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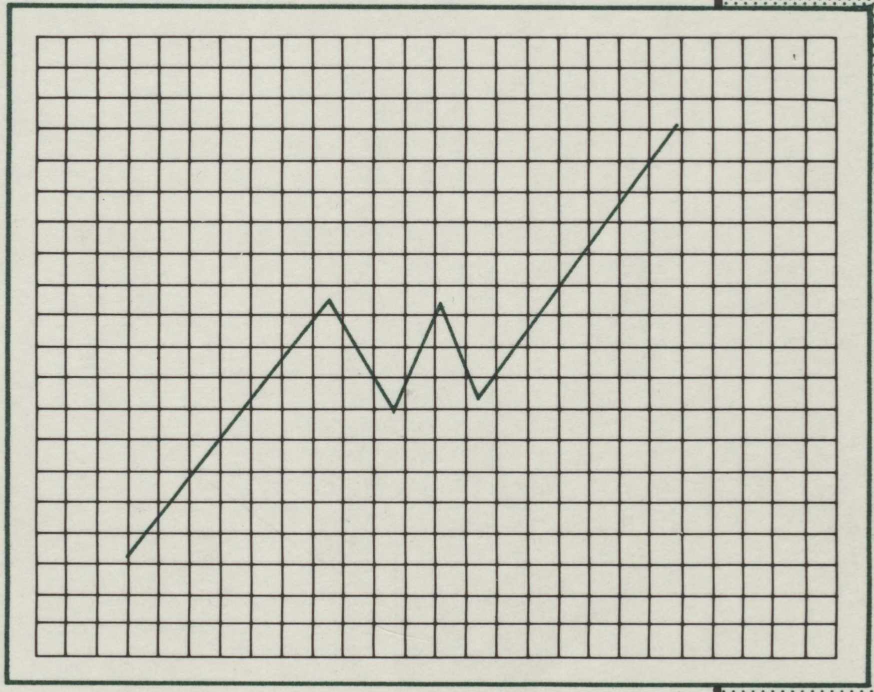

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PRICE INTER-RELATIONSHIPS IN THE SOUTH AFRICAN MEAT MARKET I: THEORETICAL AND EMPIRICAL CONSIDERATIONS*

by A.F. VAN HEERDEN, J. VAN ZYL and F.L. VIVIER**

ABSTRACT

This article explains the theoretical aspects underlying the determination of price inter-relationships, price leadership and the time that it takes for prices to react to change. The model is discussed and expounded on the basis of four steps: stationary-stochastic processes, simple autoregressive models, causality testing and multiple autoregressive models. The use of the model is not without limitations and pitfalls, but when applied with economic realism and logic, the results can be useful.

INTRODUCTION

The greater part of the South African agricultural products market functions in terms of the Marketing Act, which means that there is interference in the marketing mechanism. The meat market, for example, is for the most part subject to statutory interference by floor prices and supply control, which affects the amount supplied and therefore also the prices. This causes the loss of much of the natural economic dynamism, with the consequence that prices cannot fully fulfil the role expected by the market, since price signals do not reflect actual market realities.

A free market economy, particularly in a controlled economic situation, where decisions constantly have to be formulated and/or taken on price, promotion, distribution, production and product policy, requires the decision-makers to strive continuously for better knowledge of the product or service as well as its external environment. Knowledge with regard to the prices of products is therefore also at issue in the search for complete knowledge. This knowledge includes the price interaction between prices of substitutes and complements and also the determination of price leadership. Awareness of the total effect of the change of a price in a specific market segment or industry will enable the decision-makers, particularly in a controlled economic situation, to take their decisions with more circumspection and overall responsibility.

Various studies and empirical analyses of the demand for meat have already been conducted in South Africa. The calculation of price and cross-elasticities of the demand for meat received particularly close attention. Studies by Du Toit (1982), Hancock *et al.*, (1984), Laubscher & Kotze (1984) and Lubbe (1984) and others bear witness to this. The research conducted up to the present in South Africa, however, concentrated to a lesser extent on price interactions, and price leadership was largely ignored. Price interaction was indeed taken into account to a certain extent through the calculation of cross-elasticity of demand. The period taken for changes to filter through was completely ignored, however. The utility of this time aspect and price leadership is obvious and the job of market analysers and policy-makers could be greatly facilitated and made more comprehensive. This study aims at filling the gap that exists and establishing a model within which price interactions and market price leadership can be identified, empirically analysed and proved.

The approach followed is both descriptive and logically structural. This offers the researcher the advantage of the emphasis falling on analysis, measurement and interpretation of the four components of time series, namely the trends and the seasonal, cyclical and irregular components.

With the above taken into account, this analysis is based on a time series model. The relationships and interaction between retail trade meat prices are first determined by means of Haugh Pierce chi-squared causality tests and the research then includes the determination of suitable autoregressive (AR) models, which form the basis for the analysis of dynamic price behaviour. Calculation of the dynamic multipliers of the AR models provides values of the net impact of price changes in a market segment.

This article establishes the theoretical aspects basic to such an approach. The practical application of these is illustrated in a subsequent article, with the help of an empirical system.

STATIONARY-STOCHASTIC PROCESSES

A time series model forms the basis of the analysis. The statistical theory of time series analyses accepts that the series under investigation is stationary: this means that the mean and the covariance are not a function of time (Gregory, 1975: 62). The first step in the analysis is therefore to remove the deterministic

*This article is the first of two. The second article illustrates the theory with the help of a practical case study

**University of Pretoria

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nature of the time series by means of a differencing filter, and in this way to transform the time series into stationary-stochastic components. This process is subsequently explained.

Gregory (1975: 62) defines a stationary time series as follows: "In a stationary time-series the mean and covariance are not a function of time." Weekly cash prices of commodities have certain patterns caused by components such as inflation, storage costs and population growth. If a time series could be made stationary by measuring differences, these deterministic patterns would have been filtered out (Grant *et al.*, 1983: 3).

A stationary-stochastic process is absolutely stationary if the process is independent of the epoch of origin, i.e. if the joint observations of data points with m observations $Zt_1, Zt_2 \ldots Z_{tm}$, taken at times $t_1, t_2, t_3, \ldots {}_{tm}$ are the same as m observations $Zt_{1+k}, \ldots Zt_{m+k}$, taken at times $t_{1+k}, t_{2+k}, \ldots t_{m+k}$. If a time series is absolutely stationary, the joint distribution of any group of observations will therefore not be affected by the forward or backward adjustments of the epoch at which the series of observations was made (forward or backward adjustment takes place at an integral constant quantity, e.g. k) (Box & Jenkins, 1976: 26).

When $m = 1$, the stationary assumptions imply that the probability distribution p(zt) will be the same for any epoch and it can therefore be written as p(z). The stationary process therefore has a constant mean. The stationary time series will also have a constant variation which measures the distribution around the levels of the mean (Box & Jenkins, 1976: 1-9).

The stationary assumptions also imply that the common probability distribution $p(Zt_1, Zt_2)$ will be the same for all periods t_1, t_2 which vary by constant intervals. The relationship between the joint distribution may be proposed by plotting the paired values $(Zt, Zt + k)$ of a time series divided by a constant lag k. It is accordingly clear that neighbouring values of a time series are correlated; the correlation between Zt and $Zt + 1$ is negative and the correlation between Zt and $Zt + 2$ is positive. The covariance between Zt and $Zt + k$ with time intervals of k are known as autocovariance with lag k.

SIMPLE AUTOREGRESSIVE MODELS

Step two in the model is the filtering of the stationary-stochastic components by means of simple autoregressive models of the order p (AR(p)), so that the residues are reduced to white noise. Depending on the order of the AR that is necessary to reduce the residues to white noise, it may be explained that the specific order of AR has removed the correlation that remained and that the AR (p) process therefore explains the correlation. The Box and Pierce Q statistic is used to test to what extent the AR(p) model has succeeded in reducing the residues to white noise (Box & Pierce, 1970: 1509-1526).

The purpose (action) of a filter is to transform the input X(t) to an output Y(t), which is then a function of the input values at time $t = 1, 2, \ldots$. Any calculation applied to a time series can therefore be regarded as a filter. A simple example is:

$$Y(t) = 1/2\ (X(t-1) + X(t)), \qquad \ldots\ldots\ (1)$$

which is a filter with input X(t) and output Y(t), such that Y(t) is the mean of X(t) and its predecessor X(t-1). The application of a measurement of differences on a time series to remove the trend is therefore also a filtering process, which may be represented as follows:

$$e_t = X_t - \hat{\mu}_t \qquad \ldots\ldots\ (2)$$

where X_t = the original time series
$\hat{\mu}_t$ = the trend (estimated mean over time)
e_t = residues

The residues e_t are then investigated by means of autoregressions of order p (AR(p)), for example, to identify the possible autocorrelation processes of the order p that may occur. If this autocorrelation is removed by the AR(p) process and the resulting residues are white noise, indicating that no further autocorrelation will occur, the causality between X and Y is explained by the autoregressive-order p process.

The purpose of linear filters is to transform the input X(t) to the output Y(t), which is then a function of the input values at times $t = 1, 2 \ldots$ In time series in which successive values are highly dependent on one another, stochastic models can be helpful if they are generated from a series of independent "shocks" a_t. These shocks are random samples from a fixed distribution of values usually having a normal distribution with the mean equal to zero and the variance σ_a^2. This order of stochastic variables $a_t, a_{t-1}, a_{t-2}, \ldots$ is known as white noise (Box & Jenkins, 1976: 8). White noise therefore means that no further correlations exist. The transformation process can be explained as follows:

$$Z_t \longrightarrow \boxed{\text{Linear filter}} \longrightarrow A_t$$

where Z_t = stationary series
A_t = white noise

If the AR(p) filter is sufficient, the calculated Q (according to the Box and Pierce Q statistics) will assume a value that is less than the chi-squared value and it may be accepted that the residues are reduced to white noise by the AR(p) filter.

CAUSALITY TESTING

Step three is the determination of causality between the series by means of Haugh-Pierce causality tests. If no series correlation occurs in the residues of the series, the cross-correlation of the variables of two series can be analysed to determine whether there is a possible causal relationship between the series (Pierce & Haugh, 1977: 121-130).

This cross-correlation at lag k for k greater than zero provides an estimate of the impact of Y_1 on Y_2, for example. The opposite of this, i.e. the effect of Y_2 on Y_1, will occur with cross-correlation at lag k for values of k less than zero. The total test for determining how significant the relationship between time series is, is the chi-squared statistic (Pierce, 1977b: 11-22).

The hypothesis that two time series, Y_1 and Y_2, are independent (no relationship) of each other (written $Y_1 \not\leftrightarrow Y_2$), can be rejected at the α level of significance as

$$U_m = T \sum_{k=-m}^{m} \bar{r}_k^2 > \chi_{2m+1}^2 (\alpha) \quad \text{........ (3)}$$

where $\bar{r}_k^2$ proposes the squared cross-correlation between Y_1 and Y_2 at lag k, m is equal to the number of lags at which the cross-correlation is calculated and T is the length of the time series. The test statistic (U_m) in the equation above is split as a chi-squared variant with 2m + 1 degrees of freedom. In the same way, the hypothesis that Y_1 does not have a causal relation with Y_2, written ($Y_1 \not\rightarrow Y_2$), may be rejected at the α significance level as

$$U_m = T \sum_{k=1}^{m} \bar{r}_k^2 > \chi_m^2 (\alpha) \quad \text{........ (4)}$$

and the hypothesis that Y_1 is not affected by Y_2, written ($Y_2 \not\rightarrow Y_1$), may be rejected at the significance level as

$$U_m = T \sum_{k=-1}^{-m} \bar{r}_k^2 > \chi_m^2 (\alpha) \quad \text{........ (5)}$$

The empirical use of the Haugh-Pierce test is not without problems, however. Bishop (1976: 1-6) describes one of the problems as follows: "If relevant variables have been omitted, as is likely in the analysis of many economic time series, one is more likely to identify a feedback structure than a unidirectional system of causation." As a result, the results of causality analyses should be interpreted very carefully (Grant *et al.*, 1983: 3).

Causality analyses can be used to determine the effectivity of a market or market segment, in other words, how quickly and strongly a market reacts for a product on information reflected by its own price. If it is accepted that the first-order filtering process (differencing) removes all deterministic components from the time series, the corresponding residues should reflect to what extent new information is processed in every market. The application of univariate AR(p) models to the residues provides evidence to a certain extent of the measure of market effectivity at a low significance level (Fama, 1970: 383-417). According to Fama (1970), the test for market effectivity can be carried out by classifying all information into three categories:

- a strong-form test, which means that inside information is included;
- a semi-strong-form test, which includes all information that is available to the public; and
- a weak-form test, which includes all public information that relates to historic prices.

This therefore implies that if it is found that residues react as an AR model of the order zero, the corresponding market will be effective since the market will react immediately to information reflected by its own price.

When a specific market segment is analysed, it is, however, better to expand the approach in order to deal with various price series simultaneously. This can determine own effectivity and cross-effectivity. Multivariate AR(p) models are generalisations of the univariate model, since various price series can be investigated simultaneously. The causality properties between commodity prices can also be analysed by the above (Grant *et al.*, 1983). By using this method, a market which did appear effective when studied alone, may appear ineffective when the relevant information system is extended by also including other price series. We are therefore moving from a strong-form information system category to a semi-strong or weak-form information system category.

MULTIPLE AUTOREGRESSIVE MODELS

In step four the dynamic interaction of the various commodity prices (meat prices) is investigated by applying multivariate AR(p) models to the filtered price series. The multivariate AR(p) type of model is, according to Grant *et al.*, (1983: 4), as follows:

$$\begin{bmatrix} Y_1(t) \\ \\ Y_2(t) \end{bmatrix} + \sum_{j=1}^{p} \begin{bmatrix} a_{11}(j) & a_{12}(j) \\ \\ a_{21}(j) & a_{22}(j) \end{bmatrix} \begin{bmatrix} Y_1(t-j) \\ \\ Y_2(t-j) \end{bmatrix} = \begin{bmatrix} e_1(t) \\ \\ e_2(t) \end{bmatrix} \quad \text{... (6)}$$

where

- Y_1 and Y_2 are filtered representations of two original price series;
- P is the order of the joint AR model; and
- $e_i(t)$ is a normally distributed disturbance with the mean equal to zero and a covariance matrix of

$$E[e(t); e(t^1)] \quad \begin{array}{l} 0 \text{ for } t = t^1 \\ \sigma_{ij} \text{ for } t = t^1; i,j = 1,2 \end{array} \quad \text{...... (7)}$$

By using Equation (6) it is possible to evaluate the effectivity of every market by considering one channel of the model at a time. If the effectivity of the first market is evaluated, channel one can be represented as follows:

$$Y_1(t) + \sum_{j=1}^{p} [a_{11}(j) Y_1(t-j) + a_{12}(j) Y_2(t-j)] = e_1(t) \quad \text{...... (8)}$$

where $a_{11}(j)$ measures the impact of past values of the first pre-filtered price series on the present values of the series.

If the pre-filtering of the price series has removed all deterministic components of the price series, $a_{11}(j)$ must, in accordance with the simple testing procedure, be equal to zero for all values of j, and the market is then effective with regard to its own history, while $a_{12}(j)$ measures the impact of filtered prices from the second market on present prices of the first series. The $a_{12}(j)$ values should be zero for all j values if this market is effective with regard to information transmitted from the second market.

If the first market is effective, therefore, with regard to both information systems (first and second market), $a_{11}(j)$ and $a_{12}(j)$ will be zero for all values of j. The effectivity of the second market can be evaluated in a similar way. The causal structure of the model can therefore be studied by using the following matrix:

$$a(j) = \begin{bmatrix} a_{11}(j) & a_{12}(j) \\ a_{21}(j) & a_{22}(j) \end{bmatrix}, \quad j = 1, ..., p \qquad .... (9)$$

Granger's causality for a multivariate AR(p) process can be evaluated as follows:

Y_2 does not affect Y_1 and only if $a_{12}(j) = 0$ for $j = 1, \ldots, p$; and Y_1 does not affect Y_2 if and only if $a_{21}(j) = 0$ for $j = 1, .., p$; and Y_1 and Y_2 are independent if and only if $a_{12}(j) = a_{21}(j) = 0$ for $j = 1, \ldots, p$ (Tjostheim, 1981: 157-176).

Besides the Tjostheim-Haugh-Pierce-Sims procedure for the identification of causality relationships between time series, it is useful to quantify these properties so that the impact of one variable on another can be interpreted better at different lags (Grant *et al.*, 1983: 4). The dynamic properties of models were investigated in this research by means of dynamic multipliers (Gregory, 1975: 65), which measure a reduced form of impact at lag values of the i^{th} and j^{th} variables at the present values of the i^{th}. These multipliers have the advantage of being able to sum up in a simplified way the complex interactions which may exist between related price series. The speed of adaptation can be measured by calculating the number of time periods which are needed for the intermediate-term multipliers to stabilise within a 5% deviation from the long-term multipliers. This information is useful in the economic interpretation of the results (Grant *et al.*, 1983: 4).

LIMITATIONS OF THE MODEL

Bishop (1979) clearly states that the construction and use of causality tests is a technique for the empirical testing of the hypothesis that Y_1 is affected by Y_2 ($Y_2 \rightarrow Y_1$), rather than making this assumption. If applicable variables are used, such as will usually be the case in analysing the economic time series, there is a chance that a feedback structure will be identified rather than a one-way system.

As a result of this, the identification of a feedback system can be wrong. Sims (1977) mentions, in respect of one-way causality, that the Haugh-Pierce chi-squared test has a certain degree of bias by not rejecting the zero hypothesis of no causality. The chi-squared test can also, according to Grant *et al.*, (1983:6), be affected by the filters used to achieve the white noise stage in the residues which are used in the determination of cross-correlations.

If the expected future change in one variable affects the change of another variable, the direction of causality may be affected. If this is the case, this means that a two-way system could possibly rather look like a one-way system (Sims, 1977). Pierce (1977a: 159-162) further warns that if errors of measurement or imperfect white noise (including seasonality) are present, causality tests will not be suitable or applicable. From this it appears, therefore, that the use of causality tests, which constitute an important component in this study and model, is not without its problems and that the results should be interpreted with the necessary circumspection and not according to strict statistical rules and laws only. Some degree of economic realism and logic should therefore be applied when the results are weighed up.

CONCLUSION

This article has focused on the theoretical aspects basic to a time series analysis for the determination of price leadership, price inter-relationships and the period that it takes for price changes to filter through in the market.

A time series model forms the basis of the analysis. The first step in the analysis is to remove the deterministic nature of the time series, which will transform the time series into stationary-stochastic processes, by means of differentiation. Step two in the model is the filtering of the stationary-stochastic components by means of simple autoregressive models of the order p (AR(p)), so that the residues are reduced to white noise. Step three is the determination of causality between series by means of Haugh-Pierce causality tests. In step four, the dynamic interaction of the various commodity prices (meat prices) is investigated by applying multivariate AR(p) models to the filtered price series.

The use of causality tests, which is an important component of this model, is not without its problems. Economic realism and logic should be applied when the results are weighed up and interpreted. Despite these potential pitfalls, this is a functional method for quantifying price relationships between commodities. It is therefore at least potentially possible for price inter-relationships in the South African meat market to be quantified empirically by using the theoretical model described here.

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