

Breeding delays determine the wavelength of the pork cycle

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Abstract

The pork cycle exhibits persistent oscillations in prices and production with a wavelength of three to six years. We develop a system dynamics model in which cyclical behaviour arises endogenously from biological delays and a simple adjustment rule, without the explicit modelling of price or forward-looking optimization from decision-makers. The model reproduces the cyclical component of Dutch pork prices, matching its wavelength and turning points, and explains the gradual shortening of the cycle through technological changes that reduced production lead times. Sensitivity analysis further separates the parameters that govern the cycle's wavelength from those that govern its amplitude, and identifies policy levers acting on each. Our findings do not imply that prices are irrelevant; rather, they highlight that a significant part of the pork cycle is structural, with prices primarily reflecting underlying production delays. This perspective complements rational-expectations models and clarifies why similar 'pork cycle' patterns appear in other industries with long lead times.

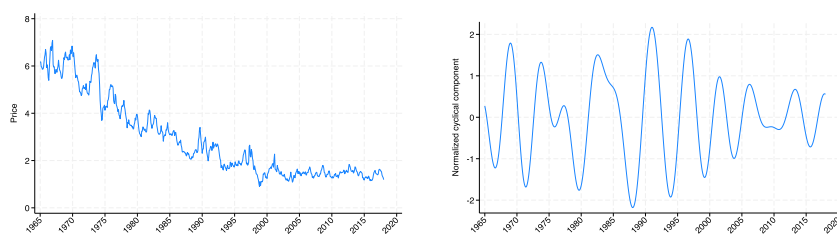
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1. Introduction

The price of pork oscillates. Across countries and more than a century of records, we observe price cycles three to six years long, resistant to decades of policy intervention (Parker and Shonkwiler, 2014). In the Netherlands, the wavelength of this cycle has not been constant: the oscillations of the 1970s

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(a) Monthly pork prices [euro/kg, 2016 prices]. (b) Normalized cyclical component.

Fig. 1. Monthly pork prices for producers in the Netherlands, 1965–2017, and the extracted cyclical component using a 48–168 month Christiano–Fitzgerald filter. The results show persistent oscillations with wavelengths of 5–9 years that shorten after 1990. Data source: Agrimatie. Prices expressed in real terms, deflated to 2016 euros using the Dutch CPI (CBS StatLine).

and 1980s ran longer than those observed after 1990. Existing explanations, built on the lag between price and the farmer's supply response, can reproduce a cycle, but do not explicitly identify what sets its length, why that length should drift over time, or why the same pattern recurs in non-agricultural industries. In this paper, we show that the wavelength of the pork cycle is mainly driven by the biological delays of breeding, and that a simple model of these delays, without any explicit representation of price or price-setting behaviour, can reproduce both the Dutch cycle and its gradual shortening.

Pork is the world's largest meat market, with roughly 124 million tons produced in 2024 (OECD/FAO, 2024). At such a scale, price instability raises the risk of production, increases employment volatility, and erodes the competitiveness of the sector, with thin margins hitting small independent farmers hardest due to their limited scale (Backus *et al.*, 2011; Backus *et al.*, 2012; Regiegroep-Vitale-varkenshouderij, 2016). Fig. 1a shows the real producer price of Dutch pork from 1965 to 2018; Fig. 1b isolates its cyclical component using a Christiano–Fitzgerald band-pass filter tuned to 48–168 month frequencies. Two features stand out. The real price level trends downward over the sample, falling from above 3 euro/kg in the 1970s to roughly 1.5–2 euro/kg after 2000.¹ And the observed wavelength of the cyclical component shortens after 1990: the broad swings of the early decades, five to nine years apart, give way to tighter cycles of roughly five years. The same shortening appears in American data (Holt and Craig, 2006), and the broader phenomenon has been documented well beyond Europe and North America, including South America (Fliessbach and Ihle, 2020), which points to a structural rather than a context-specific origin.

The dominant explanations of this cycle locate its source in expectations. In the cobweb tradition and its descendants, farmers respond to current prices, and the lag between a breeding decision and the resulting supply produces oscillation. These models capture the existence of the cycle, but they treat its

¹ Data source Agrimatie—<https://bit.ly/3wuiZYf>, Wageningen Economic Research.

central quantitative feature, its period, as something to be matched rather than explained. The canonical commodity-cycle model of [Meadows *et al.* \(1970\)](#), closest in spirit to our work, illustrates the problem: it produces a cycle that damps out faster than the persistent oscillations in the data, with a period roughly 60 per cent of what is observed. More fundamentally, no existing model offers a theory-based account of why the wavelength should decrease over time, as [Fig. 1b](#) shows it does. The lag that drives these models is typically imposed to fit the data; when it is, an unexplained additional delay of about a year must be assumed to recover a realistic period ([Harlow, 1960](#)), with no empirical or theoretical grounding.

In this paper, we treat the delays of pork production as measurable physical quantities rather than as free parameters. A pig destined for slaughter passes through maturation, gestation, and finishing before it reaches the market, and each stage takes a biologically determined amount of time. We model the pork-breeding market as a stock of mature breeding sows, fed by a flow of newly purchased young sows and drained by slaughter. Farmers buy sows to close the gap they observe between supply and demand. Importantly, we do not model price expectations or forward-looking optimization at all. The only behavioural parameter in the model is the speed at which farmers adjust their purchases to the observed gap, which we call the adaptation time. Everything else is the production technology: the time it takes to turn a purchasing decision into pork. This positions our work within the endogenous tradition of agricultural price fluctuations ([Chaudhry and Miranda, 2024](#)), in which cycles emerge from the structure of production rather than from the rational anticipation of future prices.

We treat the adaptation time as a reduced-form summary of well-documented adjustment frictions in livestock markets. Expanding sow capacity is a largely irreversible investment whose return is realized a full biological lead time later, so the option value of waiting rises with price uncertainty ([Dixit and Pindyck, 1994](#)); rapid herd expansion disrupts the age and genetic structure of the breeding stock; and credit-constrained small farmers cannot adjust quickly regardless of the price signal. Empirically, [Chavas \(1999\)](#) finds that backward-looking adjustment predominates in U.S. pork markets, and [Rosen *et al.* \(1994\)](#) shows analytically that adjustment costs and biological delays together sustain persistent cattle cycles even under rational expectations. Our adaptation time captures the aggregate consequence of these frictions without explicitly modeling a specific channel.

Our contribution is threefold. First, we show that a model driven solely by measured biological delays and a single adjustment rule reproduces the cyclical component of Dutch pork prices, matching the wavelength and turning points of the observed cycle without recourse to price expectations or lags fitted to the price series. The wavelength is determined, in our model, by the breeding delays themselves: this is the sense in which breeding delays determine the wavelength of the pork cycle. Second, by allowing those lead times to vary, we provide what is to our knowledge the first explanation that derives the gradual shortening of the cycle from the production technology itself. The

shortening follows from the decline in production lead times in the Netherlands over the second half of the twentieth century, driven by improvements in technology and breeding, and it explains why the wavelength differs across regions: lead times are intrinsic to where and how pork is produced. Third, through systematic sensitivity analysis we separate the parameters that govern the cycle's wavelength from those that govern its amplitude, and we discuss this separation for policy. We argue, for example, that consolidation toward vertically integrated production could shorten the cycle by reducing lead times through production efficiencies, without necessarily making it less severe. Conversely, the adaptation time is the only lever available for damping the cycle's amplitude: interventions that discourage rapid adjustment of the breeding stock raise the dampening factor and would thus reduce the severity of the oscillation. Finally, measures which synchronize farmers' responses, such as a published price index or futures market, may reinforce the cycle rather than dampen it.

These results do not imply that prices are irrelevant. Farmers cannot observe the supply–demand gap directly and use price as its proxy, so price remains the channel through which the gap is perceived. We argue that a large part of the pork cycle is structural: the oscillation is generated by production delays, and price largely reflects those dynamics rather than driving them. This perspective complements price-expectations models, and it clarifies why ‘pork cycles’ appear in industries with long lead times and little in common with agriculture, such as semiconductors, where the same delay structure produces similar oscillations.

The remainder of the paper is organized as follows. [Section 2](#) reviews the history of the pork cycle and the modeling traditions on which we build. [Section 3.2](#) presents our model and methodology. [Section 4](#) parametrizes the model with Dutch data and reports the simulations. [Section 5](#) draws out insights, policy implications, and directions for further research.

2. Related literature

This paper sits at the intersection of two research streams. The first is the agricultural economics of commodity cycles, which has documented and theorized the pork cycle for over a century and supplies both the phenomenon we study and the behavioural intuitions we build on. The second is the operations and system dynamics literature, which approaches cyclical behaviour not through the formation of expectations but through the structure of the system that generates it: the stocks, flows, and time delays that produce oscillation regardless of how individual agents reason.

Observations of a cycle in the price of pork are not new. Early descriptions date to the late nineteenth century ([Benner, 1876](#)). Through the early twentieth century, analysis centred on the ‘corn–hog’ cycle, on the premise that pork and corn prices were tightly linked: at the time, 85 per cent of corn production was destined for feedstock ([Wright, 1925](#); [Sarle, 1925](#)). An early approach

to model the pork cycle focused on the interaction between the end product and the feed (see, for example, [Ezekiel, 1938](#)). Backed by the USDA, early research on the topic prioritized forecasting over explanation; the aim was to obtain an empirical method of price prediction rather than an explanation of the underlying mechanism ([Haas and Ezekiel, 1926](#)).

The first theoretical explanation came with the cobweb model ([Tinbergen, 1930](#)), which locates the source of oscillation in the lag between supply and demand decisions. Applied to pork, the intuition is a feedback loop: the current price drives breeding, breeding determines future slaughter capacity, slaughter capacity moves the price, and the new price drives breeding again. [Harlow \(1960\)](#) showed that the cobweb model reproduces a roughly four-year cycle, but only if one assumes an additional one-year lag between price and breeding for which there is neither empirical evidence nor theoretical justification.

The intuition behind the cobweb tradition is consistent with later feedback-based modeling, and in particular with system dynamics. Introduced by [Forrester \(1958\)](#), system dynamics uses stocks and flows as the building blocks for representing feedback-rich structures, and over the past half-century it has been applied to weather systems ([Ford, 1999](#)), managerial decision-making ([Sterman, 1989](#)), e-business growth ([Oliva et al., 2003](#)), and process-industry supply chains ([Udenio et al., 2015](#)), among many others. Closest to our work is the commodity-cycle model of [Meadows et al. \(1970\)](#), itself an extension of the cobweb model. Meadows introduces two feedback loops from inventory to price, via capacity and via consumption, and adds a feed-price correction that in effect tracks the farmer's gross margin. The model does not, however, fully reproduce the observed pork cycle; generating dampened oscillations that are too short in period.

Later work emphasizes nonlinearity. [Chavas and Holt \(1991\)](#) present evidence that the process generating the pork cycle is nonlinear and cannot be captured adequately by linear time-series analysis, and [Holt and Craig \(2006\)](#) find that these nonlinear features have themselves evolved over time, following structural changes in production. [Chaudhry and Miranda \(2024\)](#) organize the broader literature into two contrasting accounts of agricultural price fluctuation. The exogenous view, dominant in much of the field, rests on rational-expectations models of storage ([Williams and Wright, 1992](#)) and animal breeding ([Rosen et al., 1994](#)). The endogenous view describes boundedly rational farmers who form backward-looking expectations and expand production when prices are high.

Our approach draws on both traditions: we adopt the endogenous view of the pork cycle, with cyclicity as an emergent property of the production structure rather than of forward-looking price anticipation, but we depart from the cobweb and commodity-cycle models that share this view in two respects. First, we do not impose the lag that generates the oscillation; the delays in our model are the measured biological stages of pork production. Second, by analysing the sensitivity of the model to these delays, we investigate how the cycle responds when they change; allowing us to explain the gradual short-

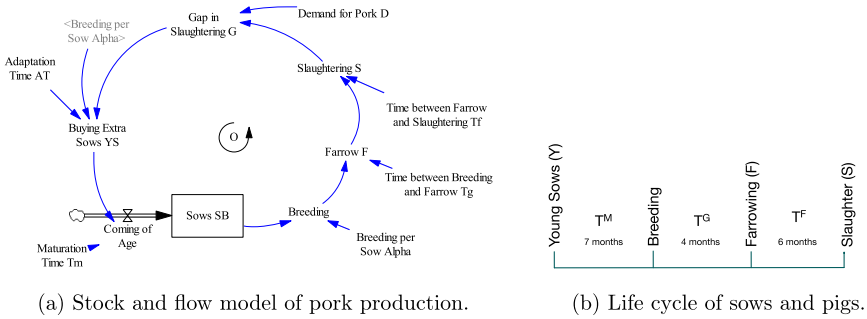


Fig. 2. Stylized stock–flow representation of pork production and the associated life cycle of sows and pigs. This structure highlights the biological delays (maturation, gestation, finishing) that drive cyclical dynamics in supply.

ening of the wavelength that existing work documents but does not account for.

3. Model and methodology

3.1 Methodology

We model the pork production cycle as a set of linear time-delay ordinary differential equations, implemented using system dynamics. While our model reduces to a delay-differential system that can be solved analytically, this approach is particularly useful in the current setting. First, it allows us to represent biological and logistical delays in a transparent way, making the underlying mechanisms intuitive to agricultural economists and practitioners alike. Second, system dynamics has a long tradition in modelling commodity and production cycles (e.g., [Meadows *et al.*, 1970](#)), where cycles arise from physical processes rather than from expectations alone. We structure our model using the canonical stock-replenishment cycle as formalized in [Sterman \(2000\)](#).

3.2 Model specification

[Fig. 2a](#) shows our stylized stock and flow model of pork production. We base this model on the life cycle of pigs destined to consumption (see [Fig. 2b](#)) and on the replacement of sows destined to breeding. Meat producers acquire young sows for breeding in the market.² These sows are unproductive until they reach the age of maturity (this period is called the maturation period). Once they reach maturity, sows are bred and give birth to newborn piglets after the gestation period. After weaning, pigs are fed until the age of slaughter

² We assume that culled old sows trigger a 1:1 replacement with young sows (i.e., gilts) from the market. Thus, in the model, the selecting of young sows is only that part of the total selecting of young sows that is influenced by the cycle.

and sows will be bred again.³ The period between farrowing and slaughtering we call the finishing period (which comprises nursery, rearing, and growing-finishing).

Our interest is to model the pork cycle, i.e., the cyclical change of the price of pork. In recent years, worldwide operating breeding companies breed a line of sows that is referred to as the great grandparents (GGP), which give birth to sows which are referred to as grandparents (GP), which give birth to the sows called F1, which give birth to the pigs (referred to as the 4th generation) that are raised for slaughtering. (There are also F1 boars that are raised and used for insemination, but this is less relevant here.) After a number of weeks, the F1 young sows are bought by farmers who breed with them and raise the resulting 4th generation pigs for pork. The total period between the buying of the F1 at birth and slaughtering of the first litter of the 4th generation is 17 months. Hereby we assume that all F1 sows that have been bought will eventually be bred and that there is no shortage of farm space.⁴ Thus, conceptually, we model mature breeding F1 sows as a stock (i.e., the number of productive sows at any given time) and the change in mature breeding sows as a flow (i.e., the rate of increase/decrease in F1 breeding sows). Given the above assumptions, the stock of mature breeding sows is directly proportional with future slaughter volume of 4th generation pigs, one gestation period and one growing and finishing period later. The gap between slaughtering and consumption drives the buying of young F1 sows, which one maturation period later are added as a flow into the stock of mature breeding sows.

In this model, we make the following assumptions. (1) The life cycle of the animals is deterministic and common to all producers in the market. (2) The number of breeding sows is directly related to future slaughtering volume. This implies that all sows that can be bred, are bred. (3) Consumer demand for pork is stable and inelastic (see [Section 3.2.2](#)) below. (4) There is ample supply of young sows for buying at any moment in time. (5) There is not a significant import or export of pork to areas that are not part of the same pork cycle, which means in effect outside the EU. (We further discuss this assumption in the conclusions.)

Formally, for a given time t we denote the quantities of the model (both endogenous variables and fixed parameters) as follows. The stock of mature, breeding-age sows, $B(t)$, the buying of young F1 sows $Y(t)$, the number of newborn 4th generation piglets $F(t)$, the number of slaughtered 4th generation pigs $S(t)$, the volume gap between slaughtering and consumption $G(t)$, the adaptation time T^A ,⁵ and the consumer demand (i.e., consumption) $D(t)$. Additionally, let us denote the time-invariant lead times corresponding to the

3 The average number of piglets per sow per month in the Netherlands in 2011 was 2.25 ([Hoste, 2013](#) /Interpig). In the remainder of this article, we focus on the piglets that are going to be slaughtered and ignore mortality, assuming it has no effect on the pork cycle.

4 Conceptually, space considerations would introduce a second order delay; being that land expansions and building of new infrastructure to accommodate livestock require themselves a substantial time to be realized.

5 The adaptation time models the expected time that a farmer takes into consideration for closing the gap between slaughtering and consumption. For example, if $T^A = 1$ buying decisions are

life cycle of the pigs as T^M , T^G , and T^F , respectively the maturation period (i.e., from the buying of a young F1 sow until maturity), the gestation period (i.e., between breeding/insemination of an F1 sow and farrowing/birth of the 4th generation litter), and the growing and finishing period (i.e., time between farrow and slaughter). The total lead time (i.e., the time between the buying of a young F1 sow and the slaughtering of its first 4th generation litter) is thus $T = T^M + T^G + T^F$.

The model is then defined by:

$$\frac{d}{dt} B(t) = Y(t - T^M), \quad (1)$$

$$Y(t) = G(t) / (\alpha T^A), \quad (2)$$

$$G(t) = D(t) - S(t), \quad (3)$$

$$S(t) = F(t - T^F), \quad (4)$$

$$F(t) = \alpha B(t - T^G), \quad (5)$$

where α is an estimate of the average number of piglets produced per sow per time unit (the litter yield). Due to zoological innovations, α tends to increase over the years. In this article, however, we consider it a constant. The main stock in the cycle is formed by the sows SB_t that are available for breeding. Note that the replenishment cycle switches dimension twice: from sows per month to sows to pigs per month as shown in Fig. 2a, according to the ratio α .

We model the behaviour of the farmers in the market through the parameter adaptation time, T^A . This adaptation time expresses the eagerness of farmers to close the gap between the desired and actual pork output; between consumer demand and slaughtering. When $T^A = 1$ the ordering of young sows in period t is equal to the 100 per cent of the gap, i.e., the full difference between desired and actual pork output. When $T^A = 2$ then the market adjusts half of the gap in period t , and so on. Prior research suggests that, in practice, decision makers tend to close the gap between desired and actual quantities using a large T^A (Springer and Kim, 2010; Udenio et al., 2015). This is because a large adaptation time dampens and stabilises the dynamics of the model.

The adaptation time T^A has a natural microeconomic interpretation that connects our model to the broader livestock economics literature. Consider a farmer deciding how many additional young sows to purchase in period t . The marginal benefit of purchasing more sows is the expected profit from closing the supply-demand gap sooner. The marginal cost has three components. First, sow capacity expansion requires capital investment that is largely irreversible: barn space, breeding contracts, and skilled labour cannot easily be redeployed if prices fall before the new cohort reaches slaughter weight. This irreversibility creates a real option value of waiting that increases with price uncertainty (Dixit and Pindyck, 1994). Second, rapid herd expansion

such that enough sows are bought to completely close the gap, in general, if $T^A = \tau$ then the farmer buys enough sows such that the gap will be closed in τ periods. This way of modeling the 'nervousness' of a decision-maker is a common feature in system dynamics models used to model behavioural aspects of decision-making (see, e.g., Sterman, 1989).

may disrupt the operations of the farmers, potentially reducing per-sow productivity during the transition period. Third, independent farmers face credit constraints that limit the feasible speed of adjustment regardless of the profitability signal. These costs suggest that gradual adjustment is consistent with profit-maximizing behaviour under irreversible investment and uncertainty, rationalizing a large T^A .

3.2.1 *The relationship between adaptation time, model stability, and model dampening.*

A dynamical system can be characterized in terms of its response to arbitrary changes on its inputs. At the highest level, a system can be stable or unstable. A stable dynamic system yields a finite output for any finite input. In our model, the customer demand is the input, and the number of slaughtered animals per time period is one of its outputs. Hence, in this context, stability guarantees that the system does not explode as a response to changes in demand—a precondition for any real-life system.

It can be shown that for the system presented in this study, the stability of the system depends on the relationship between T^A and T . In particular, the system is stable if $T^A/T \geq 2/\pi$. Based on this observation, we define the pork cycle ratio (PCR) for a given time period t as $PCR(t) = T^A(t)/T(t)$.

The pork cycle ratio is a useful definition because it directly determines whether the model's response is dampened. Specifically, a system with $PCR_t = 2/\pi$ is a critical system, i.e., a one-time change in its input results in an infinitely oscillating output with a constant amplitude; a system with $PCR_t > 2/\pi$ is a sub-critical system, i.e., a one-time change in its input results in an oscillation at a decreasing amplitude; and a system with $PCR_t < 2/\pi$ is a super-critical system, i.e., a one-time change in its input results in an infinite, increasing oscillations. For notational convenience, we define the dampening factor (ϕ) as the ratio between the PCR of any given system and the PCR of a critical system; $\phi = \frac{\pi}{2}PCR$. It is intuitive to see that a system with $\phi = 1$ is critical, a system with $\phi > 1$ is sub-critical, and a system with $\phi < 1$ is super-critical.

In our model, provided that the lead time is time invariant (i.e., the maturation, gestation, and growing and finishing periods do not change in time) then the adaptation time fully determines the dampening of the system, and thus its dynamics.

3.2.2 *Linking pork supply, pork demand, and pork price*

Our model treats price as an outcome of supply-demand imbalances rather than as a driver of production decisions. This perspective highlights a complementary mechanism to existing rational-expectations models: even in perfectly competitive markets, structural delays alone are sufficient to generate persistent cycles. This section explains the mechanisms behind that choice and formalizes the link between the simulated supply gap and observed farm-gate prices.

3.2.2.1 Market clearing mechanisms. While markets ultimately clear, the mechanisms are imperfect and costly. In practice, excess supply is absorbed through four channels: (i) limited short-run storage, (ii) exports of lower-value cuts, (iii) delaying slaughter (with higher feeding costs), and (iv) retail promotions to accelerate sales. When demand exceeds supply, these dynamics reverse. Although our model does not explicitly include a stock of pork, in practice small mismatches between supply and demand are absorbed through these channels. Because both supply and demand are highly inelastic in the short run (farmers cannot easily adjust output due to biological constraints, and consumers respond little to farm-gate price changes) even small imbalances in supply are sufficient to trigger large price swings. This implies that the corresponding adjustments in inventories or exports are limited in magnitude, dispersed across the supply chain, and not visible in aggregate data. For this reason, we do not explicitly include inventories of pork: The effect exists in reality, but does not alter the cyclical dynamics captured by the model.

3.2.2.2 The link between Supply, Demand, and Price. In the Netherlands, farm-gate pork prices are determined in a competitive market based on the difference between supply and demand ([Regiegroep-Vitale-varkenshouderij, 2016](#)). We formalize this through a simple inverse demand equation:

$$P(t) = \bar{P}(1 - \eta G(t)/D(t)) \quad (6)$$

where $\bar{P}$ is the long-run average price, $G(t)$ is the supply-demand gap as defined in Equation (3), and η denotes the short-run price flexibility of demand. This parameter captures how sensitively farm-gate prices respond to supply imbalances. Empirical estimates for pork markets consistently find η to be large: supply and demand are both highly inelastic in the short run, so even a 2–3 per cent supply surplus is sufficient to generate price swings of 10 per cent or more at the farm gate ([Chavas, 1999](#); [Backus et al., 2012](#)). This response to large price movements is a central stylized fact of pork markets and is consistent with our model structure.

The supply side is equally rigid. The growing and finishing period T^F is assumed time-invariant given an assumed economic optimum for slaughter weight. All sows that are mature enough for breeding, are bred. After they have farrowed, they are bred again after a fixed, optimal time period which is a few days after weaning. As a result, the number of inseminations per period is directly proportional to the stock of sows. Thus, the supply of pork is the result of past decisions, especially those taken when purchasing young F1 sows. The long biological lead time makes the system inherently sluggish, so even large price movements cannot induce immediate adjustments.⁶ The persistence of the pork cycle despite stabilization efforts suggests a low short-run elasticity of

6 This sluggishness is not unique to pork: [Asche et al. \(2017\)](#) demonstrate that biological production processes with long lead times systematically generate large price responses to shocks, as the inability to adjust output within the production horizon amplifies price volatility. Their findings in salmon aquaculture support the general principle underlying our model.

supply. Consequently, a supply fluctuation of only 2–3 per cent can generate price waves of 10 per cent or more, obscuring the physical drivers of the cycle in aggregate data.

Equation (6) establishes price as a deterministic function of $G(t)$. The key question is whether price feeds back into production decisions. Specifically, whether farmers adjust their sow purchasing in response to current or expected prices rather than to the observed supply gap. We argue that this feedback, while present in principle, does not alter the qualitative dynamics of the cycle for two reasons. First, the supply gap $G(t)$ and farm-gate price $P(t)$ are essentially the same signal: $P(t)$ is a monotone transformation of $G(t)$ under the assumptions above. In the absence of exogenous shocks, a farmer responding to price is therefore responding to the same information as a farmer responding to the supply gap directly; the dynamics of the signals are equivalent from the perspective of the production decision. Demeaning and variance-normalizing both series, as we do in [Section 4.1.3](#), is equivalent to treating η as a scaling parameter. The wavelength, turning points, and phase of the simulated price series are therefore entirely determined by the structural delays in $G(t)$, and are invariant to the specific value of η .

Second, even if farmers observe price perfectly, the biological lead time T imposes a hard cap on adjustment speed: no price signal can bring new pigs to market faster than the fixed sequence of maturation, gestation, and finishing allows. Persistent pork cycles therefore survive repeated attempts at stabilization through information provision and market transparency initiatives ([Regiegroep-Vitale-varkenshouderij, 2016](#)).

We therefore model farmer behaviour through the adaptation time T^A (i.e., the rate at which farmers adjust sow purchasing to close the observed gap) and treat price as a derived output of the model. This perspective does not imply that prices are irrelevant to farmers; rather, it implies that price and the supply gap are two representations of the same underlying imbalance, and that the biological structure of production, not the price signal, is the driving constraint on adjustment speed.

3.2.3 Simplified ODE representation

For clarity, the feedback structure described in Equations (1)–(5) can be reduced to a single delay differential equation. Define $X(t) \equiv B(t) - \frac{D}{\alpha}$, as the deviation of the stock of breeding-age sows $B(t)$ from its steady-state value D/α , where D is the constant consumption of pork and α the average litter yield. Using the definitions of the lead times, the system reduces to a linear first-order time-delay ODE: $X'(t) = -\frac{1}{T^A} X(t - T)$, where $T = T^M + T^G + T^F$ is the total biological lead time and T^A is the adaptation time. Given initial conditions, the subsequent evolution of the system is fully determined by T^A and T . All other endogenous variables (slaughtering, piglet births, consumption) follow directly from $B(t)$ and its lags.

The mathematical properties of such linear time-delay ODEs are well studied in the control theory and biological systems literatures (see, e.g.,

Table 1. Description and estimation of observable parameters.

Parameter	Description	Estimate	Source
Maturation period (T^M)	Period between the buying of a young sow and first breeding	192 days (6.3 months)	KWIN (2017)
Gestation period (T^G)	Period between breeding and farrowing	113 days (3.7 months)	KWIN (2017)
Finishing period (T^F)	Period between farrowing and slaughtering	183 days (6 months)	KWIN (2017)
Litter yield (α)	Average number of piglets per sow per month	2.25	Hoste (2013)
Consumption (D_t)	Pork consumption	Constant	

[Nise, 2011](#)). Stability requires that the ratio T^A/T is not too small: specifically, the system exhibits bounded, oscillatory behaviour if $\frac{T^A}{T} \geq \frac{2}{\pi}$. Within this range, oscillations are damped and the wavelength increases with the lead time. This condition is equivalent to the ‘pork cycle ratio’ we define in [Section 3.2.1](#).

We emphasize that this reduced form is mathematically equivalent to the system dynamics formulation. The system dynamics model is useful for communicating the feedback mechanisms and for performing simulation experiments, while the ODE form makes explicit the analytical structure and links the pork cycle directly to a familiar class of time-delay systems.

4. Results and analysis

We implement the model from [Section 3.2](#) in the Vensim software package.

4.1 Model set-up and parameter estimation

We distinguish between observable and unobservable parameters. The former represent physical qualities of the structure of the model; e.g., lead times such as the gestation period of a sow, whereas the latter drive the behaviour of the system by modelling latent relationships; eg., the adaptation time a decision maker uses when buying extra sows.

4.1.1 Observable parameters

Given their physical interpretation, we use empirical estimation of the observable parameters in the model based on established estimates. [Table 1](#) provides a summary of all such parameters, along with their corresponding source.⁷

⁷ These values, which are estimates from the Dutch industry, are representative of the biological process itself. For example, [Fliessbach and Ihle \(2020\)](#) estimate the entire biological cycle (from the birth of a female piglet to the slaughter of their first litter) in South America to be 446 days; comparable to the value of $T^M + T^G + T^F = 488$ days in this paper.

4.1.2 Unobservable parameters

Unobservable parameters are typically estimated via formal calibration of the model (Sterman, 2000). Our model contains an unobservable parameter that requires estimation through calibration: The adaptation time, T^A .

Due to its more intuitive interpretation, we consider T^A through the dampening factor ϕ (see the discussion in Section 3.2.1) and thus calibrate the model using this parameter.

4.1.3 Model output and model fit

The model output of concern is the endogenous variation in the supply of pork. This is defined by Equations (2) and (3); a straightforward gap between pork supply and demand. To assess the fit of our model we compare the model output to the historical de-trended price difference, as detailed in Fig. 1b.⁸ This data processing step allows us to disentangle the underlying price variations attributed to the ‘pork cycle’ from other, unaccounted shorter term fluctuations. The error of the model at time t is hence formally defined as the modelled value of the endogenous gap between demand and supply.

We rely on the observed pork price as a proxy for unobserved supply fluctuations; justified under the assumption that short-term demand for pork is relatively inelastic and stable. This approach aligns with standard assumptions in commodity market models and is particularly appropriate in the case of perishable goods where inventory smoothing is limited. While we do not calibrate an explicit price-supply elasticity, the objective is not to predict price levels but to test whether the simulated dynamics arising from the delay and feedback structure are consistent with observed price cycles. This observed qualitative match supports the model’s plausibility in the absence of direct supply data.

4.1.4 Critically dampened model

To assess the stability of the parametrization, we initialize the model under a stable demand condition (i.e., $D(t) = 100 \forall t$) with critical dampening ($\phi = 1$, i.e., $T^A = 2/\pi \times (T^M + T^G + T^F)$). Fig. 3 shows the oscillation at the slaughtering under these demand conditions. The oscillation has a wavelength (peak to peak) of 68 months. This is consistent with the observations for the European pork industry, which oscillated in the period 1986–2010 with an average period of approximately 66 months (5.5 years, see Fig. 1b). This suggests that the mechanisms behind the model, under the empirical estimation of the observable, structural, parameters, are capable of qualitatively explaining the

⁸ We deliberately exclude the period from 2019 onward, which was disrupted by two exogenous shocks that fall outside the mechanisms our model represents. African swine fever (a panzootic fatal to pigs but harmless to humans) spread rapidly through China in 2019, causing losses of 30 to 50 per cent of the national herd and reaching other Asian and several European countries; Dutch pork prices rose on the order of 50 per cent between December 2018 and December 2019 (Agrimatie). The resulting global undersupply, compounded by the COVID-19 pandemic, produced market turbulence unprecedented in recent history (Jongeneel et al., 2021). Because these disruptions originate outside the production-delay structure we study, we restrict our empirical analysis to the pre-2019 period.

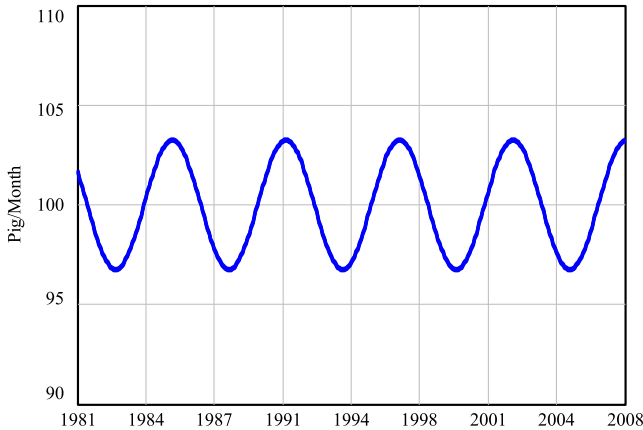


Fig. 3. Oscillation of slaughter output under stable demand in the critically damped model ($\phi = 1$). The simulated 68-month wavelength is consistent with observed European pork cycles.

oscillations observed. We next calibrate the unobservable parameters to assess the fit of the model.

4.1.5 Model calibration

The dampening factor is a crucial parameter for the dynamics of the model. Not only does this unobservable parameter govern the stability of the model, but it also affects the dynamics of the output in other ways, specifically in determining the turning points, and thus the wavelength of the oscillations.

For this reason, we follow a two-step procedure to calibrate this parameter: We first use the built-in parameter calibration tools in the Vensim software to find the parameter value that best fits the data, and then use bootstrapping to determine a confidence interval for the calibrated parameter.

Calibration in Vensim is performed via a non-linear least squares approach, through an implementation of a modified Powell hill-climbing algorithm (see the software documentation for implementation details). To avoid ‘getting stuck’ in a local optimum, we perform multiple runs of the calibration, using stochastic starting points in the parameter space.

To determine the 95 per cent confidence interval for ϕ we apply the bootstrapping procedure of [Dogan \(2007\)](#), which accommodates the autoregressive, non-i.i.d. error structure typical of dynamic models.⁹ The residuals from the calibrated model follow an AR(2) process in first differences; after removing this autocorrelation structure, the remaining innovations are i.i.d. normally distributed. We generate 500 bootstrapped historical series from this error structure and re-calibrate the model on each, yielding an empirical distribution of ϕ . Our best estimate is $\phi = 1.067$ with a 95 per cent confidence interval of (1.042, 1.094), confirming a sub-critical, stable system.

⁹ Even a correctly specified linear model produces complex residual structure when external shocks create regime-like perturbations in the data.

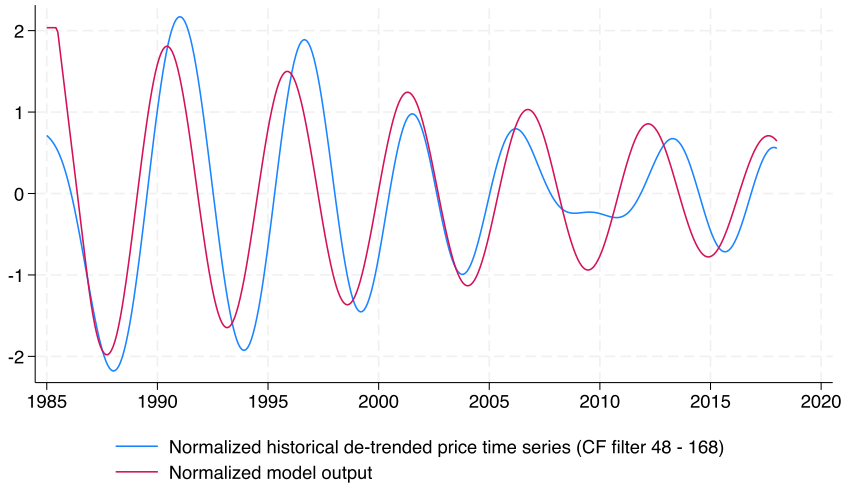


Fig. 4. Simulated pork price variation (red) compared to the historical de-trended price series (blue), 1985–2015. Both series are demeaned and normalized by their respective standard deviations. Under Equation (6), the simulated price series $P(t)$ is a scalar transformation of the supply gap $G(t)$; variance normalization is therefore equivalent to treating the price flexibility η as a free scaling parameter. The model replicates both the wavelength and turning points of the observed cycle, confirming that structural production delays are sufficient to generate realistic pork cycle dynamics.

A complementary argument motivates why T^A should cluster near the critical threshold $2T/\pi$ in particular, rather than simply being large. Within a competitive market, farmers with a smaller T^A generate larger amplitude swings in production and therefore, given asymmetric upward profit margins (Backus *et al.*, 2011), earn higher average returns. This creates selection pressure toward faster adjustment. However, farmers whose T^A falls below the critical threshold operate in a supercritical regime: their production oscillations grow without bound, eventually producing losses large enough to force exit from the market. The interplay between these two forces: competitive pressure rewarding faster adjustment, bankruptcy risk penalizing excessive speed, selects for a market-level T^A near the critical boundary. This market-selection mechanism (Alchian, 1950) provides a theoretical rationale for our calibrated dampening factor $\phi \approx 1.07$, which sits just above the critical threshold. We note that this argument assumes the delay-driven dynamics modelled here are the primary mechanism through which extreme adjustment strategies become unprofitable: an assumption consistent with, but not independently proven by, our model.

Fig. 4 shows the simulated supply gap (red) compared to the Christiano-Fitzgerald filtered historical price realizations (blue). Both series are demeaned and normalized by their respective standard deviations to highlight cyclical co-movement.

Table 2. Historical fit statistics.

RMSE	R^2	U_m	U_s	U_c
0.7476	0.54	0.0047	0.0040	0.994

The calibrated model generally tracks the variation in prices in both amplitude and phase. Observe that the period 1998–2003 is characterized by a lower actual price than predicted.¹⁰

4.2 Historical fit

To validate the model, we formally compare the de-trended CF series with the model output, after mean-centring and variance normalization (Fig. 4). Table 2 shows the root mean squared error (RMSE), R^2 , and Theil inequality statistics for the data series shown in the figure. These inequality statistics decompose the mean square error into three fractions representing: unequal means (U_m), unequal variances (U_s), and imperfect correlation (U_c) (Theil, 1966). A low U_m indicates a strong correspondence between the modelled mean and the actual mean, and a low U_s indicates a similar correspondence between variances. Therefore, low variance and means statistics indicate that the error is unsystematic, and thus desirable (Oliva and Sterman, 2001).

The model closely follows the empirical cycles, with a good correspondence in turning points. Quantitatively, the fit is strong: RMSE is 0.75 standard deviations, and the correlation yields $R^2 = 0.54$. Theil’s decomposition further shows that almost all error arises from imperfect co-movement ($U_c = 0.994$), while bias ($U_m = 0.005$) and variance mismatch ($U_s = 0.004$) are negligible. This pattern is expected given that the comparison emphasizes cyclical alignment rather than absolute levels. Overall, the model captures both the wavelength and amplitude of the cycle well, and performs particularly well in anticipating turning points.

4.3 Sensitivity analysis

4.3.1 Sensitivity to lead time

To investigate the influence of lead times in the model output, we simulate a critical system (i.e., $T^A = 2T/\pi$) with different values for T : 12, 15, 17 and 19 months. As expected from theory, increasing the lead time lengthens the cycle. The contribution here is to show that, when calibrated with empirical data, this simple structural relationship is sufficient to reproduce the observed

10 A possible explanation for this deviation is the ‘97/98 classical swine fever epidemic: 1.8 million pigs were euthanized between February 1997 and March 1998 in the Netherlands. In addition to the direct effect of the consumer loss of trust, studies estimate a loss of 5 billion euros in the sector directly related to the epidemic, which took over 5 years to recover (Bruijnen, 2008).

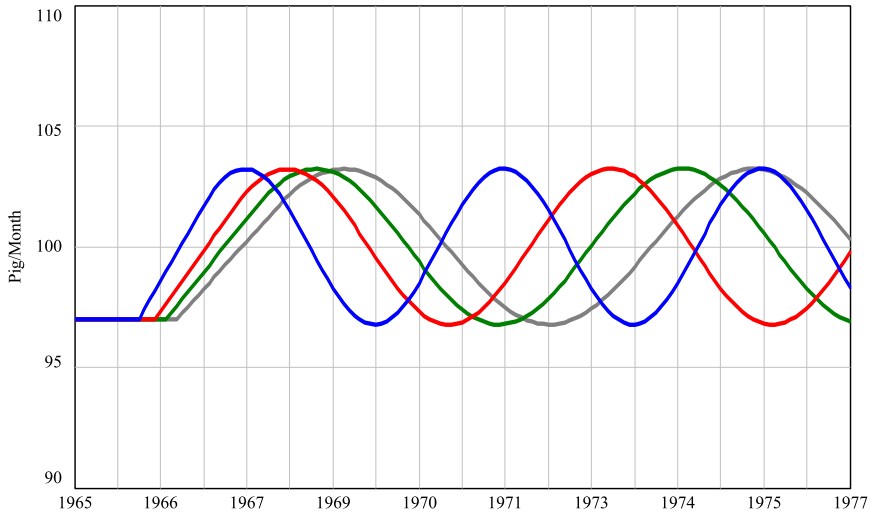


Fig. 5. Simulated cycles under critical conditions for different total lead times ($T = 12, 15, 17, 19$ months). As expected from theory, longer lead times generate proportionally longer cycles.

5–6 year cycle in the Netherlands. In particular, the oscillation wavelength is approximately 4 times the lead time.¹¹

Fig. 5 shows the output of the model based on the different lead times.

4.3.2 Sensitivity to dampening factor

Similarly, we simulate a critical system with different values for ϕ , while the T is kept constant at 17 months. Fig. 6 shows the results when ϕ is equal to 0.8, 0.9, 1, 1.1, and 1.2. This experiment confirms the theoretical role of the dampening factor. Importantly, calibrating ϕ with historical data offers empirical validation that observed cycles are consistent with a sub-critical but stable system. It also shows that the adaptation time affects the dynamics of the response; given that the T is fixed, the changes in wavelength observed stem from changes in T^A .

4.3.3 Statistical calibration of observable parameters

Thus far, we used empirical estimates of observable parameters. To test the robustness of this choice, we relax the assumption that these are structural parameters that can be physically measured and instead rely on pure statistical calibration. Following the same calibration procedure as in Section 4.1.5, we obtain the best estimates for the observable parameters as reported in Table 3. The calibrated values for the individual delays are aligned with the empirical

¹¹ This factor 4 has been observed before by Goodwin (1994), who mentions that as a rule of thumb for the length of a livestock reproduction cycle, the minimum length of a cycle is about quadruple the time required from birth to first reproduction.

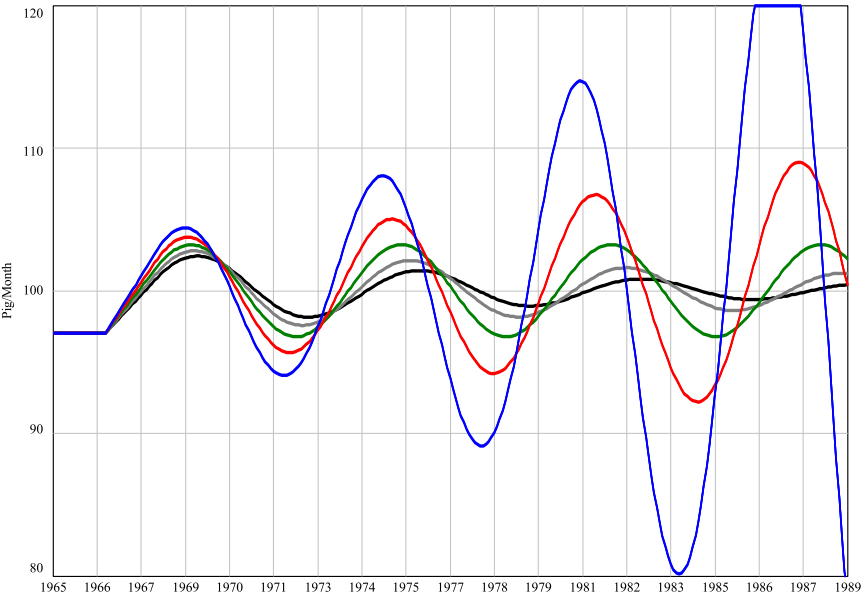


Fig. 6. Simulated cycles with constant lead time ($T = 17$ months) and varying dampening factor (blue: 0.8, red: 0.9, green: 1, gray: 1.1, black: 1.2.). Increasing ϕ stabilizes and damps oscillations, while $\phi < 1$ generates instability.

Table 3. Description and estimation of parameters.

Parameter	Description	Calibrated Value
Maturation period (T^M)	Period between the buying of a young sow and first breeding	6.51 months
Gestation period (T^G)	Period between breeding and farrowing	4.97 months
Finishing period (T^F)	Period between farrowing and slaughtering	5.19 months
Litter yield (α)	Average number of piglets per sow per month	2.28

estimates. While the calibrated values for the gestation (finishing) period are longer (shorter) than the empirical estimates, the total calibrated lead time is within 5 per cent of the empirical estimate.

4.3.4 Variable lead times

In the Netherlands, we observe a wavelength of approximately 5.5 years for the pork cycle over the last 25 years, but anecdotal data¹² suggests that the cycle of pork production in the Netherlands has varied during the twentieth century. In the period before the 1980s, all pig farmers kept sows and produced a generation of slaughter pigs. Breeding was not organized as it is now. More

12 Source: See footnote 1.

recently, part of the farmers have specialized in breeding GGP and GP sows, and producing F1 sows for sales, while other farmers have specialized in producing 4th generation pigs, buying F1 sows. If the old all-round farmers made their selection decisions for the GP sows at birth based on the price of pork, they effectively experienced a lead time for pork of $16 + 1.2 + 12.2$ months. (The 1.2 months being the period between birth and buying of the F1 sow and the 12.2 months being the period between birth of the GP sow and birth of the F1 sow.) This shift in decision-making is likely caused by the described specialization and, as a result, the average critical lead time under such circumstances decreases gradually from 28.2 to 17 months. Our model (Fig. 2) assumes that, in recent years, the start of the cycle is the buying of young sows by the pig farmer. Thus, the breeding and selection of GP sows for further breeding is in recent years effectively cut from the capacity-determining path. The shift between these two modes of pork production occurred gradually in the 1960's and 1970's. Accordingly, we model this shift in sow production methods by explicitly including the time to produce GP sows starting from the selection of the GP sows ($T^M + T^G$), (2) generalizing the formulation of the lead time of the pork cycle such that the lead time is time-dependent; formally, $T = x(t)(T^M + T^G) + T^M + T^G + T^F$, where $x(t)$ represents the share of the farmers making the selection decision at the GP sow stage at time t . In our data, we observe that $x(t)$ can be approximated empirically as decreasing from a maximum of 1 in 1979 to a minimum of 0 in 1993. When $x(t) = 0$ and the other stages of the cycle are time-invariant, this general lead time formulation reduces to the one presented in Section 3.2.

Figure 7 shows the modeled (blue) and actual (red) variation in pork price for the years 1970–2015. The period of the observed pork cycle (red) decreases from 9 years in 1970 to approximately 6 years in the past decade. This is consistent with a decrease in the effective lead time from ~ 28 months in 1978 to ~ 17 months in 1993. We use an exponential decay function, consistent with a gradual shift from the old to the new production method.

4.3.5 The effect of lead time shocks

We finally simulate the output of a critical system with a nominal T of 17 months with sudden shocks in the lead time. Specifically, we simulate shocks of 1 month (positive and negative) to test for temporary (in)efficiencies in the pork cycle. Fig. 8 shows the results. This experiment suggests that minor disturbances influence the output but do not prevent the oscillation from continuing.

4.3.6 Application to other markets

While our primary focus is on the Netherlands, the structural logic of the model is not country-specific. In the United States, the pork cycle averages around four years compared to 5.5 years in the Netherlands (Harlow, 1960; Meadows *et al.*, 1970); our framework attributes this directly to shorter effective lead times, as U.S. producers more commonly maintain idle sow stocks and vary slaughter ages, reducing the biological delay from decision to mar-

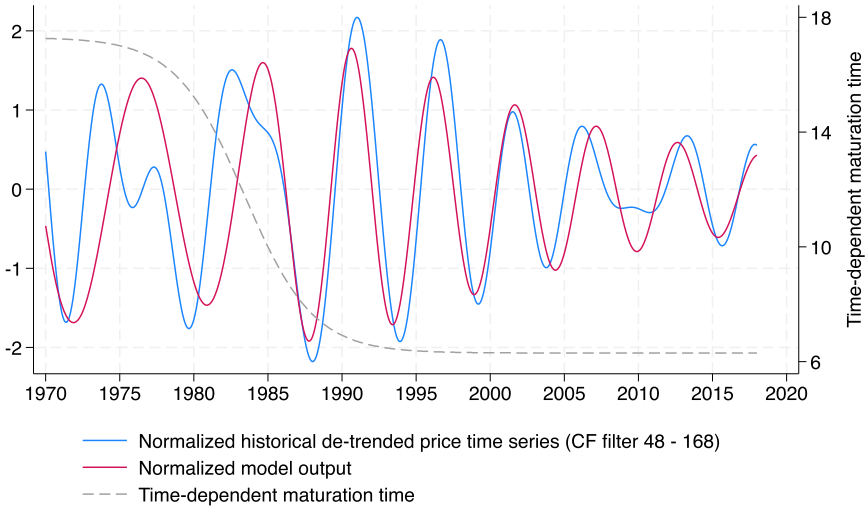


Fig. 7. Simulated cycles with variable lead times compared to historical Dutch pork prices, 1970–2015. The observed shortening of the cycle from 9 to 6 years is consistent with declining effective lead times due to specialization in breeding practices.

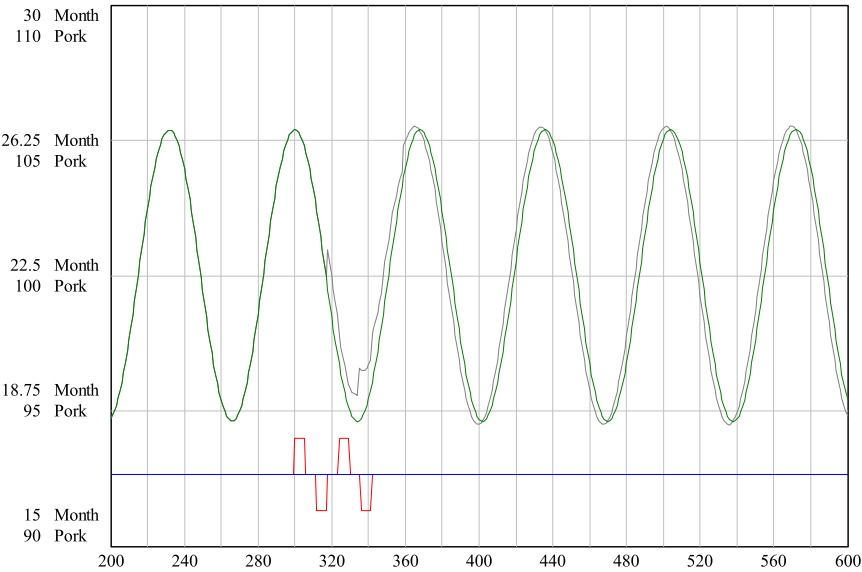


Fig. 8. Simulated response of the pork cycle to one-month positive and negative shocks in lead time around the nominal 17 months. Shocks shift the phase and amplitude but do not eliminate oscillations, underscoring the robustness of the cycle to temporary inefficiencies.

ketable output. In China, despite repeated government interventions such as subsidies, strategic reserves, and a pork price index, cycles persist ([The Economist, 2017](#)). Our model suggests why: interventions that synchronize farmer expectations can even reinforce cyclical behaviour, since the underlying biological delays remain unchanged. These examples are illustrative; a full cross-country estimation of lead times and dampening factors is left for future work.

5. Conclusions and insights

When a cycle persists for so long, under so many different settings and countries it is reasonable to expect that the cause is not a fundamental misunderstanding of the players (or even policy makers) but, rather, a structural issue. Research shows that time delays are enough to provoke and sustain cyclical behaviour in multiple settings ([Forrester, 1958](#); [Sterman, 1989](#); [Feng et al., 2013](#)). In this paper, we developed a stylized model of the cycle of pork production with results consistent with the above observation.

Our model considers the breeding and the farrow-to-finish operations of farmers: each of these stages introduces a delay between the decision to buy sows for breeding and the end-result of pork production. We parametrize our model using empirical estimates of observable parameters and statistical calibration of the unobservable parameter. Testing the model output against the historical (de-trended) evolution of pork price in the Netherlands, our results show that the time delays inherent in the production of pork explain the oscillatory nature of its price to a large extent, suggesting that it is the production technology, specifically, the biological delays inherent in pork production, that drives an endogenous variation in price. These results should not be interpreted as new theoretical mechanisms, as they are well known in control theory. Rather, our contribution is to confirm that once biological delays are parameterized with real data, the predicted dynamics align closely with the historical Dutch pork cycle.

In this view, pig farmers try to compensate a shortage (excess) that they observe in the market by buying more (fewer) young sows for breeding, but do this on average too eagerly, so they overcompensate and create a new gap, now with the opposite sign. The behaviour is rational and understandable, and under competitive conditions difficult to change. Our results demonstrate that persistent pork cycles can arise from structural delays alone, even without forward-looking optimization. This complements rational-expectations approaches by showing that biological constraints themselves provide a robust explanation for cyclical behaviour in competitive markets.

Modelling the pork cycle makes it possible to understand, analyse, and forecast it. Sensitivity analysis allows us to better understand the drivers of the pork cycle, and thus propose mechanisms that can aid policy-makers trying to control it. By relaxing the assumption that the lead times in the production of pork are constant, we show that observed variations in the length

of the pork cycle (i.e., a gradual decrease in the time between peaks) are consistent with a gradual decrease in the total lead times observed by pork producers. Such a decrease in lead times (anecdotally) took place through the latter part of the twentieth century in the Netherlands thanks to improvements in technology and production methods. This also explains why the length of pork cycle depends on the region; processes, and thus lead times, are intrinsic to the production location. Our analysis of the effect of the lead time on the pork cycle shows that its influence is in the wavelength of the cycle and not in the severity. Thus, given that reducing the number of decision-makers (here: farmers) can reduce production lead times through specialization and streamlined supply chains, our results suggest that a transition toward more vertically integrated production will eventually result in a shorter pork cycle but not necessarily in a less severe one.

Our experimentation also shows that reducing the amplitude of the pork cycle is achievable through an increase in the dampening factor, i.e., increasing the adaptation time of decision-makers buying new sows (assuming relatively stable lead times). This, however, would require different trade-offs from producers and policy makers, e.g., increasing the adaptation time increases the variability of the animal stock in the system, which may also lead to undesired consequences. Other options to dampen the pork cycle could centre on decreasing the observed gap between supply and demand, thus reducing the requirement for decision-makers to dynamically change their breeding stocks. Strategic reserves of pork, for example, can buffer the dynamics but again, come with operational challenges. Conversely, measures intended to improve market transparency, such as a published price index, or a futures market, may reinforce the cycle rather than dampen it, by synchronising the responses of individual farmers. It should be noted here that the Dutch pork market is not an isolated phenomenon but integrated in the European market, and increasingly influenced by the global market. In a world where the meat industry has access to different markets, and can choose to sell to regions with the (temporary) highest price, effective dampening actions cannot be local.

Considering the significant influence of the pork cycle in the economy of a nation, the ultimate goal of our research is to inform policy decisions. As such, our work provides a number of directions that merit further research. One such direction is empirical. We would like to estimate the adaptation time from actual data from the Dutch agriculture. Related to this, the estimation of all relevant parameters for other significant pork markets (US, China, Germany, the EU as a whole) will prove an important test for the soundness of the model. Moreover, since the substantial pig market disruption due to ASF outbreaks is not reflected in the model calculations in this paper, it might add insight if the modelling exercise would be repeated after market recovery.

Another research direction is practical. The effect of the increasing export volume needs to be taken into account in future research, as this may synchronize the pork cycles in trading countries (Holst and von Cramon-Taubadel, 2012). A number of the recommendations outlined above can be implemented as small-scale pilots. This will require collaboration with the industry and can

form the first step for testing the proposed mitigation strategies for the pork cycle, as well as a source of empirical data.

Finally, our system dynamics formulation highlights that structural delays alone are sufficient to generate persistent oscillations. This perspective allows us to study the biological and logistical constraints of pork production in a transparent and flexible way, while maintaining empirical rigour. Future research may build on this by integrating richer behavioural elements, such as expectation formation, forward-looking investment decisions, and structural estimations of pork demand elasticity into the system dynamics framework, thereby bridging the strengths of both approaches.

Conflicts of interest. None declared.

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