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A STUDY OF BANANA SUPPLY AND PRICE PATTERNS ON THE SYDNEY WHOLESALE MARKET: AN APPLICATION OF SPECTRAL ANALYSIS*

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Spectral analysis is applied to weekly supply and price series for bananas traded on the Sydney wholesale market. Many interesting features are revealed such as the pronounced seasonal component and the two week lag structure between the supply and price series. These results are discussed in relation to the known behaviour of the market and some implications for marketing decisions are tentatively drawn.

Introduction

Data employed for empirical studies in agricultural marketing are usually available as series recorded at discrete equally-spaced time intervals. As a preliminary step in the analysis of such data a researcher may wish to study its characteristics in some detail in order to describe more precisely the salient features of the underlying mechanism.

Various methods such as the periodogram analysis [3] and the correlogram have been used for this purpose in the past, but the spectral technique is rapidly gaining prominence in modern time series analysis as a means of detecting important periodic components in data sets. The technique, originally developed and used in the physical and earth sciences, has recently been employed with economic data as a means of investigating measurable periodicities and also quantifying relationships between pairs of time series [1], [4].

This paper presents a brief description of the supply and price movements on the Sydney Wholesale Banana Market and then discusses an application of the technique using these observed series.

Supply and Price Patterns on the Sydney Wholesale Market

The two weekly series examined are the quantities of bananas consigned to Sydney wholesale markets from New South Wales and Queensland (supplies),¹ and the prices at which wholesalers sell these bananas

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¹ Source: Banana Growers' Federation Co-operative Limited, New South Wales. The original figures do not differentiate between wooden cases and fibre-board cartons. These together are labelled as 'packages'. To standardize the figures, appropriate conversion factors were applied to convert the data to bushel weight equivalents (52 lb. net).

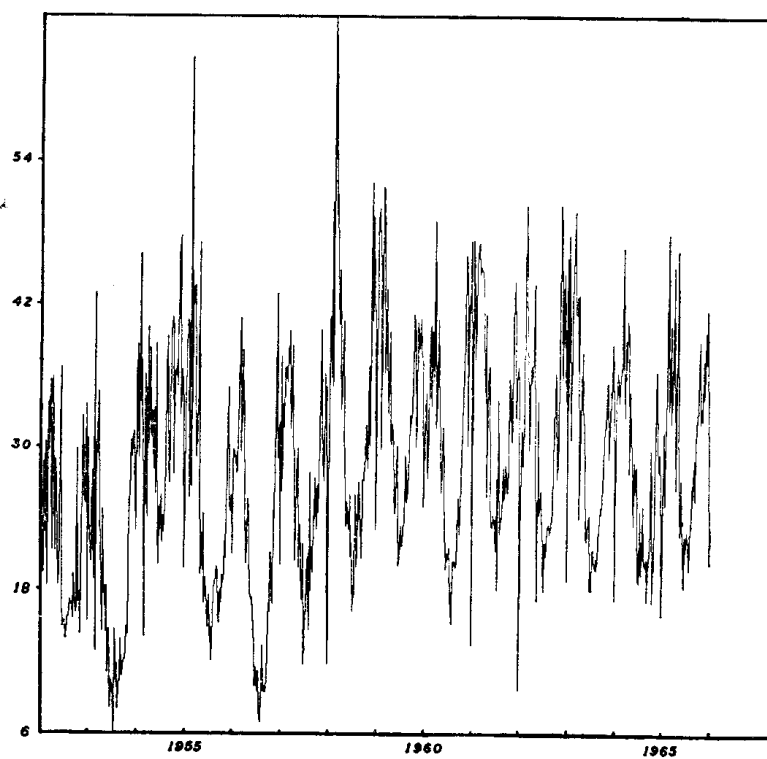


FIG. 1—Original supply series.

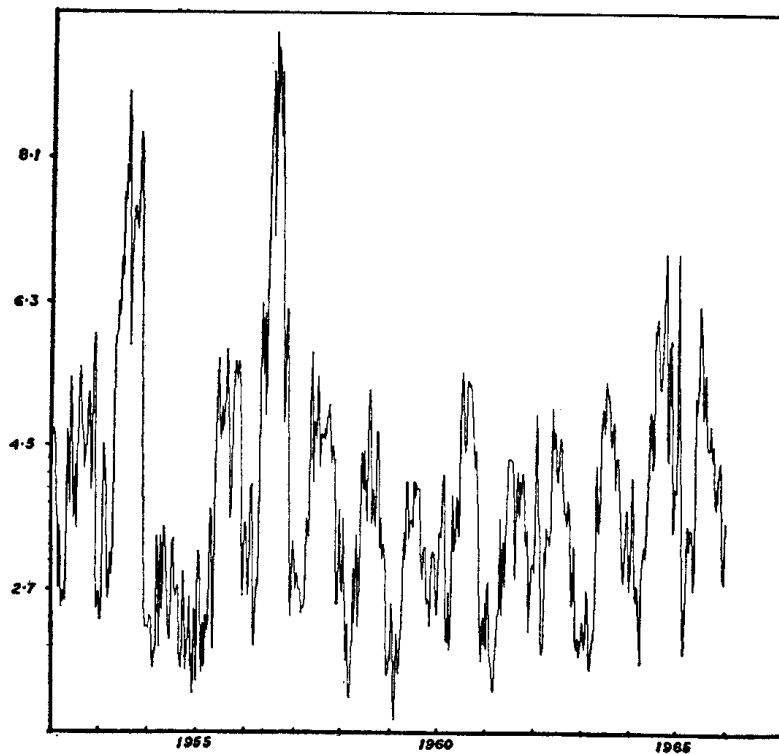


FIG. 2—Original price series.

to retailers (prices).² Quantities are expressed in bushels and prices refer to average prices in dollars per bushel of grade 'sevens' bananas which are assumed to represent banana prices in general.³ Computer plots of the two data sequences are shown in Figures 1 and 2.

A striking feature of the two diagrams is the regular within-year movements in both series. For example, the regular swing of the weekly supply series from a low point in mid-winter to a peak in mid-summer is one of the most persistent and characteristic features of the supply pattern⁴ (Figure 1). As can be seen from the two diagrams, supply and price move in inverse relation with peaks in supplies corresponding to troughs in prices and vice-versa. In order to compare the two graphs, the raw figures of weekly supplies and wholesale prices have been reduced to index numbers in which the mean supply and price for 1953-66 are taken as the respective bases. The graphs of these index numbers are shown in Figure 3. In each case the series show a definite seasonal pattern.

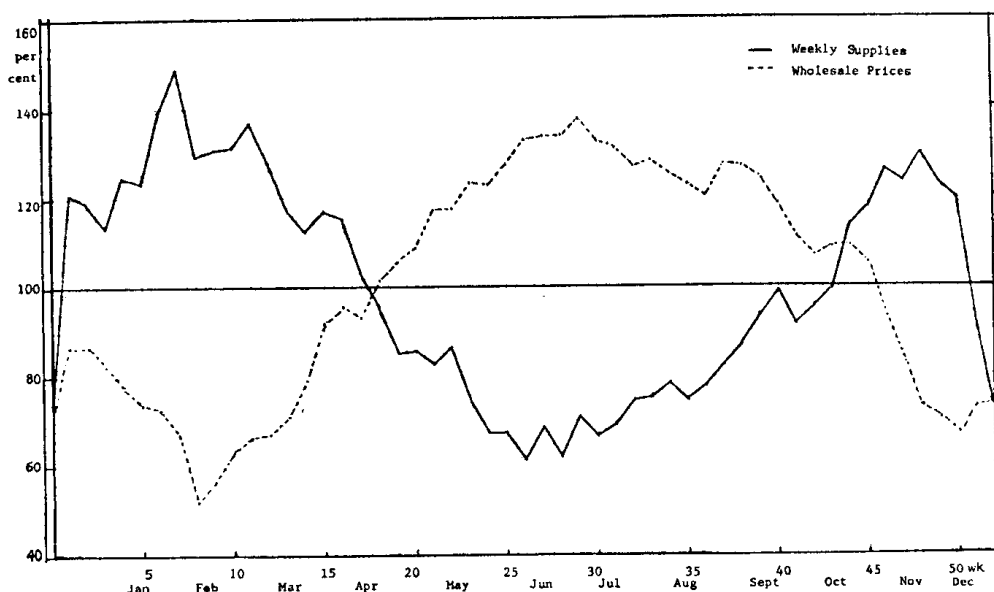


FIG. 3—SEASONAL PATTERN OF BANANA SUPPLY AND PRICES. Indices of average weekly Supplies of bananas and wholesale prices of grade "sevens" at Sydney Wholesale Market based on data for the fourteen year period 1953 to 1966. (Average per 52 weeks = 100%).

² Source: Official records of the Division of Marketing and Agricultural Economics of the New South Wales Department of Agriculture.

³ Bananas are marketed in several grades according to size. These grades are 'Small', 'Sixes', 'Sevens', 'Eights' and 'Nines', the number giving the length of fruit in inches. The prices collected daily cover most of the common grades of 'Sixes', 'Sevens' and 'Eights'. A weighted daily average for each grade is calculated, the weight being dependent on the reporting officer's assessment of the prices for each grade at which most sales occur. From these weighted daily averages an arithmetic weekly mean is calculated. The proportions of 'Sevens' of the total supply show some fluctuations, but these are not as wide as those of the proportions of either 'Sixes' or 'Eights'.

⁴ The seasonality of supply was accentuated as production moved southwards from Queensland to New South Wales, where the climate is semi-tropical.

The wide fluctuation appearing in the supply pattern is, however, being gradually reduced as a result of recent adjustments within the industry. Two important developments are: (1) the planting of new varieties and adoption of improved cultural methods to achieve some control over production; and, (2) the increasing production of winter fruit from Queensland to take advantage of the higher prices on the market. Though these measures tend to reduce the amplitude of the seasonal fluctuations in supplies, they have not affected the short-run erratic changes in supplies which are mainly attributable to temperature variations in the growing areas.

Although the glut keeps prices very low in summer, there is seldom any large quantity of bananas left unharvested, since the fruit ripens rapidly after reaching maturity. Individual growers, facing a perfectly elastic demand curve, ship their fruit to the market as long as the price covers the variable costs of harvesting and marketing. The amount of fruit supplied in the short-run therefore tends to be dependent more on the weather conditions prevailing in the growing areas than on the ruling market prices.

The marketing of bananas is also characterized by some inherent features which make the handling of the crop peculiarly different from that of other fruits such as oranges and pineapples. The fruit is harvested in a green condition and railed to the southern markets where it is immediately put into a ripening room. Here it is subjected to controlled temperatures and humidities which permit the wholesale merchants to hold the fruit for varying lengths of time (up to two weeks) depending on supply expectations, weather and demand conditions. This action by the wholesale merchants to regulate the flow of fruit to retailers partly accounts for the existence of a time-lag between the supply and price series and partly explains why prices are more stable than supplies in the short-term.

So far the discussion has been based on our prior knowledge of the market, supplemented by visual examination of the patterns exhibited in Figures 1 to 3. Before such information is used for constructing an economic model, we may wish to analyse the data in more detail in order to define more precisely some of the observations made and also to be able to specify more accurately the relationship between the two series. The spectral techniques provide us with a means of quantifying these relationships.

Spectral Methods of Analysis

Since we are mainly concerned with spectral methods as a tool of analysis, only a brief outline of the theory underlying the technique and estimation procedures is given. Further details need not be given here as the object of this study is largely to describe the characteristics of the banana market rather than being concerned with the testing of specific hypotheses. More detailed treatments may be found elsewhere [1] [4].

In most statistical applications where the data consist of an observed time series $\{x(n); n = 0, \pm 1, \pm 2, \dots\}$, $x(n)$ and $x(m)$, where m

belongs to the same set as n , will rarely be independent as n approaches m . Assuming $E\{x(n)\} = \mu$ where μ is a constant and E is the expectation operator, the set of finite second moments

$$E\{(x(n) - \mu)(x(n + \tau) - \mu)\} = \gamma(\tau);$$

$$\tau = 0, \pm 1, \pm 2, \dots,$$

defined as the covariance function, will allow us to investigate the nature of this dependence. If oscillations of a known period—a seasonal pattern—are thought to exist in the data, the Fourier cosine transform of the covariance function (spectrum) will often prove a useful measure in determining the relative importance of these various components.

Mathematical Formulation

In this paper we shall adopt the following notation to represent the spectrum and the associated cross-spectra functions.

$\hat{f}(\lambda)$ is the estimated spectrum

$\omega(\lambda)$ is the coherence

$\theta(\lambda)$ is the phase

$b(\lambda)$ is the gain.

λ is the frequency and $\hat{}$ notation denotes an estimate. The spectrum and the associated quantities are estimated in the frequency range; $0 \leq \lambda \leq \pi$. For the time series $\{x(n), n = 0, \pm 1, \pm 2, \dots\}$ generated by an unknown stochastic process, we assume a condition of (weak) stationarity in which

$$E\{x(n)\} = \mu, \quad E\{(x(n) - \mu)^2\} = \sigma^2 < \infty \quad \text{and}$$

$$E\{(x(n) - \mu)(x(n + \tau) - \mu)\} = \gamma(\tau) \quad \text{depends only on } \tau.$$

As a consequence of this stationarity we may represent $x(n)$ in the form

$$(1) \quad x(n) = \int_{-\pi}^{\pi} e^{i\lambda n} dZ(\lambda) \quad -\pi < \lambda \leq \pi$$

where $dZ(\lambda)$ is a complex stochastic increment such that

$$E\{dZ(\lambda_1) \overline{dZ(\lambda_2)}\} = dF(\lambda_1) \quad \lambda_1 = \lambda_2$$

$$= 0 \quad \lambda_1 \neq \lambda_2,$$

the bar denoting complex conjugation.

For $x(n)$ real, an alternative representation of (1) is

$$x(n) = \int_0^{\pi} \{\cos n \, du(\lambda) + \sin n \, dv(\lambda)\}$$

and $dZ(\lambda) = \frac{1}{2} \{du(\lambda) - idv(\lambda)\}$. We may thus regard $x(n)$ as being composed of cosine and sine waves of frequency λ with amplitudes represented by the uncorrelated, orthogonal random variables $du(\lambda)$, $dv(\lambda)$.

The function $F(\lambda)$ is the cumulative power spectrum and we restrict $F(\lambda)$ so that it becomes absolutely continuous with derivative $f(\lambda)$. The covariance function $\gamma(\tau)$ may then be expressed in the form

$$(2) \quad \gamma(\tau) = \int_{-\pi}^{\pi} e^{i\lambda\tau} dF(\lambda).$$

Clearly, $\gamma(0) = \sigma^2$ indicating that the power spectrum $f(\lambda)$ may be regarded as a decomposition of the total variance attributable to different frequencies. The concentration of this variance is known as the 'power' or 'mass' and reflects the amplitude of the stochastic increments $du(\lambda)$, $dv(\lambda)$. In addition,

$$(3) \quad f(\lambda) = \frac{1}{2\pi} \sum_{-\infty}^{\infty} e^{-i\lambda\tau} \gamma(\tau)$$

such that the spectrum and autocovariance function represent a complex Fourier transform pair.

For two jointly stationary series $x(n)$ and $y(n)$ where $E\{(x(n) - \mu_x)(y(n + \tau) - \mu_y)\} = \gamma_{xy}(\tau)$, the cross spectrum is of the form

$$\begin{aligned} f_{xy}(\lambda) &= \frac{1}{2\pi} \sum_{-\infty}^{\infty} e^{-i\lambda\tau} \gamma_{xy}(\tau) \\ &= \frac{1}{2} \{c_{xy}(\lambda) - iq_{xy}(\lambda)\}, \end{aligned}$$

the real part being the co-spectrum and the complex part the quadrature spectrum.

We use the following functions of the cross-spectrum to show how the two time series are related.

The *coherence*

$$\omega(\lambda) = [(c_{xy}^2(\lambda) + q_{xy}^2(\lambda))/f_x(\lambda) f_y(\lambda)]^{\frac{1}{2}}$$

measures the strength of association between two variables. It is analogous to the square of the correlation coefficient between the corresponding frequency components of the two series.

The *phase* $\theta(\lambda) = \arctan \{q_{xy}(\lambda)/c_{xy}(\lambda)\}$ describes the lead or lag relationship in the y series relative to the x series. If $\theta(\lambda) = k$ constant, this implies the lag is proportional to the period of the component (fixed angle lag), and $\theta(\lambda) = k\lambda$ implies a simple time lag relationship of k intervals.

The *gain* is essentially the regression coefficient when y is regressed on x and is defined as

$$b(\lambda) = [c_{xy}^2(\lambda) + q_{xy}^2(\lambda)]^{\frac{1}{2}}/f_x(\lambda)$$

The *spectrum of residuals* $f_u(\lambda)$ is derived from the relation

$$f_y(\lambda) = b^2(\lambda) f_x(\lambda) + f_u(\lambda)$$

and is analogous to the error term in the simple linear relation $y = \beta x + u$. (The dependent variable is the spectrum (y) and the independent variable is the spectrum (x) and the regression coefficient is the square of the 'gain').

For an observed time series $x(n)$ we may wish to carry out a transformation on the data to obtain a new series $y(n)$; this process of digital

filtering may be represented in the form $y(n) = \sum_{-\infty}^{\infty} \delta_j x(n-j)$. The

properties of this filter may be summarised by the Fourier transform of

the δ_j sequence $h(\lambda) = \sum_{-\infty}^{\infty} \delta_j e^{i\lambda j}$, the frequency response function of the

filter. The spectra of the y and x series are then related in the following manner:

$$(4) \quad f_y(\lambda) = |h(\lambda)|^2 f_x(\lambda).$$

The filter coefficients δ_j can thus be chosen so that the response function will leave unaltered (pass) input amplitudes at certain frequencies and appropriately modify them at others.

Estimation Procedure

The basic theory has been developed in terms of a series observed at an infinite number of time points and the estimation methods in terms of a series recorded at N discrete equally spaced time intervals.

The observed series $\{x(n), n = 1, 2, \dots, N\}$ may be regarded as a single realisation generated by an unknown stochastic process. Since it is impossible to estimate all parts of the true spectrum $f(\lambda)$ from a finite data set, we attempt to estimate the average value of the power spectrum over a specified number of frequency bands.⁵

Noting that

$$\begin{aligned} 2\pi f(\lambda) &= \lim_{N \rightarrow \infty} \sum_{-N+1}^{N-1} e^{-i\lambda\tau} \gamma(\tau) \\ &= \lim_{N \rightarrow \infty} \{ \gamma(0) + 2 \sum_1^{N-1} \cos \lambda \tau \gamma(\tau) \}, \lambda \in [0, \pi], \end{aligned}$$

we begin the search for a desirable estimate of spectrum, $f(\lambda)$ with the sample periodogram $I_N(\lambda)$ which has the form,

$$2\pi I_N(\lambda) = \frac{1}{N} \left| \sum_1^N e^{-i\lambda\tau} x(\tau) \right|^2 = c(0) + 2 \sum_1^{N-1} \cos \lambda \tau c(\tau)$$

where $c(\tau)$ is the covariance estimator.

The periodogram is an asymptotically unbiased estimate of the spectrum but since its variance does not approach zero, it is not a consistent estimate. We thus estimate the spectrum with a weighted average of the periodogram values at several frequencies, the weights being concentrated towards the point λ . This weighting procedure $K(\theta)$ is the spectral window and is the Fourier transform of the set of weights $k(\tau)$, the lag window. Then,

⁵ The estimation method used in this study is based on a program developed by Karreman [5]. The original program has been slightly modified by members of the staff of the Department of Statistics of the Australian National University to make it more suitable for the computer on which it was used and the problem it was to handle.

$$\hat{f}(\lambda) = \int_{-\pi}^{\pi} K(\theta - \tau) I_N(\theta) d\theta - \frac{1}{2\pi} \sum_{-N+1}^{N-1} \cos \lambda \tau k(\tau) c(\tau).$$

For a discussion of the choice of spectral window see [1].

Each succeeding $c(\tau)$, being based on fewer observations, becomes increasingly less reliable and so only the first M should be used in the estimation procedure. The number of lags M essentially represents the number of frequency bands over which we estimate $f(\lambda)$. If M is too small large peaks in the spectrum will be underestimated (poor resolution); however, if M is too large the variance will be increased. The spectrum may then be estimated at the $(M+1)$ equidistant points.

$$\lambda_j = \pi j/M; j = 0, 1, \dots, M.$$

Spectral Results

The Estimated Power Spectra

For $N = 728$, representing the total number of observations for each series, and $M = 130$, representing the number of lags used for the estimation of spectra, the two estimated spectra are plotted in Figures 4 and 5. In each case we note that the spectrum possesses substantial

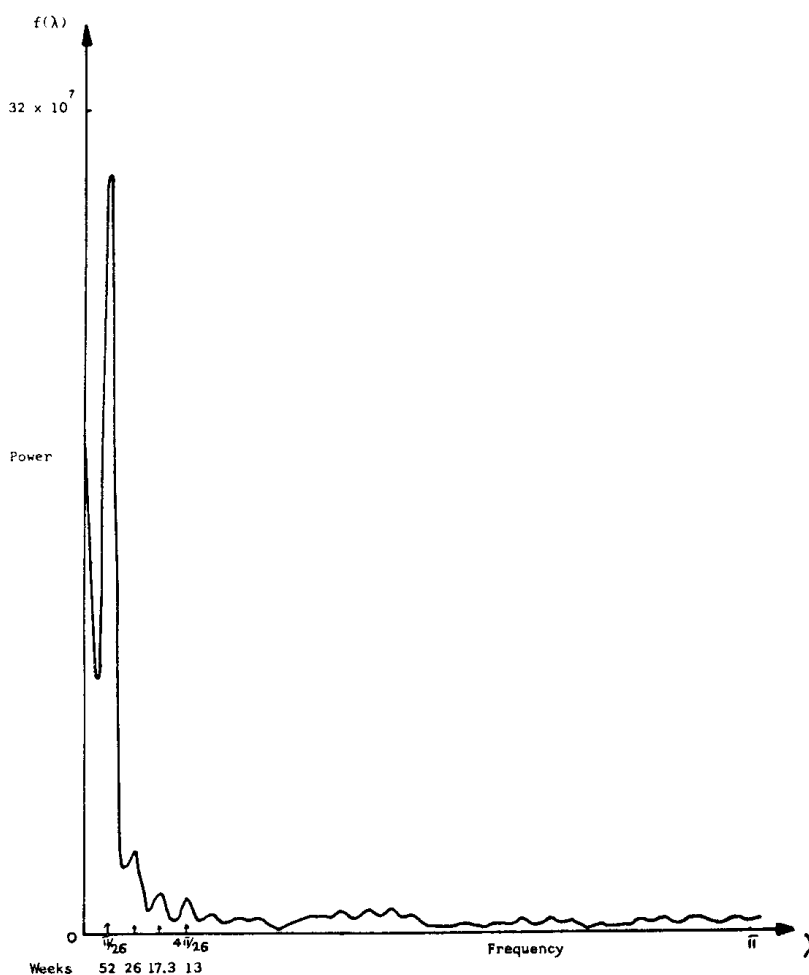


FIG. 4—Estimated power spectrum of banana supplies.

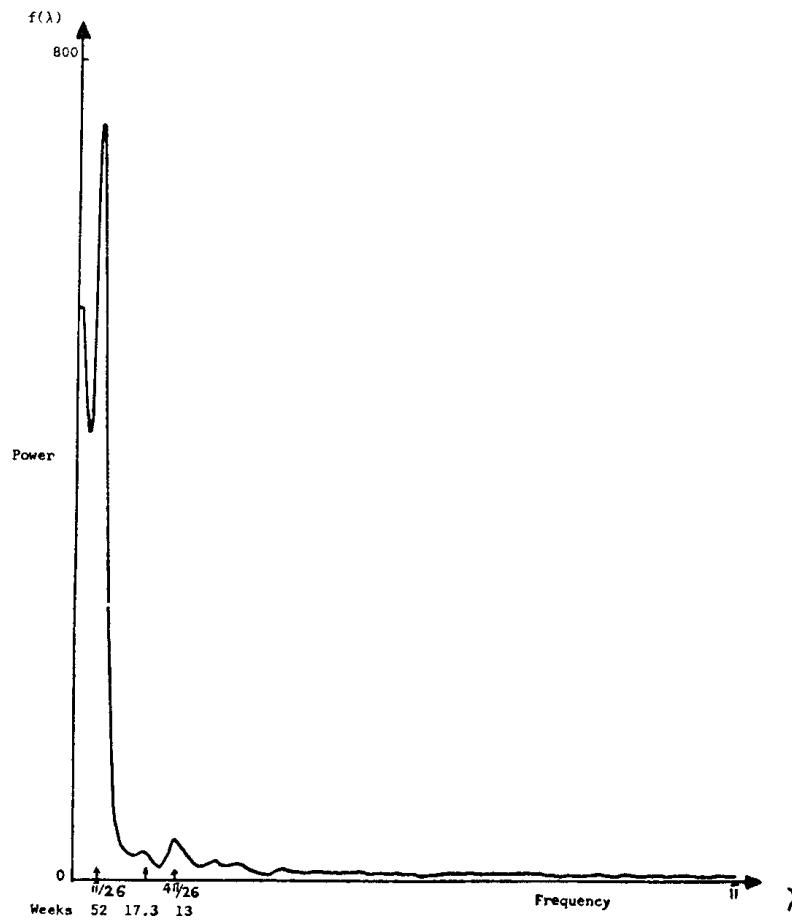


FIG. 5—Estimated power spectrum of banana wholesale prices.

power close to the origin, indicating a trend component, and a marked peak at $\pi/26$. This suggests that the trend and the seasonal components dominate the distribution of variance in the two estimated spectra. Since the j -th frequency corresponds to an oscillation of period $2M/j$ weeks, this distribution of the spectral mass implies that a substantial proportion of the total variance is attributed to a 52 week cycle or the annual component.

Examining the spectra in more detail, a number of other features are observable. The 52 week cycle peak is particularly strong in the spectrum of quantities and is also joined by minor peaks at frequencies corresponding to cycles of lengths 6 months, 4 months and 3 months which are harmonics⁶ of the annual component; only the peak at $4\pi/26$, the

⁶ The seasonal component in the series may be represented as a sum of 26 narrow band signals centred about the frequencies $\lambda_k = \pi k/26$; $k = 1, 2, \dots, 26$. We note here that appropriately designed filters to estimate and remove trend and seasonal component would drastically reduce the spectral peaks at these specified frequency bands. The occurrence of peaks at these frequencies provides further evidence for the presence of seasonality in the supply series.

quarterly cycle, is common to both estimated spectra. The 52 week cycle appears to contribute more to the variance in prices than quantities.

Although both spectra exhibit low power in the high frequency range, implying that short-term frequencies are less important in explaining the movement in the series, we observe that the spectrum of supplies shows greater variation than that of prices. This suggests that the high frequency components contribute more to the variation in quantities than they contribute to the variation in prices. This observation is consistent with the short-term fluctuations in banana supplies to the market, which was discussed earlier in the paper.

The Estimated Cross-Spectra

The estimated power spectrum diagram is essentially the basic tool with which the properties of a single series are analysed. In addition we may wish to use cross-spectral analysis to describe the relationship between pairs of series. Cross-spectral analysis has two main objectives: first, to measure the extent to which the series are inter-related; and second, to determine the type of lag structure involved. The coherence diagram provides information about the first of these objectives and the discussion of this diagram normally precedes discussion of the phase diagram which is concerned with leads and lags, as it is pointless investigating possible lags between two series if they are unrelated. The coherence and phase diagrams are shown in Figures 6 and 7.

Because of the oscillatory nature of the diagrams, subsequent discussions will be based on the general shape of the diagrams rather than by reference to specified frequency points or bands. For purposes of discussion, the entire frequency range $[0, \pi]$ is arbitrarily divided into three broad zones: $[0, \pi/26]$, $[\pi/26, \pi/2]$ and $[\pi/2, \pi]$, which will be referred to as low, medium and high frequency ranges respectively.

The *coherence* diagram is negatively sloped with the coherence value generally becoming smaller as λ approaches π . In the range $[0, \pi/26]$ the coherence value is very high indicating a strong correlation between the two series over the low frequencies. In the range between $\pi/26$ and $\pi/2$, the coherence is noticeably smaller in value and shows a marked variation. As λ increases from $\pi/2$ further variation and generally low values are apparent. The general shape of the coherence diagram indicates that the extent to which the corresponding components in the two series are related generally decreases as the period becomes shorter. In other words, the long-term cycles are more highly inter-related than the short-term cycles.

In the three frequency intervals, the *phase* diagram is of considerable interest although its interpretation is often difficult. The estimates of phase at frequency components having large coherence values are usually good, but at frequencies with small coherence values little confidence can be placed in the phase estimates since these are generally unreliable. This is because the variance of $\theta(\lambda)$ is functionally related to $\omega(\lambda)$, whereby low coherence implies large variance. Clearly, little can be concluded from the phase diagram for $\lambda > \pi/2$, since the coherence in this range is low.

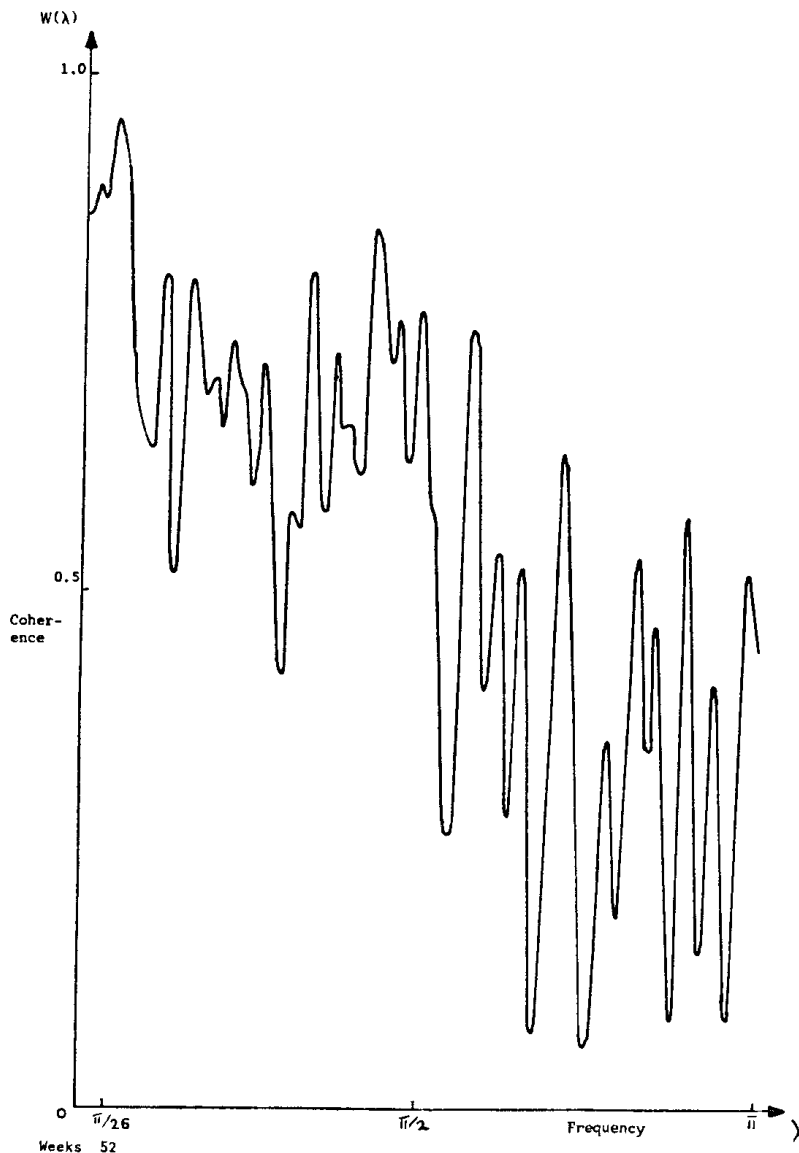


FIG. 6—Coherence between supplies and prices.

Turning now to Figure 7, we observe that in the frequency range $[0, \pi/26]$, $\theta(\lambda) \approx \pi$ (constant) indicating a fixed angle lag. This suggests that if each frequency in prices was shifted through π , the low frequency components of the two series would come into phase. Clearly then, for the long-term cycles, peaks in supplies correspond to troughs in prices and vice-versa. This is in line with our prior knowledge of the seasonal movements of banana supply and prices (Figures 1 to 3). In the range $[\pi/26, \pi/2]$, a reasonable functional relationship between phase and frequency might be $\theta(\lambda) = \pi + 2\lambda$, implying a fixed time lag in the medium range of two time intervals (that is, two weeks). Thus for cycles varying in periods between 4 weeks and 52 weeks we might

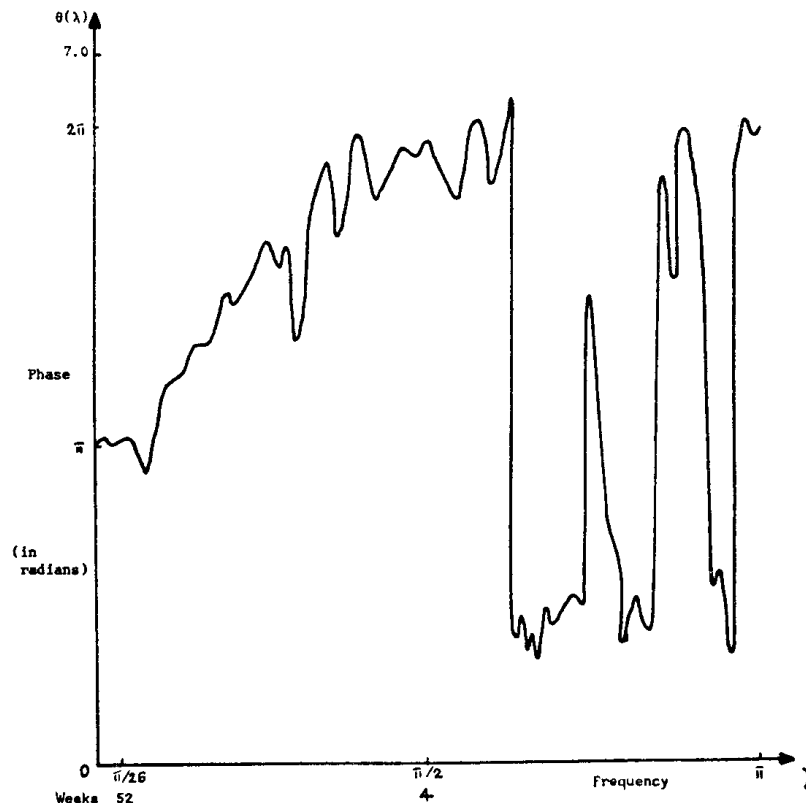


FIG. 7—Phase difference between supplies and prices.

suggest that supplies lead prices by two weeks. This reflects the lag of a fortnight between the time the fruit is loaded at the railway siding and its emergence from the ripening room.

The results from the *coherence* and *phase* diagrams illustrate the advantages of decomposing the variables into their frequency components. If this had not been done, but instead, an ordinary correlation coefficient had been obtained, it would approximately represent the average of the degree to which the various frequency components are related, thus missing much of the relevant detail. Moreover, it would clearly have been more difficult to characterize the lag relationship. Even if this had been observed as in Figure 3, this causal relationship would have been hypothesized with less confidence.

Further information about the nature of the relationships between the corresponding frequency components in the two series may be obtained from the *gain* and the *residual* diagrams shown in Figures 8 and 9 respectively.

The *gain*, analogous to the regression coefficient when quantities are regressed on prices, appears to be generally decreasing with λ . This indicates that the high frequency components in the price series are not as important as the low frequency components in explaining the movements in the supply series. In other words, consignments to the market do not respond readily to short term variations in current prices. On the

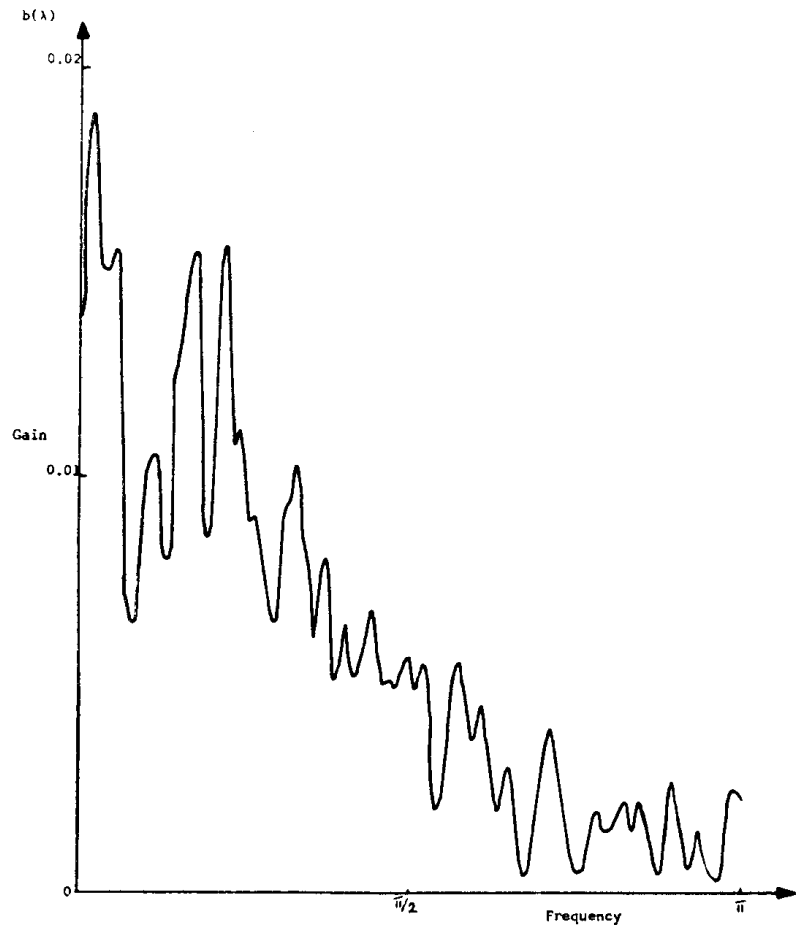


FIG. 8—Gain: supplies on prices.

other hand, the gain value is very high in the range $[0, \pi/26]$, indicating that supplies in the long-run are influenced by the average level of prices received, over some period in the past.

A careful scrutiny of banana market statistics reveals that this, in fact, is what actually takes place in the industry. The yearly production figures indicate that production of bananas moves in characteristic cycles averaging about two to three years in length. These cycles are generated by opposite cycles in prices. A drought, for example, which reduces the size of the crop, will cause prices to rise. Ordinarily, this induces farmers to increase production. The resulting larger crop depresses prices and farmers reduce production again. Thus the price and production of bananas continue to fluctuate around the equilibrium point without ever settling at it.

In the plot of the *spectrum of residuals* we note the heavy concentration of power close to the origin and the absence of marked peaks at other frequency bands. This implies that a large proportion of the unexplained variance in supplies is attributed to long term frequencies

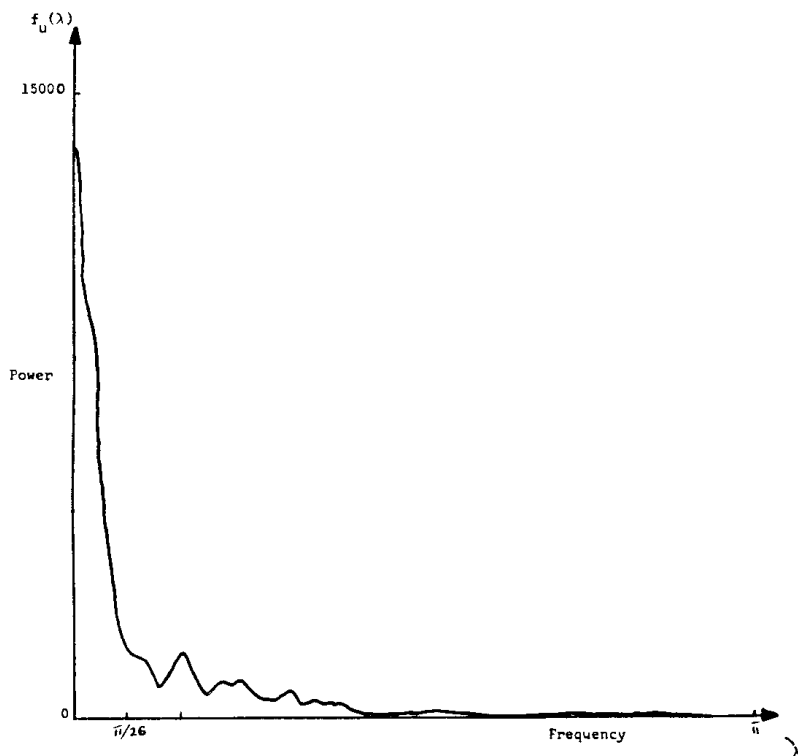


FIG. 9—Spectrum of residuals: supplies on prices.

in general. Some factors external to the simple price-quantity mechanism, for example the new varieties and improved cultural practices, may be responsible for this unexplained variance.

The Estimated Seasonal Patterns

Since the seasonal component is such a large contributor to the total variance of the two series, we have taken this up for further consideration, even though seasonal analysis strictly lies outside the topic of spectral analysis. The main objective is to find out whether the seasonal patterns have been constant or have been changing gradually through the time. The nature of this seasonal evolution may well prove of some value in helping to describe the movements of the series over time.

To justify many of the results relating to the evolution of the various seasonal patterns, the reader is referred to Tuckwell [7] where a full discussion of the theory underlying the estimation procedure is given. Here we shall merely restate the main assumptions and conclusions relevant to the present study.

Both series were adjusted for the seasonal influence under the assumption of an additive evolving model:

$$(5) \quad X(n) = p(n) + s(n) + u(n)$$

where

- $X(n)$ is the original data,
- $p(n)$ is the estimated trend cycle,
- $s(n)$ is the seasonal component,
- $u(n)$ is the residual.

For an evolving pattern

$s(n)$ will vary with n ,

whereas a fixed pattern implies that

$$s(n) = s(n + 52).$$

The trend estimate was derived using a centred 52 week moving average and consequently the first and the last 26 observations are lost from the analysis. The computer plots of the seasonal components of supplies and prices are shown as Figures 10 and 11 respectively.

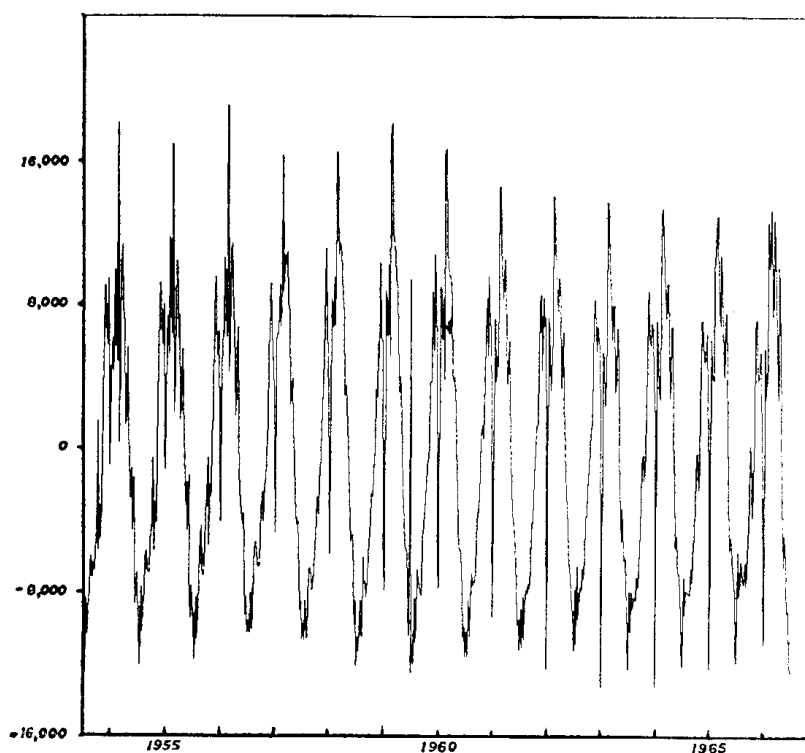


FIG. 10—Evolving Seasonal Pattern—Supplies

From the diagrams it is clear that both series exhibit evolving seasonal patterns, with the amplitude of the seasonal component generally declining with time. This is particularly evident in the price series where the amplitude appears to be decreasing particularly when allowance is made for the slight over-estimation which occurs at the end of the series.⁷ This observation is in line with the attempts by growers to reduce fluctuations in seasonal supplies which have been discussed previously.

⁷ Much importance cannot be attached to the amplitude of the estimated seasonal component in 1966, since the estimation procedure used shows a tendency to over-estimate near the beginning and end of the series. The amplitude change was estimated for the 52 week cycle. It will therefore be unwise to place too much reliance on these estimates as true reflections of the overall seasonal evolution since the seasonal component is a summation of 26 narrow band signals. [See Footnote 6].

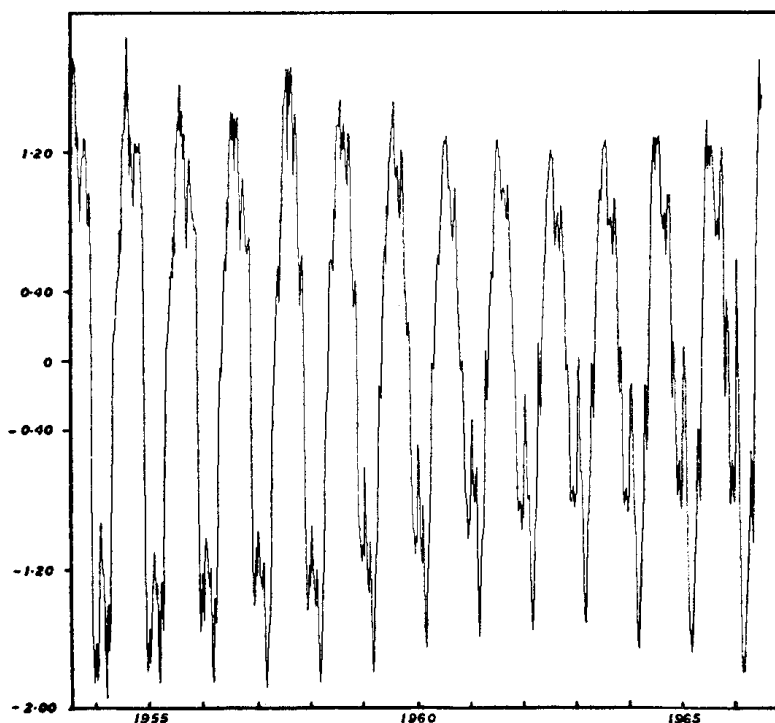


FIG. 11—Evolving seasonal pattern—prices undeflated.

Summary and Conclusions

From the results obtained, it is clear that spectral and cross-spectral analysis can be of considerable value in helping to describe the characteristics of observed data sets. The advantage of decomposing the economic variables, i.e. supply and price series into their several components (low, medium and high frequencies), which is inherent in the spectral approach has been well illustrated. Some of the results may have remained hidden if other statistical methods such as least squares were used—for example, the different degrees to which the various frequency components in the two series were related. In addition, a number of features of movements over time of the individual series were found, and in general, plausible explanations were offered based largely on the authors' prior knowledge of the banana market. The results were found to be consistent with the practices of producers and wholesale merchants.

It is apparent from the study that the effect of short run changes in supplies is dampened by the action of merchants to regulate the flow of bananas to retailers. This suggests that possibilities for holding the fruit in the short period are already being fully exploited, with merchants attempting to take reasonably full advantage of the rather restricted technological possibilities available. It is therefore unlikely that significant gains can be achieved by undertaking short-term storage operations, unless more drastic steps are taken to modify the seasonal pattern of supplies. Recent technological advances now seem to make long-term banana storage feasible [2]. Costs and benefits associated with such a venture will, however, have to be examined more thoroughly and in depth, before any worthwhile conclusions can be drawn on this question.

We may also add that the spectral technique does not explain the basic generating mechanism of the banana market as a normal econometric model would seek to do. It only highlights the physical features of the series and provides further confirmatory evidence of the technical relationships that are already thought to exist in the series. Great discretion should therefore be used in interpreting the results, as this offers an outstanding example of the fact that statistical analysis is most appropriately used in the testing of hypotheses rather than their creation.

Useful as the approach can be, in applying the technique the researcher should bear in mind the assumptions on which the analysis is based. The restriction of stationarity may not always be satisfied, particularly as the basis and structure of the generating mechanism are likely to be continually changing, although perhaps very slowly over an observed time period. Also the reliability of any spectral estimates will depend on the number of observations available; if M is too small we may not be able to achieve the required resolution. The need for a large number of observations and the obviously non-stationary character of economic time series has created doubts in the minds of many economists about the prospects of using the technique in economic research. These limitations are not so restrictive when the analysis is concerned with high frequency components; for example, those produced by seasonality.

In such cases the number of observations available to the investigator generally does not prevent satisfactory estimation of the properties of the short term cycles. Much of the supposed non-stationary character of economic time series may be treated as high power at low frequencies and allowed for by filtering [6], or other transformations (for example, taking logarithms to help stabilize the variance, or first differences to remove trend effects). With these possibilities, the technique offers considerable potential for further application in other empirical studies, if it is used with skill, experience and good judgement by the analyst.

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