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Abstract

This paper examines the relevance of incorporating seasonality in agricultural supply models. Former studies have eliminated the problem of seasonality by using seasonally adjusted data. Recent developments in cointegration techniques allow the comprehensive modelling of error-correcting structures in the presence of seasonality. We consider a four-variables model for Austrian agriculture. Series on the producer price for soy beans, bulls and pigs, as well as the stock of breeding sows are included. A vector autoregression incorporating seasonal cointegration is estimated. A tentative interpretation of long-run and seasonal features is considered. The model is also used to generate forecasts for the supply of pigs in Austria.

Zusammenfassung

Dieses Papier überprüft die Bedeutung der Saison in landwirtschaftlichen Angebotsmodellen. Frühere Studien haben das Saisonproblem i.a. durch Verwendung saisonbereinigter Daten eliminiert. Neuere Entwicklungen in Kointegrations-Techniken erlauben nun das gemeinsame Modellieren von Fehlerkorrektur-Strukturen und statistischen Saisonmodellen. Wir modellieren vier Variable aus der österreichischen Landwirtschaft, nämlich Zeitreihen über Produzentenpreise von Sojabohnen, Stieren und Schweinen sowie den Bestand an Zuchtsäuen. Ein vektorautoregressives Modell unter Verwendung saisonaler Kointegration wird geschätzt. Die geschätzten langfristigen und saisonalen Strukturen werden versuchsweise interpretiert. Auch zur Prognose wird das Modell herangezogen.

Keywords
Seasonality, Agricultural Supply Response, Cointegration,Time Series

JEL Classification
C32, C53, Q11

Comments
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1. INTRODUCTION

Like in other economic sectors, modeling in agriculture frequently has to deal with the issue of seasonal behavior. On the supply side, seasonality of data on crop, livestock and livestock products arises from climatic factors, biological growth processes of plants and animals, amplified by seasonality in input (feed) supplies. On the demand side, the sources of seasonality in agricultural data are usually linked to climatic factors, 'religious' holidays, and other cultural traditions.

It seems that the theoretical economic literature does not yet fully reflect these empirical facts. Only recently, economics has slowly begun to focus on analyzing the phenomenon of seasonal cycles instead of viewing them as residual nuisance. A good example for the rather divergent ideas in current economics are the two contributions by Miron (1990) and Ghysels (1990). Whereas Miron views seasonal cycles as deterministic and strictly repetitive, rooted in the synergy of production and other supply-side phenomena as well as to periodic changes in consumer preferences, Ghysels views them as stochastic and subjected to repeated and frequent changes, also due to periodic patterns in consumer preferences but in conjunction with storage and adaptation costs. Anyway, it seems reasonable to allow for cyclical variations in prices as well as in demand or supply if economic goods are seasonal by their very nature - such as agricultural products, harvested only at certain times - and storage would be costly or the utility of goods is strongly seasonal due to cultural traditions (Christmas trees) or weather conditions (anoraks).

Here, we concentrate on agricultural products in Austria, a developed European economy. In such an economy, it is reasonable to envisage the seasonal patterns in the agricultural goods market as caused by a more or less time-homogeneous demand facing seasonal cycles in supply. Again except for certain food products with some sort of cultural tradition (ice cream in summer, turkey at Christmas, mutton at Easter time), consumer demand has no outright preferences for consumption at fixed points during the year, and Austrian consumers hastily seized the opportunity of having grapes and strawberries at Yule-tide, once these became available. It is the supply side (high transport costs) that still keeps the prices of out-of-season fruits above the level typical for domestically harvested food products. Hence, we will view all seasonal variations in the following as reflecting mainly supply-side effects. In this regard, we follow Barsky and Miron (1989) and Miron (1990) who attributed seasonality in industrial production to supply-side features, such as the pooling of employees' vacations to increase productivity. However, we follow Hylleberg (1990) and Ghysels (1990) in viewing seasonality as a flexible stochastic phenomenon.

In the literature, a wide variety of econometric specifications of seasonality can be found, often based on ad-hoc considerations. Only occasionally, researchers provide an explicit justification for their handling of seasonal variation (cf. Beaulieu and Miron, 1993, and Ghysels, 1990). Despite the fact that several authors have emphasized the significance of using unadjusted time series in economic modeling, numerous studies are still based on adjusted time series data, largely ignoring the possible effect that seasonal adjustment of individual time series bears on relations between them. As has been observed by Wallis (1974), this neglect might stem from the belief that the seasonal component of a given series should be viewed as "noise", and even if correlated with the seasonal component of another series, it may still be seen that way. However, it is doubtful if such strict decomposition is applicable to real-life data series. For example, Raynauld and Simonato (1993) argue that the orthogonality conditions between the seasonal and non-seasonal components imposed by seasonal adjustment procedures, including the frequency-domain approach advocated by Sims (1974), actually remove an important linkage. Also, Sims (1993) has pointed out that observations on economic behavior related to seasonal frequencies may often be informative about the unknown parameters we are trying to estimate in a regression, so that using seasonally adjusted data at best amounts to throwing away information and at worst could severely bias results (see also Sims, 1974 and Wallis, 1974).

The traditional approach is to decompose seasonal data into three unobserved components: trend, cycle, and seasonal, with economic interest focusing on the second component and possibly a fourth irregular component added. Depending on the criterion of optimality and the nature of the specification of the stochastic structure of the unobserved components, various seasonal adjustment methods have been suggested in the literature and also applied to data, with the objective to remove the seasonal component without distorting the remainder (see e.g., Grether and Nerlove, 1970). Some authors argue that the predominant use of seasonally adjusted time series may be justified for the aims of short-term forecasting and policy analysis, where the implicit view seems to be that the seasonal component as such is of little interest, being not only exogenous to the economic system but also uncontrollable, yet predictable (Wallis, 1974).

Recent developments in time series analysis, such as cointegration in the framework of vector autoregressions (VAR), enable the comprehensive modeling of economic time series in the presence of seasonality. In modeling agricultural phenomena, one of the areas where these new econometric techniques have been especially useful are supply-response relationships (see e.g., Eckstein, 1985; Wörgötter, 1990). Output response to a price change is not specified under *ceteris paribus* assumptions, but rather assumed to be possibly correlated with changes due to supply shifts, e.g., switches between farm enterprises.

In the VAR model used by Wörgötter (1990) to analyze supply response in the Austrian milk sector, certain variables were subjected to seasonal adjustment before they were used in the analysis. Raynauld and Simonato (1993) take up the common argument that multivariate models and especially VAR models are routinely used to highlight stylized facts, which may make the usage of adjusted series look more attractive. However, they point out that even though unadjusted series may need longer delays (for example, two seasonal lags, i.e., 24 lags for monthly series in the SARIMA framework are not uncommon) and these are not easily accommodated considering the number of variables to be included and the usual size of economic samples, researchers often fail to recognize the implicit loss of degrees of freedom stemming from the seasonal adjustment process when they estimate a model with officially adjusted series.

In this paper we use a VAR model to provide forecasts for the stock of breeding sows in Austria, in the presence of seasonal unit roots in some of the variables. The size of the breeding livestock is considered to be the key decision variable in pigmeat (pork) supply. In this regard, our study follows the related work by Hallam and Zanoli (1993) who, using VAR cointegration techniques and UK data, established one long-run relation between the herd size, the feed price, and the pig price but no long-run stable relations between any two of the three variables in pairs. Our study extends their supply response system by the producer price of bulls, i.e., an alternative category of livestock, and refines the procedure by explicitly accounting for seasonality.

The organization of this paper is as follows. Section 1 is a general introduction. Section 2 expounds the econometric methodology. Section 3 reports and interprets the empirical results. Section 4 concludes.

2. METHODOLOGY

2.1 *The concept of seasonal cointegration*

It is well established that the time-series behavior of many trending economic variables can be adequately described by *first-order integrated* processes. In short, a process is said to be first-order integrated (denoted I(1)) if its first differences are covariance-stationary (denoted I(0)). Typically, this concept provides a better approximation to the generating process of economic time-series variables than the alternative conception of trend stationarity. A variable is said to be *trend stationary* if it can be represented by the sum of a deterministic trend function and a stationary process. The two alternatives are notoriously difficult to discriminate statistically particularly as they represent non-nested hypotheses and the relevant properties are long-run features only recognizable after observing long trajectories of the processes.

Based on the Wold Theorem, any first-order integrated variable can be represented formally by the moving average representation of its first differences. Excepting certain cases of non-invertibility of this moving average representation, an equally valid and empirically handier representation is the autoregressive one, which in turn can be approximated to an arbitrary degree of precision by finite-order AR models such as:

$$\Delta y_t = y_t - y_{t-1} = a + \sum_{i=1}^{p} \varphi_i \Delta y_{t-i} + \varepsilon_t \tag{1}$$

The constant a gives rise to a linear trend in the process y_t of the form $y_0+\tilde{a}\,t$ for some $\tilde{a}$. In our analysis, we will henceforth assume that the data follow models like (1) with respect to their trend behavior.

I(1) models do not provide an adequate description of other non-stationary features of data series, in particular of non-stationary seasonal behavior. Again, there are two conflicting model conceptions available from the literature. Deterministic seasonal models assume seasonality to be explicable by adding a linear combination of seasonal dummies to models like (1). In contrast, seasonal unit root models view stationarity to be attainable only after application of a seasonal moving average filter $S(B)$, for the case of quarterly data

$$S(B) = 1 + B + B^2 + B^3 = (1+B)(1+B^2) \tag{2}$$

Joint application of first differencing (to remove the trend non-stationarity) and of seasonal averaging (to remove the seasonal non-stationarity) is equivalent to seasonal differencing or differencing at the seasonal lag, e.g., 4 for quarterly data, i.e., $\Delta_4=1-B^4$. The operator Δ_4 can be decomposed as $\Delta_4 = (1-B)(1+B)(1+B^2)$, hence if seasonal differencing is necessary to achieve stationarity, one speaks of processes with "unit roots at ± 1 and $\pm j$". Usage of the operator Δ_4 suggests replacing the basic model (1) by the *seasonally first-order integrated model*

$$\Delta_4 y_t = y_t - y_{t-4} = a + \sum_{i=1}^{p} \varphi_i \Delta_4 y_{t-i} + \varepsilon_t \tag{3}$$

In the following, we will work with our data as if they had been generated by a model of type (3). If actual variables are non-seasonal but have been seasonally differenced for the representation (3), then this imposes non-invertibility on the moving average representation of $\Delta_4 y_t$ and makes reasonable approximation by p-th order autoregressions impossible. We will see, however, that this difficulty can properly be accounted for in a multivariate framework.

Although the idea of error correction is much older, the seminal paper by Engle and Granger (1987) is to be credited for drawing attention to the fact that dynamic filtering with the goal of achieving stationarity may create severe problems in n-variate models, even in those cases where this filter is needed to make all individual series stationary and hence working with filtered data would be appropriate for univariate processes. Two or more series may be individually I(1) but a linear combination may be I(0). There may be up to n-1 such linear independent "cointegrating" combinations of this type ("cointegrating vectors") and the proper representation would be

$$\Delta Y_t = a + \alpha\beta' Y_{t-1} + \sum_{i=1}^{p} \Phi_i \Delta Y_{t-i} + \varepsilon_t \tag{4}$$

with $Y_t = (y_{1t},\dots,y_{nt})'$ and Φ_i being matrices of order $n \times n$. α and β are now matrices of full rank and order $n \times r$ with r the number of linear independent cointegrating vectors, usually called the *cointegrating rank*. It is interesting to note that possible stationary components y_i do not invalidate the representation but logically are "self-cointegrating" and the corresponding cointegrating vector is the unit vector with 1 at the i-th position. The matrix β contains the cointegrating vectors as columns and is therefore sometimes called the *cointegrating matrix*. The matrix α describes the influence of the r cointegrating relationships on the n variables and is therefore sometimes called the *loading matrix*, in analogy to classical principal components analysis.

If the n-variate vector is seasonally integrated, some components may be non-seasonal, some linear combinations may be non-seasonal but trending, other linear combinations may be non-trending but seasonal and again others may be non-seasonal and non-trending. Such features are called *seasonal cointegration* and are well presented in the work of Hylleberg et al. (1990). The overall representation (4) changes to:

$$\Delta_4 Y_t = a + \alpha_1\beta_1' S(B)Y_{t-1} + \alpha_2\beta_2' A(B)Y_{t-1} + \alpha_3\beta_3'\Delta_2 Y_{t-2} + \alpha_4\beta_4'\Delta_2 Y_{t-1} + \\ + \sum_{i=1}^{p}\Phi_i\Delta_4 Y_{t-i} + \varepsilon_t \qquad (5)$$

with $A(B)$ denoting the alternating dynamic operator $1-B+B^2-B^3$. In (5), β_1 contains (as columns) the long-run cointegrating vectors that sweep out stochastic trends in Y but, in general, not seasonals; β_2 contains semi-annual cointegrating vectors that sweep out the quicker seasonal patterns but neither the annual cycles nor the trends; β_3 and β_4 handle the annual seasonal cycles but not the other two frequencies, i.e., the long run and the biannual patterns. If $\beta_4=0$ then β_3 contains the annual seasonal cointegrating vectors. Just as in (4), non-seasonal variates show up by their corresponding unit vectors belonging to the β_2 and β_3 column spaces. In many empirical applications, it is safe to assume that so-called asynchronous cycles represented by β_4 do not really play a role, hence we will proceed under the assumption $\beta_4=0$. In this case, it may also be interesting to check whether the column spaces of β_2 and β_3 overlap. Then, certain linear combinations sweep out all seasonality at both the annual and semi-annual frequency.

From (5), note the idea of decomposing seasonal cycles with an annual frequency into a "faster" component (the "biannual" or "semi-annual" cycle) and a "slower" component (the annual cycle proper). The former part can be viewed as a sequence of type (+*a*,-*a*,+*a*,-*a*,...), the latter part as a sequence of type (+*a*,+*b*,-*a*,-*b*,+*a*,...). The two frequencies can also be envisaged in the frequency domain as distinct spectral peaks at the spectral frequencies π and $\pi/2$, respectively.

An algorithm to efficiently estimate the coefficient matrices has been provided by Siklos (1990) who based his GAUSS program on the procedure by Lee (1992). In analogy to the algorithm for estimating cointegrating structures in the absence of seasonality by Johansen (1988), the cointegrating vectors at each frequency evolve as solutions to conditional canonical correlation problems. The paper by Lee (1992) also contains some simulated significance points to check on the ranks of the matrices β_i (i=1,2,3). Lee and Siklos (1991) tabulate further significance points for the empirically relevant situation of augmenting (5) by deterministics such as constants, seasonal dummies, or linear trends. Although several procedures have proved to be useful in generating rank estimates from repeated LR-type tests on null hypotheses of lower ranks against alternatives of higher ranks, the entire strategy of estimating ranks based on tests appears awkward. Keeping in mind that the goal is rank estimation, not testing per se, and without any safe knowledge of criteria for evaluating the efficiency of discrete-parameter estimates in an otherwise continuous framework, all statistics and significance points should always be viewed as guidelines rather than rigorous statistical procedures.

This warning against over-reliance on statistical hypothesis tests in the seasonal cointegration framework in particular and in VAR models in general is supported by the observation that diagnostic checking tests in multivariate models rarely find a data set that passes all tests. Some authors save their assumptions - such as linearity, normality, homoskedasticity - by introducing dummies, usually ignoring the effect of this action on further testing. It is perhaps more reasonable to view the linear VAR as a fairly adequate approximation to a much richer economic reality. As long as the description remains "fairly adequate", some interpretation can still be given to identified statistical objects such as estimated long-run or seasonal features. A basic requirement for this aim is that the approximating VAR model is adequate within the class of *linear* structures, hence estimated errors should be ,e.g., reasonably free from serial correlation.

2.2 *The model*

The object of this study is a four-dimensional model of Austrian quarterly agricultural time series. In particular, we selected the following four variables:

SOB The real producer price for soy beans

BULL The real producer price for bulls

HOG The real producer price for pigs

SFB Stock of breeding sows

The real producer price series have been obtained by dividing nominal prices by the producer price index. These data series were available from the first quarter of 1972 to the second quarter of 1994. Time series plots of the four series (in logarithms, see below) are shown as Figure 1. A downward trend in all price series is clearly recognizable. The stock of breeding sows shows an upward slope followed by a downward slope, which could possibly point to a longer-run cyclical pattern. The downward part of the pattern also has an economic interpretation. It is probably due to farmers' expectations of the outcome of Austria's entry into the EU. Before January 1995, Austria's agricultural protection rate exceeded the EU average (see OECD, 1994). Entry into the EU will imply a reduction in price support and open up intense competition with meat products from other EU member countries due to the Common Agricultural Policy (CAP). The expected fall in pig product prices causes a corresponding fall in supply.

Beginning from Dean and Heady (1958), most previous studies on response in pig supply have used modifications of the original Nerlove model (Nerlove 1958). In this regard, the most common approach has been to employ some form of capital stock model embodying a Nerlove adjustment mechanism. Most researchers have also included a price expectations formulation in their supply models, with expectations often incorporating recent prices as well as those of one or several past periods, which reflects the lags between adjustment decisions (Askari and Cummings, 1976; Hayes and Schmitz, 1987). Following Hallam and Zanoli (1993), we model the stock of breeding sows directly.

Some earlier studies have considered the prices of pigmeat and of feed either individually (e.g., Holt and Johnson, 1988) or in combination as margins or ratios (e.g., Ness and Colman, 1976). Hallam and Zanoli (1993) exclude the possibility of significant cross-price effects as far as other outputs are concerned arguing that the specialist nature of pig production does not warrant the inclusion of a major substitute in a supply model. However, Jumah and Stehlik (1994) have found the producer price for pigs to be cointegrated with the producer price of bulls in the Austrian market. Also a look at the 1993 Austrian pig farm structure revealed that only 23.2% of all pig farms are pure stands, whilst 43.7% and 33.1% are mixed farms of pig and cattle and of pig and poultry (chicken, geese, ducks and turkeys), respectively (see "Nutztierhaltung in 1993," Schnellbericht, Österreichisches Statistisches Zentralamt, Wien).

We contend that the inclusion of the price of bulls is important because a price increase in the producer price for pigs will result in buyers substituting beef for pork, thereby increasing the demand for and causing the price of beef to increase. Producers will shift the factors of production, especially family labor and financial capital, towards the production of bulls to benefit from the higher price of beef. This relative reduction in the production of pigs will cause an increase in the price of pork. Similar price transmission mechanisms could evolve from price shocks to any of the three prices (i.e., including poultry prices) and are not specific to the producer price for pigs (see also Gordon et al., 1993). We therefore include the price of bulls in our analysis but exclude the price of poultry due to the inhomogeneity of this variable. In a preliminary version of this paper, we also included the price of calves but found that it was highly correlated with bull prices.

In our analysis, we rely on an input price for Austrian farmers (SOB), two output prices (BULL and HOG) and a quantity variable (SFB). All four raw series appeared to be volatile and non-stationary. Taking logarithms turned out to be a comfortable transformation as it reduced evidence on time-changing volatility. In particular, logged data permitted more parsimonious dynamics than non-logged data. Also many theoretical economic models use logarithmic transforms of original data. Moreover, logging establishes a convenient correspondence between growth rates of original data and first differences of logged data.

The framework of cointegrated vector autoregressions enables the distinction between short-run adjustment of variables to perceived deviations from equilibria and long-run equilibrium conditions. A priori, one would expect SOB to follow its own dynamics as it probably cannot be much influenced by the Austrian agricultural market. The treatment of seasonality also allows us to trace back the sources of seasonal fluctuations and to analyze the way they dynamically spread to the variates.

3. Empirical Results

3.1 The main results

The main results are summarized in Table 1. The estimation procedure for the cointegrating ranks r_i based on the significance tests and their simulated fractiles in Lee (1992) identified three cointegrating vectors at frequency zero (long run), no seasonality (4 cointegrating vectors) at frequency π ("semi-annual", two cycles per year), and two seasonal cointegrating vectors at frequency $\pi/2$ ("annual", one cycle per year). One short-run lag of $\Delta_4 Y_t$ was necessary to achieve serially uncorrelated errors, i.e., p=1 in (5), but the main features turned out to be rather robust with regard to changing the lag length. Fortunately, the result turned out to be unique with respect to whether multiple testing was conducted bottom-up or top-down, i.e., beginning from the null hypothesis "r_i=0 vs. r_i>0 or r_i=1" or from "r_i=3 vs. r_i=4".

Before attempting to analyze the fine structure of the results, i.e., the cointegrating vectors etc., we would like to point out that the cointegrating ranks provide some interesting information on their own. Firstly, three long-run cointegrating vectors mean that there is just one "common trend" in the system that drives all four variables. Notwithstanding the fact that there is no unique definition of what such a common trend is, it is tempting to investigate whether such common trend is linked closely to one or two variables. Loosely speaking, this variable may then be viewed as "exogenous in the long run" to the other ones.

Secondly, the absence of semi-annual seasonality points to the regular "sinusoidal" nature of seasonal cycles in agricultural series, reminding of the smooth seasonal structure in meteorological data such as temperature. On the other hand, two seasonal cointegrating vectors at the annual frequency indicate that there are two independent sources of seasonal cycles in the system, which in turn could perhaps also be linked to two data series.

All of these estimation results are more reliable if the overall model conforms with the statistical assumptions. These assumptions concern serial non-correlation of the errors (innovations) as well as normal distribution but the first point is probably the more critical one. It turned out that the rank-restricted cointegrating model is "clean", i.e., without 5% significant residual autocorrelation with one short-run lag of $\Delta_4 Y$ added. Since there is no seasonality at the biannual frequency, the system should rather be written in the following way with two lags of the operator $A(B)$ whose application suffices to render all series stationary:

$$A(B)Y_t = \Phi_1 A(B)Y_{t-1} + \Phi_2 A(B)Y_{t-2} + \alpha_1\beta_1'(1+B^2)Y_{t-1} + \\ + \alpha_3\beta_3'\Delta Y_{t-2} + \varepsilon_t \qquad (6)$$

Slight evidence on remaining flaws is provided by the Ljung-Box Q statistics whose significance reaches levels of around 8% for the residuals of equations 2 and 3, i.e., the equations determining BULL and HOG.

Estimates for all parameters of model (6) under the restrictions identified from our analysis - i.e., a rank of 3 for $\alpha_1\beta_1'$ and a rank of 2 for $\alpha_3\beta_3'$ - are shown in Table 2.

3.2 Tentative interpretation of the results

As in many empirical applications of the seasonal cointegration procedure, results are not easily interpretable and occasionally are at odds with theoretical considerations (see, e.g., Kunst, 1993a,b). However, a careful look at the empirical summary in Table 1 allows some further insight into the structure of the agricultural supply system.

Typically, economic interest focuses on the long-run features summarized in the first panel of Table 1. There are four vectors evolving as solutions from a canonical correlation procedure between seasonal differences of the variables and the seasonally averaged series. According to the statistical hypothesis test, the lower three of them "cointegrate", i.e., they generate stationary variables. The uppermost does not cointegrate. The evolving "components" are graphically represented as Figure 2. This decomposition into components can be viewed as a dynamic counterpart to classical principal components analysis (PCA). Whereas PCA orders the transformed series according to their share in the total of explained variance, cointegration-based components are ordered according to the (conditional) correlation between succeeding observations. In the first three components, such correlation is sufficiently smaller than 1 to statistically reject the hypothesis of unit-root non-stationarity in favor of stationarity. In the fourth component, this correlation between past and present is so close to unity that the series is seen as first-order integrated at the zero frequency.

Counted from bottom up, the first cointegrating vector appears to tie the stock of breeding sows to bull prices. Interestingly, it is not the price of pigs that is taken as an indicator for the long-run evolution of sow stocks but the price of bulls, maybe because this is a more reliable indicator of overall price behavior. However, the difference is not extremely important, as the second cointegrating vector establishes a joint long-run movement of bull and pig prices.[1] Co-movements of bull and pig prices dominate substitution effects in the long run. Finally, the third vector relates the development of output prices (again with an emphasis on bull prices) to input prices, as we suppose these are well indicated by our variable SOB. This structure appears economically reasonable.

If there are three cointegrating vectors in four variables, there is only one common trend, a "backbone" for the long-run evolution of the system. A priori, we supposed that SOB may represent such a trend. Unfortunately, the definition of the "common trend" is not unanimous in the literature but most authors prefer $\alpha_1^{\perp}{}'X_t$ to alternative definitions (see Gonzalo and Granger (1991)). Here, $\alpha_1^{\perp}$ denotes the orthogonal complement to the matrix α_1.

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[1] This squares with the remark by Engle and Granger (1987) that prices of close substitutes in the same market are expected to be cointegrated.

Note that it is the orthogonal to the long-run or zero-frequency loading matrix and not to the cointegrating matrix β_1 that is used. In our case, this common trend turns out to be

$$\text{TREND} = 0.14 \text{ SOB} + 0.47 \text{ BULL} + 0.66 \text{ HOG} - \text{SFB} \quad (7)$$

The resulting variable TREND is smoothly changing in a way close to a random walk. Contrary to theoretical considerations, all variables contribute substantially to TREND, with the overall influence of price variables appearing to be the dominant force. Note that the sign of the common trend is technically undefined and that the variable TREND defined in (7) shows a persistent downward motion.

It is worth pointing out that our results differ in an important point from those of Hallam and Zanoli (1993) who only found *one* cointegrating vector in a set of three variables closely corresponding to our SOB, HOG, and SFB. Whereas they do not find a long-run relation between input and output prices, we do find such a relationship. Adding the alternative producer price BULL to the system then allows us to identify one further cointegrating relation linking developments in the two livestock prices. In other words, the three-variable agricultural system of Hallam and Zanoli (1993) contains two separate common trends whereas one stochastic trend suffices to describe long-run movements in our full set of four variables. Also note that Hallam and Zanoli (1993) were using a lower observation frequency (half-yearly data). In our sample, the finding of three cointegrating vectors is relatively robust against different specifications of seasonality, though the third vector becomes just marginally significant - i.e., the corresponding eigenvalue statistic just matches its theoretical 5% fractile point - if seasonality (deterministic or stochastic) is ignored completely in the VAR specification.

It is seen from the bottom panel of Table 1 that all four vectors cointegrate at the semi-annual frequency. Hence, there is no integration at this frequency and any interpretation of these vectors becomes uninteresting. Turning to the seasonally cointegrating structures at the annual frequency (center panel), we note a joint seasonal movement in the stock of sows and in the prices of soy beans (used for feeding) as well as in the market price for pigs.

Although it would be preposterous to slaughter all pigs when feeding becomes seasonally more expensive and to repeat this action every year, a marginal effect of that kind appears to be entirely rational. Such an effect is well known from colder climates where the herd sizes of sheep are greatly reduced in autumn when grazing becomes impossible due to the onset of snowfalls. Exercises parallel to those depicted in Figure 2, but now with respect to the seasonal features, are graphed as Figures 3 and 4. For definitions and further details on common seasonals, see Kunst (1993b).

3.3 Predicting future developments

Based on (6) and the coefficient estimates displayed as Table 2, a forecasting system can be set up. In a vector autoregression, all variables - including the theoretically exogenous SOB - are assumed as endogenous, hence such forecasting can be conducted for all four variables. However, we were mainly interested in the evolution of the stock of sows. The out-of-sample prediction based on the estimates and on the identified seasonally cointegrating structures is shown as Figure 5.

For an analysis of the merits and drawbacks of using seasonal cointegration in prediction, see Kunst (1993b), where it was demonstrated that the true model with respect to the number of seasonally cointegrating vectors typically fails to dominate its "misspecified" rival models with respect to forecasting accuracy (see also Reimers, 1995). In fact, this is not only true for seasonal cointegration but also for the classical case of long-run cointegration, as was shown by, e.g., Brandner and Kunst (1990), among others. Correspondingly, in the analysis of Engle and Yoo (1987), imposing the correct cointegrating restriction enhanced τ-step prediction for $\tau>5$ only. In summary, forecasting is a very special purpose for an econometric model and "best" models according to statistical criteria are not necessarily best forecasting models. In consequence, some forecasters prefer to evaluate their models by ex-post and ex-ante prediction based on some reasonable model specifications rather than by common statistical measures such as likelihood-ratio tests and information criteria.

In our setting of a seasonally cointegrating VAR, the following prediction experiments look promising:

(1) Ex-post analysis to see how well the model tracks its own reality. This experiment was conducted and produced extremely satisfactory results, as usual.

(2) The long-run and seasonal cointegrating vectors are taken from the full sample but all other short-run coefficients are re-estimated for a shorter interval and the omitted observations are then forecasted.

(3) The decision on cointegrating ranks is adopted from the full sample, i.e., Table 1. Everything else is re-estimated. Cases 2 and 3 are representative of the idea that the cointegrating features are possibly *true* and hence best estimated from a longer time span but all other features are possibly unstable or lag lengths are under-specified.

(4) Full ex-ante prediction in the European sense of the word.

(5) Out-of sample ex-ante prediction in the American sense of the word. This experiment is shown in Figure 5. In order to get a better understanding of longer-run prediction properties, we also recommend stochastic simulation, even in a linear model. The resulting pictures are possible scenarios if random shocks are drawn from Gaussian distributions with their variances taken from the sample estimates.

The qualitative result from experiments 2 to 4 can be summarized as follows. For cases 2 and 3 and for prediction intervals covering up to 2-3 years, prediction is almost as accurate as in case 1. The only exceptions are a slight under-prediction of soy-bean prices SOB with corresponding slight over-prediction of the herd size SFB. For our data set, the canonical correlations, by which the cointegrating ranks are determined, proved remarkably robust against shortening the sample from the end, hence experiment 4 was no different from experiment 3. An exemplary graphical protocol of a case 2 experiment with just the last 6 observations predicted is shown as Figure 6.

On the whole, the prediction performance of the model proved "satisfactory" according to visual criteria for known data, hence it is tempting to presume that it will also be satisfactory for future developments. However, this conclusion only holds true if the immediate future does not bring any unforeseen major changes in the economic environment.

Austria's full membership in the European Community from January 1995 could be such a major change. EU membership brought some changes in legislation emanating from the CAP. Pfingstner (1994) pointed out that, at the early stage of Austrian EU membership, the producer price of pigs will decrease by 22 %. As already outlined, Austrian farmers seem to have anticipated such a price fall by gradually reducing the level of livestock. Future data will decide on whether our assumption is correct - i.e., that the main agricultural supply response structures are stable and continue to hold - or whether this is a case for exogenously determined structural breaks.

4. Conclusion

We have examined the relevance of incorporating seasonality in agricultural supply models. Former studies have eliminated the problem of seasonality by using seasonally adjusted data. Recent developments in cointegration techniques allow the comprehensive modeling of error-correcting structures in the presence of seasonality. Without accounting for seasonality, Hallam and Zanoli (1993) have identified exactly one cointegrating vector in semi-annual data for the United Kingdom. Our conclusions for the Austrian market are different from Hallam and Zanoli's conclusions for the UK market. Whereas Hallam and Zanoli's cointegrating relation expresses one long-run equilibrium condition between herd size, input, and output prices, the three cointegrating vectors found for Austria correspond to long-run individual relations between producer's prices and the herd size, between producer's prices of close substitutes, and between input and output prices.

In many empirical applications of the seasonal cointegration procedure, results are not easily interpretable and occasionally are at odds with theoretical considerations. In contrast, the results of our analysis seem to meet economic criteria. This shows the robustness of our model's validity.

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TABLE 1: Main empirical results of seasonal cointegration analysis. Canonical vectors (shown as row vectors) at long-run and seasonal frequencies. Significant cointegration due to the specified vector at each frequency is indicated by an asterisk. Columns correspond to SOB, BULL, HOG, SFB in this order.

(a) canonical vectors at frequency 0

0.0857	-0.5100	0.0120	-0.9523	
0.6773	-1.0693	-0.3816	-0.0416	*
-0.0366	-0.9295	0.9886	0.5233	*
0.1044	-1.3044	0.5975	1.1300	*

(b) canonical vectors at frequency π (semi-annual cycles)

0.0708	7.3645	-5.8777	-2.1497	*
1.2332	-4.4036	-5.2912	10.8851	*
1.7843	2.4355	6.8005	-9.4491	*
-0.1877	13.1036	2.7092	9.0389	*

(c) canonical vectors at frequency π/2 (annual cycles)

0.1632	9.3131	2.7884	0.6245	
0.0832	6.1544	-3.5824	1.0112	
-0.7647	0.0296	1.2931	14.2996	*
2.1086	-0.3761	0.7107	5.4606	*

Example: Take the second row vector from the bottom. We see that -0.76*SOB+0.03*BULL+1.29*HOG+14.30*SFB defines a variable which is free from seasonal cycles at the annual frequency. As all variables are free from semi-annual cycles, this vector cointegrates at both seasonal frequencies and the resulting variable is non-seasonal.

TABLE 2: Parameter estimates for the seasonally cointegrated vector autoregressive model for the four series contained in the agricultural supply system with the four series (SOB, BULL, HOG, SFB) = (Y_1, Y_2, Y_3, Y_4). Estimation has been conducted by Maximum Likelihood under the rank restrictions identified from Table 1. See formula (6) in the text.

$$A(B)\begin{bmatrix} Y_{1t} \\ Y_{2t} \\ Y_{3t} \\ Y_{4t} \end{bmatrix} = \begin{bmatrix} -1.68 \\ -1.57 \\ 1.15 \\ -0.20 \end{bmatrix} + \begin{bmatrix} -0.04 & 0.70 & 0.09 & -0.02 \\ -0.01 & 0.38 & 0.07 & -0.12 \\ 0.01 & 0.41 & 0.12 & -0.76 \\ -0.00 & 0.07 & 0.01 & -0.12 \end{bmatrix} A(B) \begin{bmatrix} Y_{1,t-1} \\ Y_{2,t-1} \\ Y_{3,t-1} \\ Y_{4,t-1} \end{bmatrix} +$$

$$+ \begin{bmatrix} -0.12 & 0.37 & -0.31 & -0.09 \\ -0.01 & 0.46 & -0.14 & -0.27 \\ -0.03 & -0.22 & 0.45 & -0.99 \\ 0.02 & -0.08 & 0.11 & -0.12 \end{bmatrix} A(B) \begin{bmatrix} Y_{1,t-2} \\ Y_{2,t-2} \\ Y_{3,t-2} \\ Y_{4,t-2} \end{bmatrix} +$$

$$+ \begin{bmatrix} 0.19 & 0.03 & -0.48 \\ 0.20 & 0.06 & 0.02 \\ -0.20 & 0.10 & 0.08 \\ -0.01 & 0.10 & -0.01 \end{bmatrix} \begin{bmatrix} 0.68 & -1.07 & -0.38 & -0.04 \\ -0.04 & -0.93 & 0.99 & 0.52 \\ 0.10 & -1.30 & 0.60 & 1.13 \end{bmatrix} (1+B^2) \begin{bmatrix} Y_{1,t-1} \\ Y_{2,t-1} \\ Y_{3,t-1} \\ Y_{4,t-1} \end{bmatrix} +$$

$$+ \begin{bmatrix} 0.44 & -0.19 \\ 0.00 & 0.00 \\ 0.02 & 0.02 \\ 0.01 & 0.06 \end{bmatrix} \begin{bmatrix} -0.7647 & 0.0296 & 1.2931 & 14.2996 \\ 2.1086 & -0.3761 & 0.7107 & 5.4606 \end{bmatrix} \Delta \begin{bmatrix} Y_{1,t-2} \\ Y_{2,t-2} \\ Y_{3,t-2} \\ Y_{4,t-2} \end{bmatrix} + \varepsilon_t$$

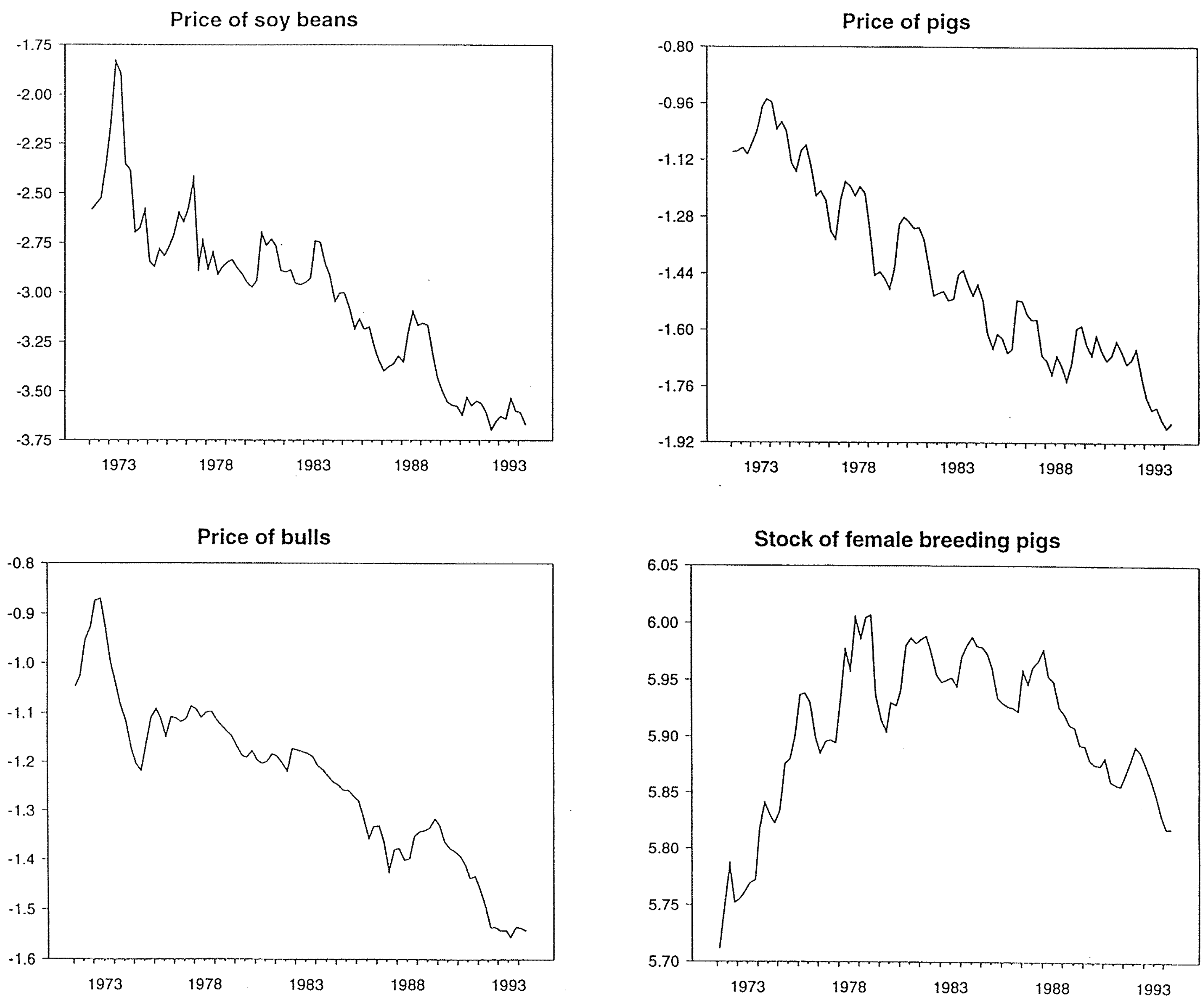
Price of soy beans
-1.75
-2.00
-2.25
-2.50
-2.75
-3.00
-3.25
-3.50
-3.75
1973
1978
1983
1988
1993
Price of pigs
-0.80
-0.96
-1.12
-1.28
-1.44
-1.60
-1.76
-1.92
1973
1978
1983
1988
1993
Price of bulls
-0.8
-0.9
-1.0
-1.1
-1.2
-1.3
-1.4
-1.5
-1.6
1973
1978
1983
1988
1993
Stock of female breeding pigs
6.05
6.00
5.95
5.90
5.85
5.80
5.75
5.70
1973
1978
1983
1988
1993

FIGURE 1

Long-run Components of Agricultural Price System

 # 1 to 3 are statistically stationary

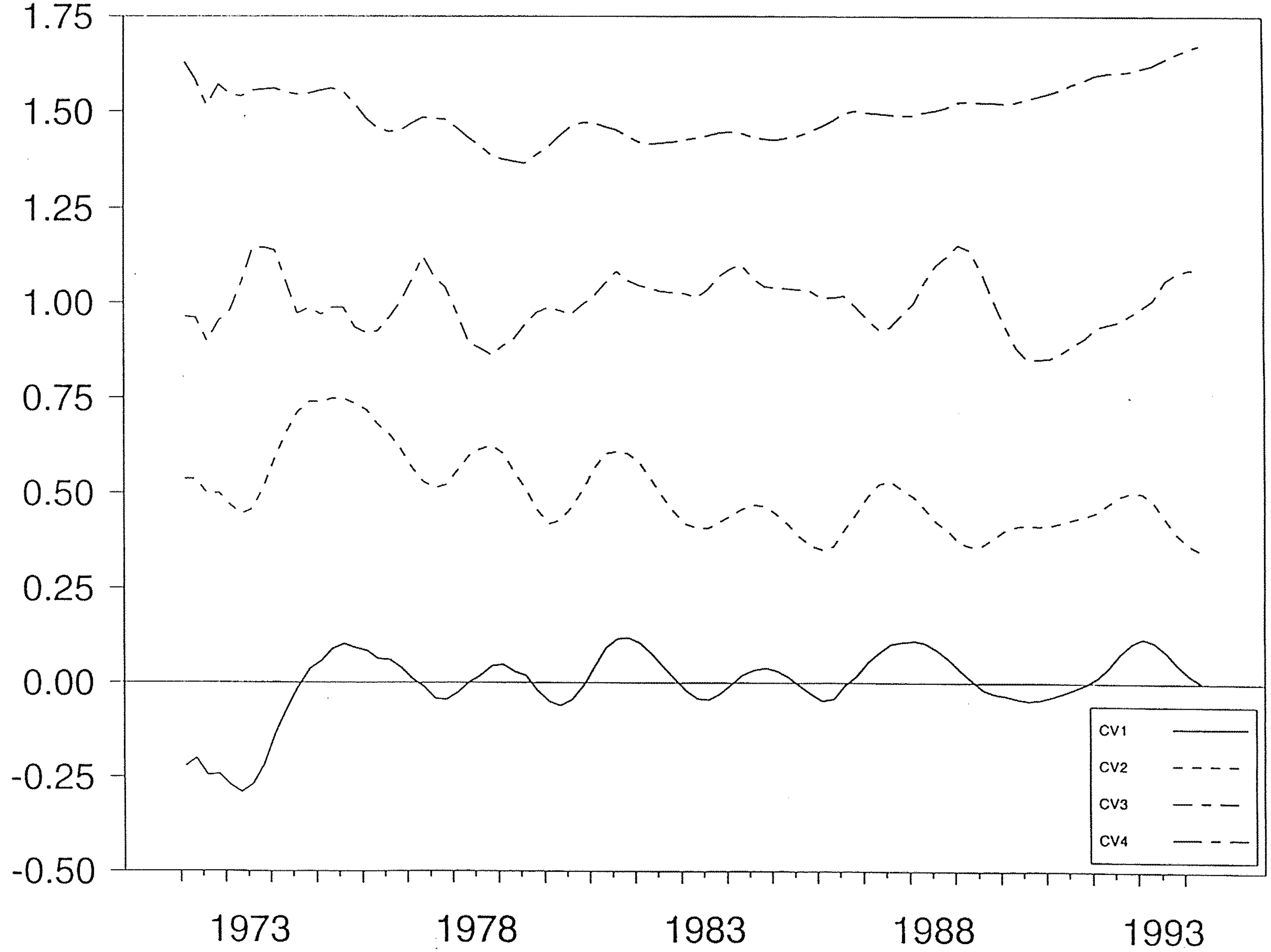

FIGURE 2

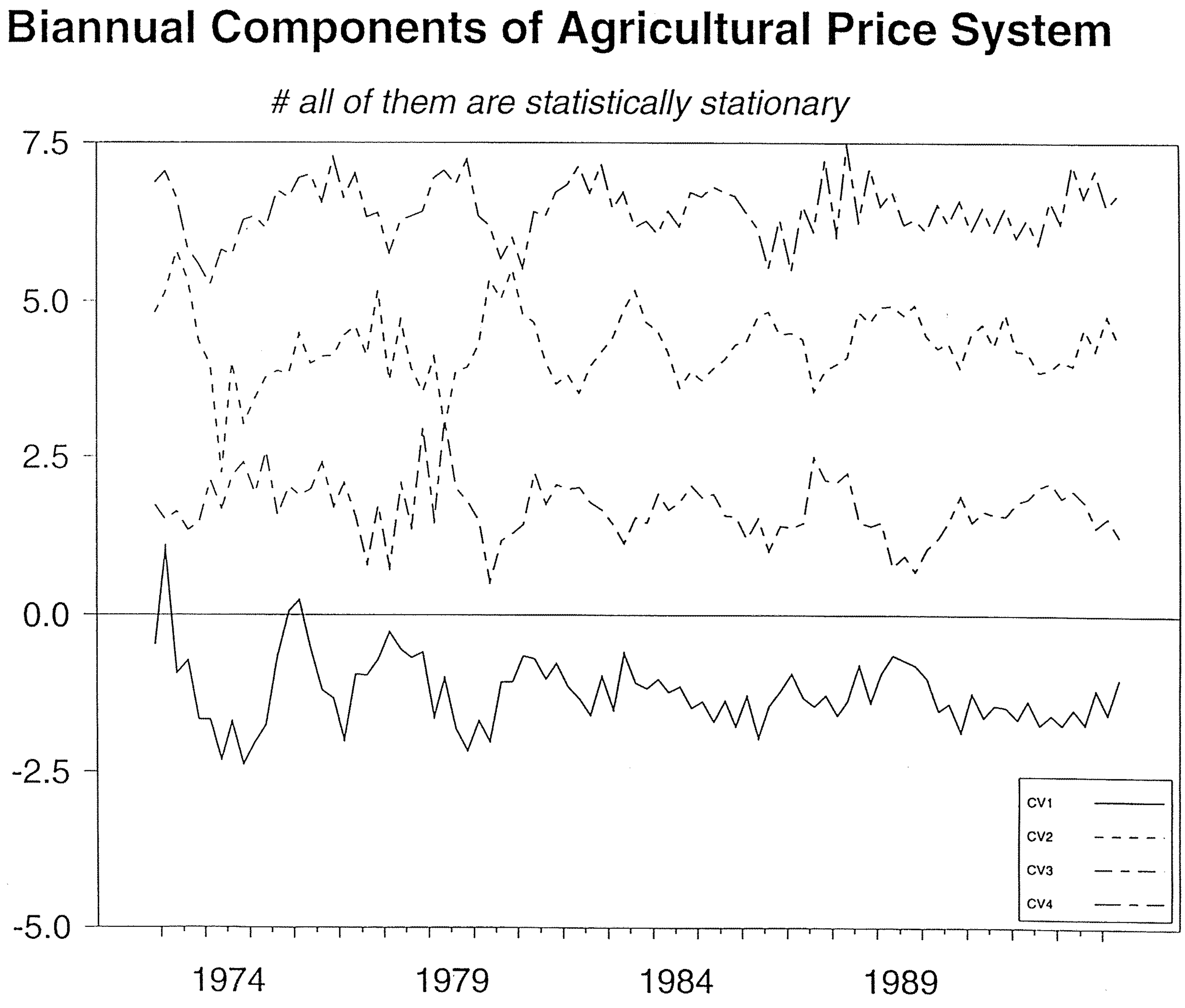
Biannual Components of Agricultural Price System
all of them are statistically stationary
7.5
5.0
2.5
0.0
-2.5
-5.0
1974
1979
1984
1989
CV1
CV2
CV3
CV4

FIGURE 3

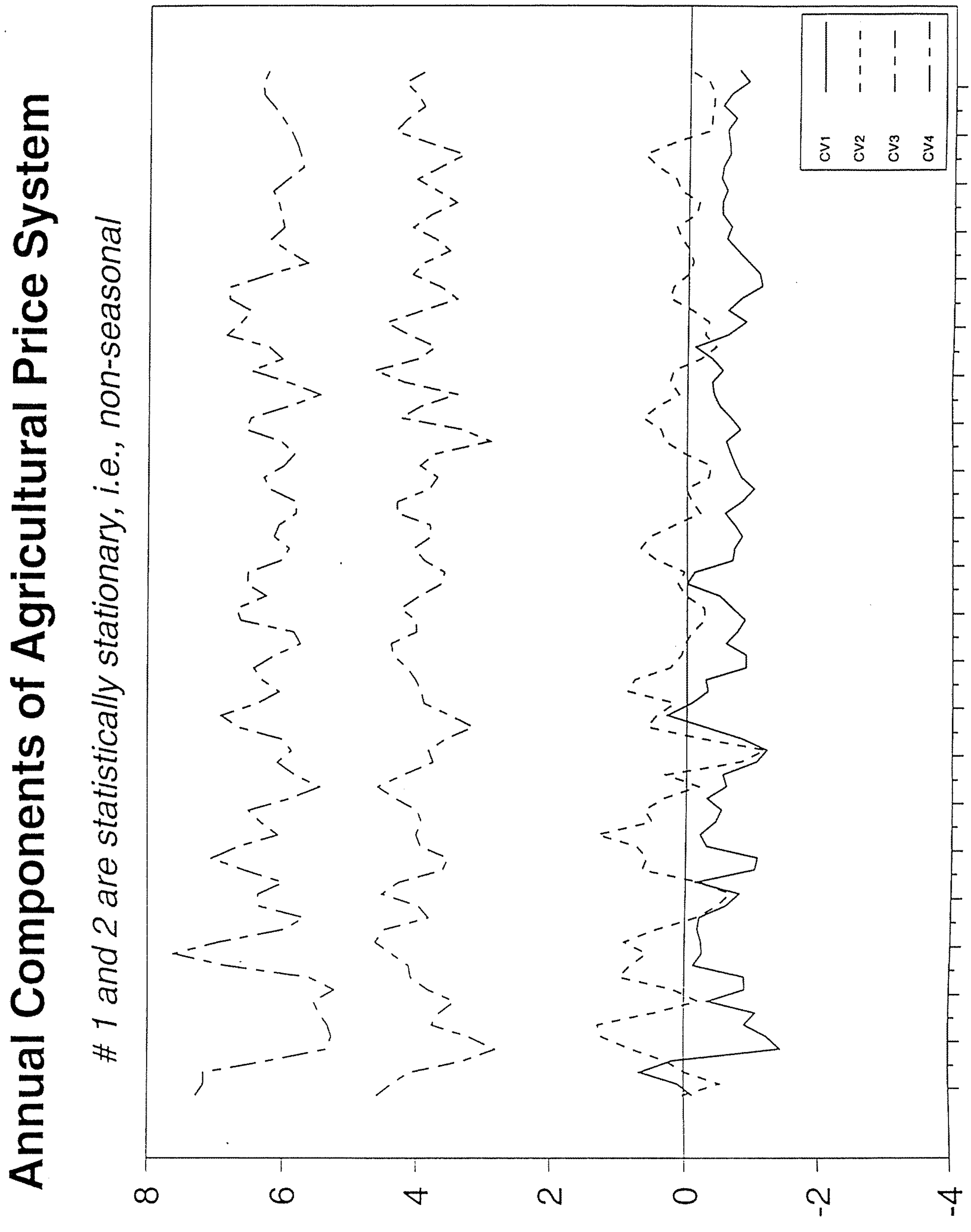
Annual Components of Agricultural Price System
1 and 2 are statistically stationary, i.e., non-seasonal
8
6
4
2
0
-2
-4
1974
1979
1984
1989
CV1
CV2
CV3
CV4

FIGURE 4

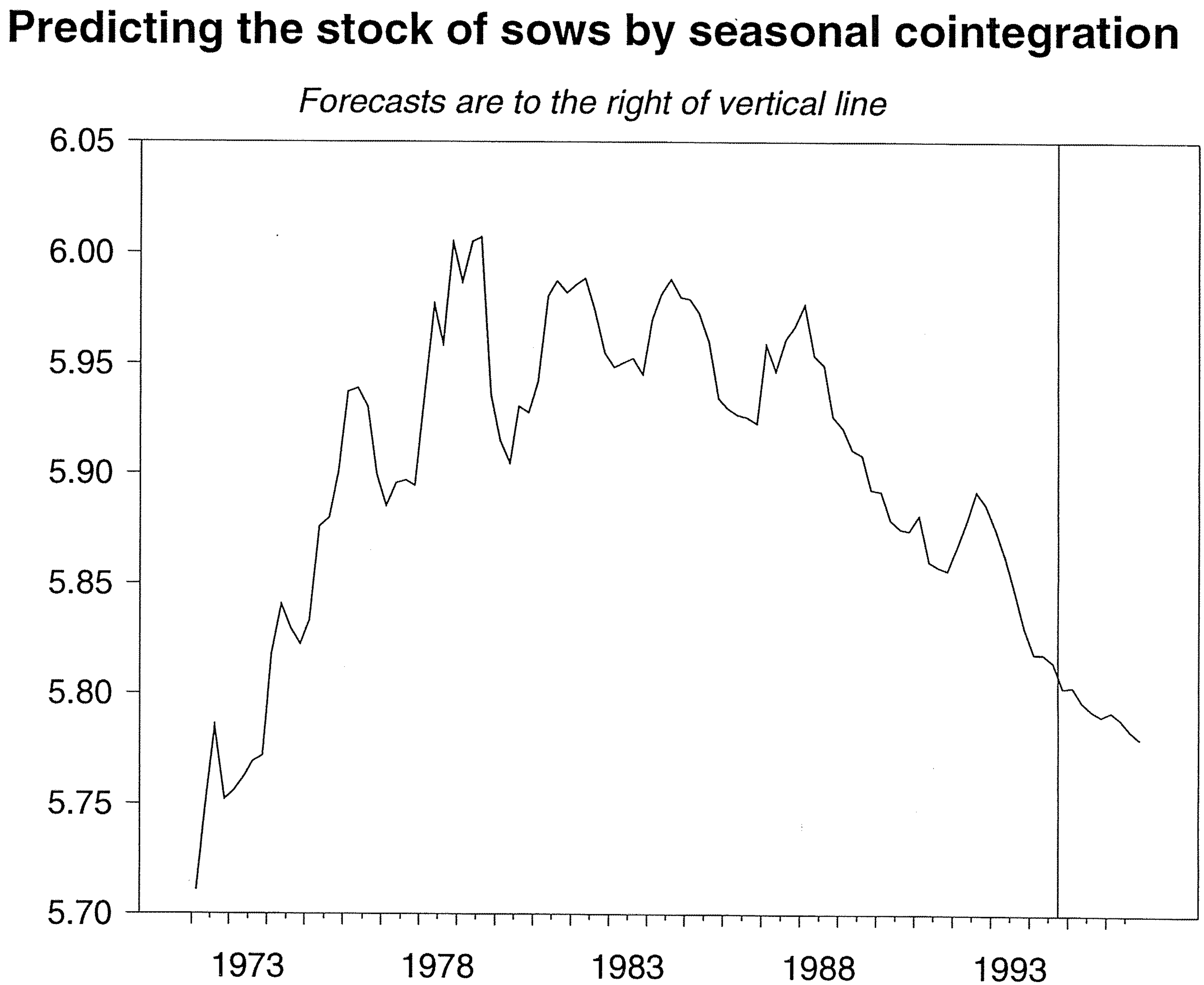
Predicting the stock of sows by seasonal cointegration
Forecasts are to the right of vertical line
6.05
6.00
5.95
5.90
5.85
5.80
5.75
5.70
1973
1978
1983
1988
1993

FIGURE 5

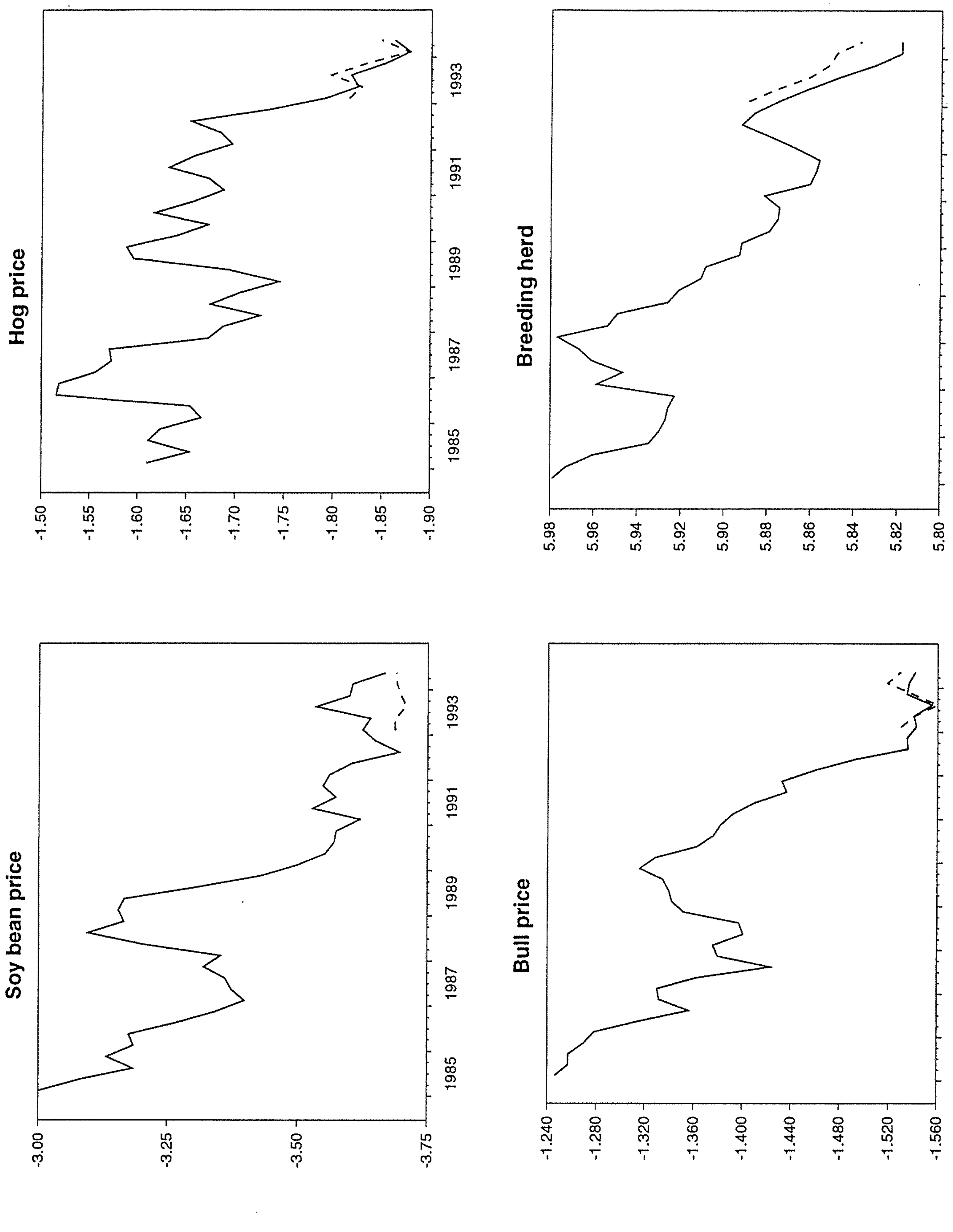
Soy bean price
-3.00
-3.25
-3.50
-3.75
1985
1987
1989
1991
1993
Hog price
-1.50
-1.55
-1.60
-1.65
-1.70
-1.75
-1.80
-1.85
-1.90
Bull price
-1.240
-1.280
-1.320
-1.360
-1.400
-1.440
-1.480
-1.520
-1.560
Breeding herd
5.98
5.96
5.94
5.92
5.90
5.88
5.86
5.84
5.82
5.80

FIGURE 6

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