig. 6 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 6

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:

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

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

$$\begin{aligned} &\dot{r}_i = \frac{k}{DEL}\left(r_{i-1} - r_i\right), \quad i = 1,2,\ldots,k \\ &\text{with} \\ &r_0 = S_p \\ &r_k = S \end{aligned} \tag{6}$$

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.

6. 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 Fig. 7. The price series generated by the base run of the model (Fig. 7a) exhibits aperiodic cyclical behavior consistent with the observed hog-price record. Fig. 7b 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 Fig. 5. Reconstructing phase space from the simulated price series results in an embedding dimension of m=4 and a time lag of d=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 Fig. 7.

Figure 7

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 Fig. 7. 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 (Fig. 7c). 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* (Fig. 7d). 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.

7. 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 modeling – 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* 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.

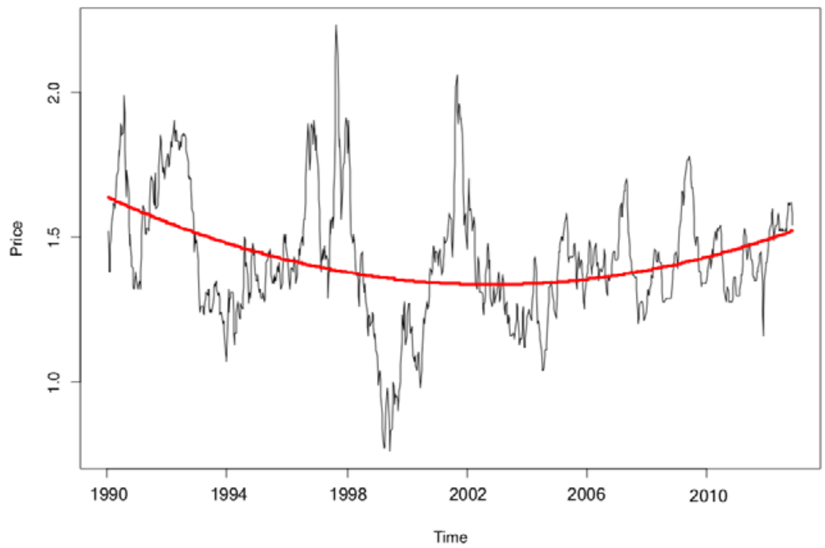


Figure 1: Time series of hog prices and estimated trend

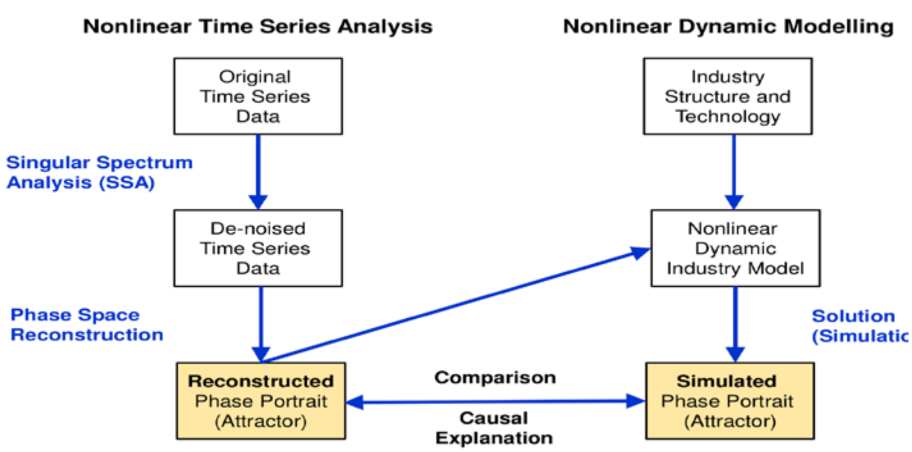
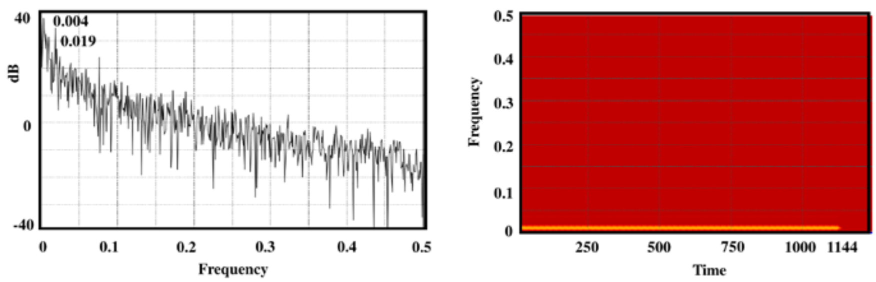


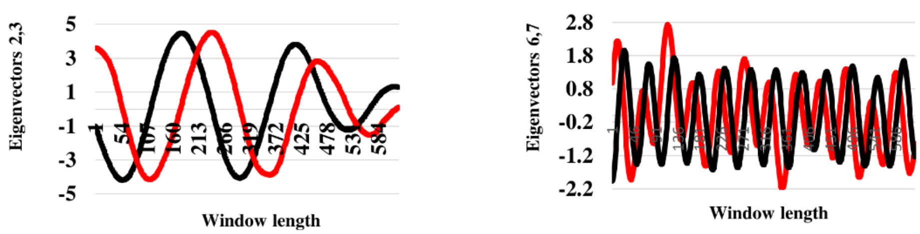
Figure 2: Diagnostic modelling approach



a. The Fourier frequency spectrum

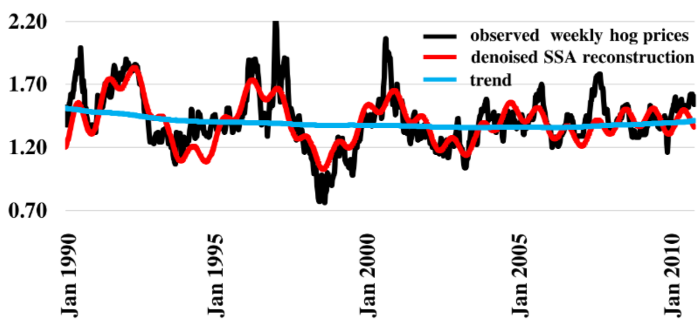
b. Continuous wavelet time-frequency spectrum

Figure 3: Spectral analysis



a. Eigenvectors associated with 5-year oscillation

b. Eigenvectors associated with annual oscillation



c. Reconstructed SSA components

Figure 4: Singular Spectrum Analysis

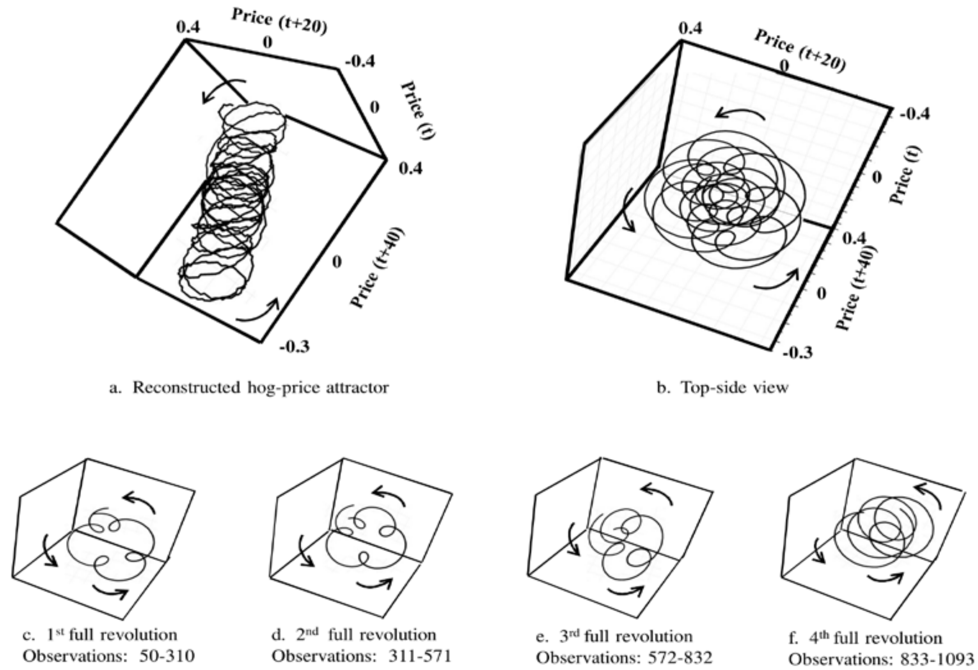


Figure 5: Anatomy of Empirical Hog-Price Attractor

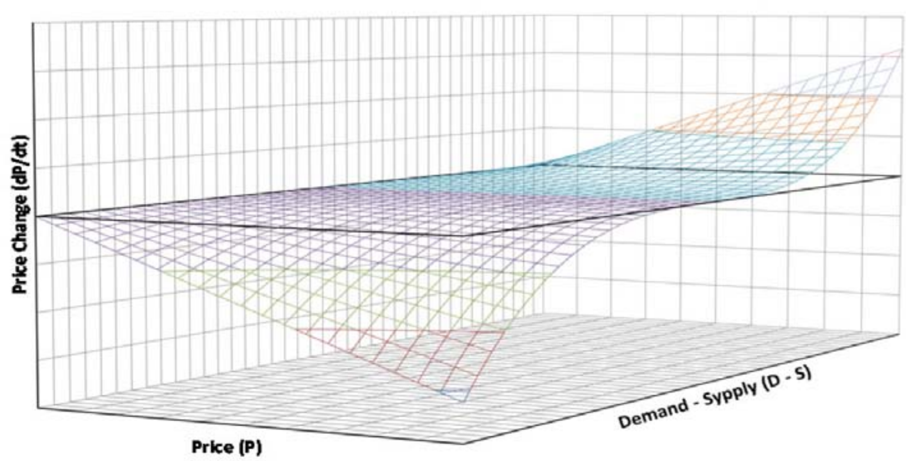


Figure 6: Price Change as a Function of Demand and Supply

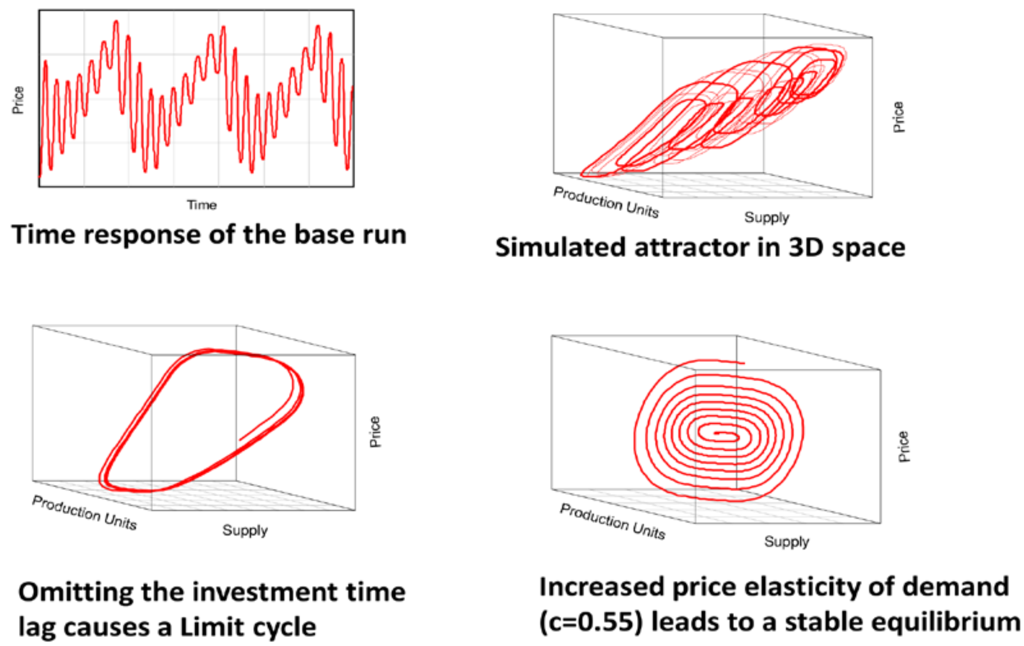


Figure 7: Simulation results

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