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Anders Christoffersson
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Anders Christoffersson
Roland Roberts
Ulla Eriksson

Department of Statistics
University of Uppsala
Box 513
751 20 Uppsala
Sweden

INTRODUCTION

The most commonly used methods for analysis of economic time series operate in the (real) time domain. This is the case for analysis of interdependent systems, ARIMA models, cointegration etc. The frequency domain did not become a real alternative until the 1960's with the advent of modern computers. For a decade or so, quite a large number of papers treating spectral methods were published (see Granger and Engle (1983)). Most earlier works in econometrics which used complex demodulation analysed a single time series or the phase lag between two series. Granger and Hatanaka (1964) found the results of the method contradictory as regards phase lag between the US industrial production index and layoff rate in different frequency bands (most probably caused by the poor filters and numerical algorithms available at that time). An excellent analysis of the Australian business cycle based on complex demodulates was presented by Burley (1969). A general description of the theory and some applications is given in Banks (1975) and Hasan (1983).

Working in the complex demodulate domain allows elegant and efficient analysis of economic time series. The data is Fourier transformed, filtered into frequency bands of interest, shifted in frequency and transformed back into the time domain. This produces time series of estimates of the real and quadrature parts (amplitude and phase) of the energy within each given frequency band. By truncating the spectrum prior to inverse Fourier transformation we can obtain estimates that are (almost) independent. Reducing the number of data in this way allows increased computational efficiency without the loss of any useful information. The series are decomposed into parts that are both time and frequency dependent, and which are near-optimally resampled in the complex time domain (two degrees of freedom per complex sample). That is, the time sampling obtained is related naturally to the frequency band-width of the signal we are examining. By forming the covariance matrix of the demodulates we can analyse most of the linear structural models commonly used in econometrics. However, by operating in the complex demodulate domain we retain the phase information throughout the processing, which means that the models in certain aspects are more general than their real time domain counterparts.

Due to the fundamental equivalence of the time and frequency domains, the complex demodulate series can be regarded either as complex time series or as time-local spectral estimators. In order to generate the time-local covariance matrices we must choose a frequency band. We can choose any frequency window in the range from zero to the Nyquist frequency. Naturally, we try to choose the frequency band that provides the greatest signal enhancement for the particular phenomena we are examining.

In a recent research report, Bergström (1991) studied the relation between production and a number of series from the Swedish Business Tendency Survey (BTS). Bergström, using the traditional econometric methodology, found that there is a reasonably close relationship between the barometer series describing changes in the volume of production and the annual changes in the ordinary volume series of total manufacturing in Sweden. Including the volume series of the BTS significantly improve the best autoprojective model for the ordinary volume series. Bergström also considered about 25 other barometer series, none of them were found to provide additional information. Öller (1990), in a study of the business cycle for the Finnish forest industry, found that the business survey data were useful in monitoring and predicting the business cycle and its turning points. While his models were all in the time domain he used spectral information together with conventional auto- and cross-correlation plots in the initial model-building stage.

In this study we will use frequency and complex demodulate methods to illuminate the relationship between manufacturing and the various BTS-series. In Sections 1 and 2 we give a short description of complex demodulates and complex-valued regression. Section 3 gives a brief presentation of the data used and Section 4 presents the results of the analysis. Finally in Section 5 we give a short summary of the main findings.

1. COMPLEX DEMODULATION

The theory of complex demodulation is well described in the literature (Bingham, Godfrey and Tukey, 1967; Banks, 1975; Hasan, 1983; Roberts, 1984; Roberts and Dahl-Jensen, 1989) and here we present only a summary. If a time series x(t) is shifted in frequency by ω

$$x'(t,\omega) = x(t)\, e^{-i\omega t} \tag{1.1}$$

and low-pass filtered from frequency $+\delta\omega$ to $-\delta\omega$ by convolution with the series a(t)

$$x_d(t,\omega) = a(t) * x'(t,\omega) \tag{1.2}$$

we obtain the complex demodulate time series $x_d(t,\omega)$ which contains instantaneous estimates of the real and quadrature parts (easily converted to amplitude and phase) of the density within the frequency band $\omega - \delta\omega$ to $\omega + \delta\omega$. The operations described by equations (1.1) and (1.2) can be achieved efficiently using the Fast Fourier Transform (FFT). The data is simply transformed to the frequency domain, band-pass filtered, shifted in frequency and transformed back into the time domain. We can, if we wish, truncate the part of the shifted spectrum that contains no energy before transformation back into the time domain. Reducing the number of data in this way greatly improves the efficiency of the inverse Fourier transform, and provides a complex time series in which neighbouring estimates are (almost) independent, allowing increased efficiency during later processing. Note that:

(1) This truncation does not imply the loss of any useful information.
(2) As the relevant elements in the inverse Fourier transformation are identically equal to zero, this truncation has no effect on the time samples which we calculate (but we calculate samples at fewer time points than if we had not truncated).
(3) It follows from this that the time domain leakage effects are essentially the same as for any filtering procedure.
(4) Sampling theory shows us that the spacing of the zeros of the time domain sinc[1] function associated with the inverse FT coincides with the sampling rate, i.e. even for finite time series neighbouring demodulates can be completely independent.
(5) In practice it is rare to have completely independent demodulates because of windowing of the data, retention of some zeros when calculating the inverse FFT

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[1] sinc(x) = sin(x) / x

etc. To avoid interdependence caused by frequency domain zero padding, we could consider using the direct inverse Fourier transform, rather than the FFT.

From the point of view of processing, the choice of frequency bands is arbitrary. Thus e.g. frequency bands can overlap (but in this case we loose orthogonality between demodulates in different frequency bands). Obviously, when analysing real data, the choice of frequency band is critical in helping to isolate the signal of interest and to enhance the signal to noise ratio. If we shift the time series in frequency and reject only the original negative frequencies we can obtain a complex time series that retains all the information contained in the original time series.

Whilst on the subject of Fourier transformation of economic time series it is perhaps worth mentioning that the varying length of months, the number of weekends in a given month etc. can lead to some aliasing problems, but that these problems are well defined and it is easy to demonstrate that from the point of view of the analysis procedures presented here these effects are of little significance.

We now examine an important property of complex demodulates. Defining the spectrum of the real infinite continuous time series $x(t)$ in terms of amplitude $M(\omega')$ and phase (ϕ') of the spectrum at frequency ω':

$$X(\omega') = M(\omega')\, e^{i\phi(\omega')}\,.$$

Then using the Fourier transform

$$x(t) = \int X(\omega')e^{i\omega' t}d\omega' = \int M(\omega')\, e^{i\phi(\omega')}e^{i\omega' t}d\omega'\,.$$

Thus

$$x'(t,\omega) = \int e^{-i\omega t}M(\omega')\, e^{i\phi(\omega')}e^{i\omega' t}d\omega',$$

and

$$x_d(t,\omega) = \int_{\omega-d\omega}^{\omega+d\omega} e^{i\{(\omega'-\omega)t+\phi(\omega')\}}A(\omega')M(\omega')\, d\omega'$$

$$= \int_{-d\omega}^{d\omega} e^{i\{(\omega'-\omega)t+\phi(\omega')\}} A(\omega')M(\omega')\, d(\omega'-\omega),$$

where $A(\omega')$ represents the Fourier transform of the filter $a(t)$, and the filter coefficients are zero for frequencies $> \omega+\delta\omega$ and $< \omega-\delta\omega$.

Now consider another time series

$$y(t) = \int B(\omega')\, e^{i\varphi(\omega')} e^{i\omega' t} d\omega',$$

where

$$B(\omega') = rM(\omega'),$$

and

$$\phi(\omega') - \varphi(\omega') = k,$$

and k and r are constant over frequency, i.e. the amplitude spectra are linearly related and there is a constant phase difference between the two series. We can write the transfer function (complex amplitude ratio) between any pair of points in the two demodulate series at time t as

$$T = \frac{\int_{-d\omega}^{d\omega} e^{i\{(\omega'-\omega)t+\phi(\omega')\}} A(\omega')M(\omega')\, d(\omega'-\omega)}{\int_{-d\omega}^{d\omega} e^{i\{(\omega'-\omega)t+\varphi(\omega')\}} A(\omega')B(\omega')\, d(\omega'-\omega)}.$$

As k and r are constants

$$T = \frac{\int_{-d\omega}^{d\omega} e^{i\{(\omega'-\omega)t+\phi(\omega')\}} A(\omega')M(\omega')\, d(\omega'-\omega)}{re^{-ik} \int_{-d\omega}^{d\omega} e^{i\{(\omega'-\omega)t+\phi(\omega')\}} A(\omega')M(\omega')\, d(\omega'-\omega)} = \frac{e^{ik}}{r}.$$

Then

$$r = \frac{1}{|T|}$$

and

$$\tan(k) = \frac{Im[T]}{Re[T]},$$

i.e. if the spectra of the two time series are linearly related in amplitude, but phase shifted with respect to each other by a constant, then we can recover this constant exactly, simply by calculating the phase of the transfer function between any pair of complex demodulates from the two series. This also holds for discrete, finite time series.

We now consider the time-local nature of the demodulates. Examination of equation (1.1) shows that the frequency shift operation operates independently on each sample, and thus introduces no leakage over time. As always, when we filter the data (equation (1.2)) some leakage over time is introduced, but if we choose a normal filter function, then the power remains strongly centred at the correct time. We know (above) that "perfect" demodulates are independent. Thus, by a correct choice of our frequency band and time window (sampling rate) we ensure that there are two degrees of freedom associated with each demodulate point. Therefore we can obtain a series of time-local and independent estimates of k and r by using each pair of points in our two time series, but we have no information about whether these time-local estimates of k and r are constant over frequency. This is a consequence of the finite information content of a band-limited signal and is always true. Thus, a complex demodulate decomposition of two time series and the calculation of the transfer function between pairs of points in them is always a valid operation in terms of the information content of the data. This does not mean that the system described by the relationship between x(t) and y(t) has a frequency independent time-local transfer function, but that we have no information with which to test this hypothesis. We can test it only if we make some further (or different) assumption, for example that the amplitude and phase relationships should be stable over a slightly longer time window, and average over time. In the application we present here this means that in practice we need to use a frequency band that is sufficiently wide that we obtain several demodulate samples in a time window corresponding to the expected duration of a 'phase'. We generally need to work with very few points (5 to 15 points is typical). This is usually sufficient to give stable results, and ensures that the calculation of the covariance matrix is a very efficient operation.

2. COMPLEX DEMODULATE REGRESSION

First, consider a finite realization of a continuous parameter, real, zero mean multiple stationary Gaussian series $x(t)' = [x_1(t), x_2(t),\ldots x_p(t)]$, $t=0,1,\ldots,T$ (' denotes transpose). Let $X(t,\omega_o)' = [X_1\ (t,\omega_o), X_2\ (t,\omega_o),\ldots X_p\ (t,\omega_o)]$, $t=1,2,\ldots,M$ denote the corresponding complex demodulates computed by the above method, i.e Fourier transformed, band-pass filtered from ω_o-$\delta\omega$ to $\omega_o+\delta\omega$, frequency shifted by ω_o, truncated, and transformed back to the time domain. It then follows from Goodman (1963) that the complex demodulates will be independently Gaussian distributed and that M times the (Hermitian) covariance matrix

$$S(\omega_o) = (1/M) \sum_{1}^{M} X(t,\omega_o)\, X(t,\omega_o)^* \quad (\text{ * denotes complex conjugate transpose})$$

is distributed as a complex Wishart provided the spectral density matrix of the original continuous series is constant over the band $\omega_o \pm \delta\omega_o$ and that the filter is sufficiently sharp. For more about the complex Gaussian and related distributions, see Goodman (1963).

The estimation of model parameters based on complex valued variables are very similar to that for real variables. To illustrate this we take the ordinary regression model with one dependent and L explanatory variables:

$$Y(t,\omega_o) = \sum_{1}^{L} \gamma_i(\omega_o)\, X_i(t,\omega_o) + \Delta(t,\omega_o) \quad t=1,\ldots\ldots M$$

Let $Y(\omega_o) = \begin{bmatrix} Y(1,\omega_o) \\ \cdots\cdots \\ \cdots\cdots \\ Y(M,\omega_o) \end{bmatrix}$ $\quad X(\omega_o) = \begin{bmatrix} X_1(1,\omega_o) \;\ldots\ldots\; X_L(1,\omega_o) \\ \cdots\cdots \quad \cdots\cdots \quad \cdots\cdots \\ \cdots\cdots \quad \cdots\cdots \quad \cdots\cdots \\ X_1(M,\omega_o) \ldots\ldots X_L(M,\omega_o) \end{bmatrix}$

$$\Delta(\omega_o) = \begin{bmatrix} \Delta(1,\omega_o) \\ \cdots\cdots \\ \cdots\cdots \\ \Delta(M,\omega_o) \end{bmatrix} \qquad \gamma(\omega_o) = \begin{bmatrix} \gamma_1(\omega_o) \\ \cdots\cdots \\ \cdots\cdots \\ \gamma_L(\omega_o) \end{bmatrix},$$

and write the model,

$$Y(\omega_o) = X(\omega_o)\,\gamma(\omega_o) + \Delta(\omega_o)$$

using least squares i.e. minimizing $\Delta(\omega_o)^* \Delta(\omega_o)$ we get the least squares estimator

$$\hat{\gamma}(\omega_o) = [X(\omega_o)^* X(\omega_o)]^{-1} X(\omega_o)^* Y(\omega_o).$$

Under regularity conditions, for example non-stochastic X and flat spectrum for the residuals Δ in the band $\omega \pm \delta\omega$, the following properties of the least squares estimator can easily be derived:

1) $E\{\hat{\gamma}(\omega_o)\} = \gamma(\omega_o)$,

2) $E\{[\hat{\gamma}(\omega_o) - \gamma(\omega_o)]\,[\hat{\gamma}(\omega_o) - \gamma(\omega_o)]^*\} = \sigma^2\,[X(\omega_o)^* X(\omega_o)]^{-1}$, (2.1)

3) $E\{[Y(\omega_o) - X(\omega_o)\hat{\gamma}(\omega_o)]^*\,[Y(\omega_o) - X(\omega_o)\hat{\gamma}(\omega_o)]\}/(M-L)$
$= E\{\Delta(\omega_o)^*\Delta(\omega_o)\} = \sigma^2$, (2.2)

4) $C^2 = \hat{\gamma}(\omega_o)^* X(\omega_o)^* X(\omega_o)\hat{\gamma}(\omega_o) \,/\, [Y(\omega_o)^* Y(\omega_o)]$
is the squared coherency,

5) $\dfrac{C^2}{(1-C^2)}\,\dfrac{2(M-L)}{2L}$ is distributed as $F(2L,2(M-L))$ if $\gamma(\omega_o) = 0$,

6) Approximate $(1-\alpha)$ confidence band for the gain $|\gamma_i(\omega_o)|$: Letting σ_{ii} denote the square root of the i:th diagonal element of (2.1)

$$|\hat{\gamma}(\omega_o)| \pm (\sigma_{ii}/\sqrt{2})\sqrt{\chi^2_{1-\alpha}(2)}\ , \tag{2.3}$$

7) For the phase $\varphi_i = \arctan[\mathrm{Im}(\gamma_i(\omega_o))/\mathrm{Re}(\gamma_i(\omega_o)]$ estimated with

$$\hat{\varphi}_i = \arctan[\mathrm{Im}(\hat{\gamma}_i(\omega_0))/\mathrm{Re}(\hat{\gamma}_i(\omega_0))]$$

we get the approximate confidence bands

$$\hat{\varphi}_i \pm \arcsin\{(\sigma_{ii}/(|\hat{\gamma}(\omega_o)|\sqrt{2}))\sqrt{\chi^2_{1-\alpha}(2)}\}\ ,\ \text{and} \tag{2.4}$$

8) For a bivariate system the above phase estimator is consistent even in the presence of measurement errors in the explanatory variable, provided these errors are uncorrelated with the errors in the y variable. However, as in the real time domain, the gain estimator (i.e. the magnitude of the elements of $\hat{\gamma}$) is inconsistent if there are measurement errors in the explanatory variable.

Comments:

If the residual variance is unknown and is estimated using equation.2.2, then F(2,2(M-L))/(M-L) should be used instead of χ^2 in formulae (2.3) and (2.4). Using the inverse FFT (after filtering in the frequency domain) to compute the complex demodulates one generally has to add zeros to the beginning and end of the frequency band to make the number of frequency points a power of 2. This in turn implies that we get too many data points in the complex demodulate time domain, i.e. the data points are not independent and the degrees of freedom in the above formulae have to be reduced. For example, if our frequency band originally has 150 frequency points, zero padding to 256 gives a 'redundancy' factor of 150/256 = .59 . So if the number of complex demodulates is M and the 'redundancy factor' is r $(.5 \leq r \leq 1)$ we have to use Mr instead of M in the above formulae. Of course, using the inverse direct Fourier transform instead of the FFT involves no zero padding, i.e. the 'redundancy' factor is 1 in that case.

As can be seen from the above, the properties of the least squares estimator in the complex demodulate time domain are very similar to those pertaining to the real time domain. The main difference is that the number of degrees of freedom has to be calculated somewhat differently because we have two instead of one degree for each independent observation. We can thus easily obtain a Two Stage Least Squares Estimator for complex demodulated time series. Alternatively we may consider the Maximum Likelihood estimator. This was used by Roberts and Christoffersson (1990) for estimating particle motion models for seismic signals. Böhme (1986) derived a maximum likelihood estimator for sonar applications using a more conventional spectral density estimator. The models used by these authors are basically complex valued factor analysis models, i.e. the factors and factor-loadings are complex quantities.

3. DATA SERIES USED IN THE STUDY

The data series used are the logarithm of the total manufacturing production index (LOGMPI) and the Business Tendency Survey (BTS) series. We refer to Bergström (1991) and Knudsen & Norlin (1990) for a more detailed description of the series.

The dependent series in this study, the manufacturing production index, consists of quarterly index figures computed by averaging monthly figures. The seasonal variability dominates the time series, making it difficult to see other fluctuations. When looking at the series in the frequency domain, the amplitude spectrum of the detrended series (Figure 1) shows huge peaks at frequencies 1 and 2 cycles per year (c/y). These are caused by the seasonal cycle and its harmonics (e.g. half year). But we can also see energy at lower frequencies, say below .5 c/y. Between this and the seasonal effects there is hardly any energy at all. This observation, together with a more detailed analysis of the coherence between the various series as a function of frequency, leads us to concentrate on low frequencies. These frequencies are also relatively unaffected by possible aliasing caused by the averaging and resampling procedure from monthly to quarterly figures.

The kind of series considered here are sometimes disturbed by conflicts on the labour market or other events that might influence the production volume temporarily. The observation period for this series is from 1968 until 1990. During this period there were two major labour market conflicts, in 1980:2 and in 1988:1. When working in the time domain these disturbances are usually handled by including dummy variables in the model. Since frequency domain methods are relatively insensitive to such time local effects, especially at lower frequencies, usually no special actions are necessary.

The Business Tendency Survey is a quarterly survey distributed to almost 2000 companies and consists of six groups of variables (see Knudsen and Norlin 1990).
We will here concentrate the analysis on group 1, reflecting judgements on the economic situation in the current quarter (BTS variables B101 - B108, which we call collectively the "B100" series) and group 3, concerning forecasts for the next quarter (BTS variables B301 - B308, the "B300" series). These two groups of variables measure the same type of variables. The first is a comparison of the present quarter to the previous whereas the third is a forecast made in the previous quarter. The variables should represent first differences, but as will be shown in the next section, it is more likely that the BTS series represent annual change. We must bear this in mind when interpreting the results of the analysis, whether we work in the time or the frequency domain (see below).

The respondents are asked to ignore seasonal effects when answering questions considering quarterly changes. The amplitude spectra reveal that they do this with variable success. For the B100 series there are hardly any noticeable seasonal components in the amplitude spectra except for the variables B103 and B104 that measure domestic and export prices. For the B300 series on the other hand there are quite large seasonal components except for variables B302 and B307 (production capacity and purchases of raw material). As an example, in Figure 2 we show the amplitude spectrum of the BTS series B101, volume of production, which was considered the variable of main interest from the BTS.

4. RELATION BETWEEN THE MANUFACTURING PRODUCTION INDEX AND THE BUSINESS TENDENCY SURVEY SERIES.

4.1 EXPLORATORY SPECTRAL ANALYSIS

In order to get an overall picture of the relation between the production index and the BTS series we consider first the amplitude spectra.

These BTS series represent first differences whereas the production index is a volume series. Differencing a series implies that we give more weight to the higher frequencies and also introduce a linear phase shift starting with 90 degrees at zero frequency and going down to zero at the Nyquist[2]. This does not affect the way in which we conduct the frequency domain analysis procedure, but the estimated magnitude and phase of the transfer function must be interpreted differently. The phase of the transfer function between a volume series and a differenced explanatory series will, at for example .3 c/y, have a downward phase shift of 77 degrees (13 months lead for the differenced series) compared to the phase between the corresponding undifferenced series (or the phase if both series are differenced). Similarly, for a fourth differenced series the corresponding phase shift will be 36 degrees (6 months lead). This effect is clearly seen by looking at the curves at the top of Figure 3 showing the logarithm of the manufacturing production index (LOGMPI), the first difference (DLOGMPI) and the fourth difference (D4LOGMPI). The first and fourth differences have been multiplied with 100 to

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[2] Throughout this paper we represent the lag between series primarily in terms of phase lag in degrees. If we believe that the phase lag is indicative of a simple time lag, then this time lag Δt can be estimated via $\Delta t = \Delta p/(360*f)$, where Δp is the phase lag and f is the central frequency of the band. We prefer the representation in terms of phase lag because an extra assumption is implicit in the conversion to a time lag.

represent percentage change. The smooth dotted curve below each index series is the corresponding series band-pass (zero phase) filtered from .15 c/y to .45 c/y, i.e. business cycles from 2.2 to 6.7 years. Each of the spectra is individually scaled to maximum amplitude so the spectrum gives for each series the relative distribution of amplitude as a function of frequency. The curves on top of the figures are also scaled individually.

In the time domain the same problem takes a different, and slightly less tractable, form. If we expect a direct relationship between two variables a(t) and b(t) it is not advisable to estimate the relationship between a(t) and for example the differenced b(t) series. If we do not compare "like" with "like", we can still with full validity use a time domain lag model, but in general more lag coefficients will be significant. Obviously, there is a danger that this can adversely affect any inferences about underlying economic mechanisms eventually drawn from the analysis.

Comparing the amplitude spectrum of B101 (Figure 2) with the spectra in Figure 3 we find that the spectra of B101 and D4LOGMPI are remarkably similar. Figure 4 shows the two spectra in the same plot and we see that the spectra are virtually identical for frequencies up to about .6 c/y and that the same is true for the business cycle component (the two smooth dotted curves on top of the figure). This is a strong indication that the BTS series B101 does not measure production of the present quarter compared to that of the previous but instead measures annual change.

We now examine cross spectra between series. These give gain and phase of the transfer function averaged over the whole time window. Later, we also analyse the data using complex demodulation, which allows us to examine possible variation with time of the relationships between the variables.

Figures 5A-F show the phase and gain of the transfer function between the BTS series B101 and the three transformed manufacturing production index series, i.e. LOGMPI, DLOGMPI and D4LOGMPI. All the cross spectra between the production index and the different BTS series show high coherency in the band 0.15 - 0.45 c/y corresponding to (business) cycles from 2.2 to 6.7 years, and we will later concentrate our analysis on this frequency band. This main finding is valid whether we use the logarithm of the production index or not, first or fourth order differenced series. There is, however, one notable dissimilarity between the phase spectra for the fourth difference on the one hand and that of the original or first differenced series, in that (in contrast to for D4LOGMPI) for LOGMPI and DLOGMPI we have significant coherency at the fundamental seasonal frequency (1 c/y) showing that there is a significant seasonal component in the B101 series. The phase lag for the LOGMPI series is around 180 degrees implying that the respondents in the Business Tendency Survey over-compensate the seasonal effects when performing the seasonal adjustment relative the present quarter. For the differenced series the corresponding phase lag is around 135 degrees which is just what could be expected from the phase lag of the difference filter. There is also significant coherency at the fundamental seasonal frequency for most of the other B100 and B300 series, exceptions are B102 and B107. The power at seasonal frequencies can vary greatly from series to series.

For the phase spectrum of D4LOGMPI versus B101 there is of course no significant coherency at 1 c/y because the fourth difference filter removes the seasonal component. However we see significant coherency on both sides close to 1 c/y. This is most probably caused by leakage from the seasonal because the fourth difference filter does not remove seasonal effects in the neighbourhood of 1 c/y, i.e. it is not an optimal filter for removing seasonal components. For some of the series there is also some slight coherency in other frequency bands but there is not enough information in the data to resolve it properly.

These cross-spectra were used primarily as an initial investigating tool. Before trying to draw any real conclusions from the data, we use complex demodulation to investigate the stability over time of the relationships between the data series.

4.2 TIME AND FREQUENCY LOCAL ANALYSIS

4.2.1 MODELS WITH ONE B100 EXPLANATORY VARIABLE

First we consider the questions concerning annual changes, i.e. the dependent variable is D4LOGMPI. Figures 6A and 6B provide examples of complex demodulate transfer function analysis in the frequency band 0.15 to 0.45 c/y. Five points are used in the regression over time, giving a sliding time window of 10 years. As the time series are 21 3/4 years long, this allows us to examine the time-stability of the relationships between the series. The figures presented, which are fairly typical, show that both the amplitude and phase of the transfer function are stable over time (within this frequency band). For some of the variables the estimated transfer function varies more with time, but these variations are associated with a decrease in coherence, meaning that the variations are not (statistically) significant. Having ascertained this, to get a "best" estimate of the transfer function, we can average over the whole available time series.
Table 1 summarizes the gain and phase relationships and coherency between the manufacturing production index and each of the BTS series 101 to 108, within the frequency band .15 to .45 c/y.

The variable B101, which describes changes in production volume from the previous quarter to the current quarter, has a phase lag relative to the D4LOGMPI series of approximately -14 degrees in the frequency interval considered (Figure 5A). If we believe that the phase lag is indicative of a simple time lag between the series, then this time lag is about seven weeks (i.e. half a quarter), with the B101 series *leading*. This lead is significantly different from zero. The gain (regression coefficient) is around 0.28 and coherence is .96.

Table 1: Models for D4LOGMPI with One Explanatory Variable from Group 1.
Frequency Band .15 - .45 c/y.
95% confidence limits

	Series	Gain	Phase lag(°)[3]	Coherence
Volume of production	B101	0.28 ± .04	-14 ± 07	.96
Production capacity	B102	0.85 ± .28	11 ± 18	.83
Prices (domestic)	B103	0.35 ± .15	5 ± 23	.75
Prices (export)	B104	0.20 ± .07	-13 ± 18	.82
Orders received (domestic market)	B105	0.26 ± .05	-27 ± 12	.92
Orders received (export market)	B106	0.19 ± .05	-49 ± 16	.87
Purchases of raw materials	B107	0.20 ± .05	-9 ± 12	.91
Time of deliveries	B108	0.26 ± .09	-23 ± 20	.81

In Table 1, we can examine the results for the analysis of the D4LOGMPI series vs. each of the series B101 to B108 in the frequency band 0.15 to 0.45 c/y. It can be seen that there is a high degree of internal consistency in the results. All of the survey series show a clearly significant relationship with the production series. The number of independent data used in the estimation is about twenty and the number of parameters in the model that we are fitting to the data is two. Thus all of the estimated coherencies are very high. Four of the series; B101, B105, B106 and B108 (marginally), show significant negative phase lags implying a lead of the corresponding BTS series over D4LOGMPI. The largest lead is for B106 (orders received for the export market) with a lead of almost half a year. For the rest of the B100 series the phase lag is not significantly different from zero, i.e. we cannot detect any significant lead or lag.

As the phase lag between the first and fourth difference filter is 40 degrees at .3 c/y we

[3] see footnote 2

expect that the phase between DLOGMPI and the various B100 will be about 40 degrees larger than that of D4LOGMPI and the corresponding B100 series. This is indeed the case as can be seen from Table 2.

Table 2: Models for DLOGMPI with One Explanatory Variable from Group 1.
Frequency Band .15 - .45 c/y.
95% confidence limits

	Series	Gain	Phase lag(°)[4]	Coherence
Volume of production	B101	0.07 ± .02	24 ± 13	.91
Production capacity	B102	0.22 ± .09	48 ± 23	.76
Prices (domestic)	B103	0.10 ± .04	53 ± 24	.75
Prices (export)	B104	0.05 ± .02	31 ± 26	.72
Orders received (domestic market)	B105	0.06 ± .02	15 ± 17	.85
Orders received (export market)	B106	0.05 ± .02	-8 ± 20	.80
Purchases of raw materials	B107	0.05 ± .02	32 ± 16	.86
Time of deliveries	B108	0.06 ± .03	19 ± 25	.72

Comparing tables 1 and 2, the largest deviation from the expected phase shift of 40 degrees is for B103 where the phase lag is 53 degrees instead of the expected 45 (5 + 40) but the difference is well within the confidence bands. We also note that the coherencies are lower than those for D4LOGMPI. This is also what can be expected as the difference filter is quite effective in removing lower frequencies, which in our case happens to be the frequency band of interest.

All of the variables except B106 show positive phase lags relative to DLOGMPI, and with the exceptions of series B105 and B108 all of these lags are significantly different

[4]see footnote 2

from zero. For series B101, B104 and B107 the estimated lag, when naively converted to a time lag, is close to one quarter. If the B100 series measured the difference between the present quarter and the previous quarter (monthly change) we would expect the phase for B101 to be around zero or slightly negative because the measurement is made in the later part of the quarter. Furthermore, we would expect the phase for B105 and B106 (orders received for domestic and export market) to be negative, implying a lead over the corresponding production variable, DLOGMPI. As this is not the case it is rather unlikely that the B100 series refer to monthly changes. On the other hand the phase of B105 and B106 relative to D4LOGMPI are both negative as expected and correspond to a lead of about 3 months for B105 and 5-6 months for B106. The lead of B101 over D4LOGMPI is between 3 to 10 weeks (95% confidence interval) which is consistent with that the survey is done in the later part of the quarter. These results, together with the earlier discussed similarity of the amplitude spectra for D4LOGMPI and the B100 series, are clear indications that the B100 series refer to annual change, not quarterly change.

Obviously, these results have important implications for the use of the BTS series in making forecast of the business cycle.

4.2.2 COMPARISON WITH THE TIME DOMAIN RESULTS

It can be difficult to compare frequency-domain results with time-domain lag models of the type used by e.g. Bergström (1991), primarily because the time domain models are often much more complicated (more model parameters). However, we consider it important to try to set our analysis into the context of more traditional time-domain analyses. We therefore attempt to compare our results with the models estimated by Bergström using B101, B102, ..., B108 as the only explanatory variable :

After elimination of the seasonal components in the DLOGMPI by using seasonal dummies, Bergström found that e.g. B101 including lags up to four quarters could only explain about 22 percent of the remaining variability. Using current B101 and lagged DLOGMPI gave a significantly better model fit. But, the fit is still rather poor, only about 55 percent of the nonseasonal variation is explained. Our analysis indicates that this is simply because the DLOGMPI leads B101.

The model finally chosen by Bergström was a comparison of each BTS variable with the D4LOGMPI series at lags 0, 1, 2, 4 and 5. He obtained an R^2 of between 0.69 and 0.83. These values are lower than those obtained in our analysis (e.g. for the "best" variable B101 the values are 0.83 and 0.96 for time and complex demodulate domain respectively). We believe that this is simply because there is little or no coherence outside the frequency band that we have used (see Figures 5E and F), and including data from these frequencies only degrades the model slightly. This appears to be a fairly important conclusion. Two possibilities exist. Either the energy in the poorly correlated frequency bands is simply noise, and there is no causal relationship between the variables at these frequencies, or at these frequencies the causal relationship between the variables is non-linear. The latter would imply that it is probably incorrect to analyse all frequency bands together - a normal time-domain lag model is linear in the same sense as our complex demodulate domain analysis, and thus will not work with a non-linear system.

4.2.3 THE FIRST AND THE THIRD GROUP OF THE BTS COMPARED

The variables B301 - B308 measure the same phenomena as the variables B101 - B108. The difference is that while the first group is intended to compare the present situation to the situation one quarter ago, the third group is the respondents' forecasts of changes from the present situation one quarter ahead. This means the variables B301 - B308 are forecasts of the variables B101 - B108 and if they are good forecasts they could be used in forecasting models to obtain a greater lead time.

We find that the B300 series are very similar to the corresponding B100 series, and they all show high coherence with the D4LOGMPI series in the same frequency band (0.15 to 0.45 c/y). Results of the analysis of the relationship between the D4LOGMPI series and individual B300 series within this frequency band are given in Table 3. All the estimated coherencies are high, but are slightly lower than for the analysis using the corresponding B100 series (Table 1). As the B300 series are the respondents' forecasts of the B100 series this is what we might expect.

Table 3: Models for D4LOGMPI with One Explanatory Variable from Group 3.
Frequency Band .15 - .45 c/y.
95% confidence limits

	Series	Gain	Phase lag(°)[5]	Coherence
Volume of production	B301	0.35 ± .06	2 ± 10	.94
Production capacity	B302	0.76 ± .30	34 ± 22	.77
Prices (domestic)	B303	0.42 ± .26	15 ± 38	.56
Prices (export)	B304	0.24 ± .09	0 ± 21	.79
Orders received (domestic market)	B305	0.36 ± .12	-18 ± 18	.83
Orders received (export market)	B306	0.28 ± .13	-43 ± 26	.71
Purchases of raw materials	B307	0.28 ± .09	5 ± 19	.82
Time of deliveries	B308	0.40 ± .15	-17 ± 21	.79

In our analysis the B300 data series have been "displaced" to match the B100 series, so apart from errors due to incorrect forecasting we would expect to observe the same phase lag for the B100 series as for the B300 series (the phase estimate is consistent in the

[5]see footnote 2

presence of random noise - see Section 2). The coherencies are lower than for the B100 series and the confidence bands wider. The only series showing phase that is significantly different from zero is B306 (orders received, export market) which has a lead of the same order as B106. Comparing the phase lag for the B100 and B300 series in Tables 2 and 3 one gets the impression that the phase is somewhat larger for the B300 series.

To clarify this point we looked at the relationship between each B100 series and the corresponding B300 series within our selected frequency band (Table 4). We find a very high coherence between the series, which allows a more thorough and definitive analysis than does the comparison of tables 1 and 3. All of the comparisons show a phase lag, of 5 to 23 degrees. Only a couple of the phase lags are (almost) significantly different from ten degrees, and one possibility would appear to be some kind of constant phase (time) shift for all the series. The very high coherence between the series allows us to verify this by examination of cross-spectra (Figures 7 and 8).

In Figure 7, at low frequencies we observe an almost linear drift in phase from zero at zero frequency up to about 25 degrees at a frequency of 0.5 c/y. Above this frequency there is insignificant coherence between the B101 and B301 series except at seasonal frequencies. A linear drift in phase lag with frequency is what we expect for a constant time lag of 1.7 months between the two series. That no significant phase shift is observed at seasonal frequencies implies that the respondents have in some way implicitly "thought" differently about seasonal and other components. By superimposing the B101 on B301 this time shift can be directly observed. In Figure 8 cross spectral phases for the B108 and B308 series are shown.

Again we see a possibly linear drift in phase with frequency from zero up to about 1c/y. Above this frequency the coherence gradually decreases. There is some coherence around 1 c/y, and in contrast to Figure 7 the observed phase shift is consistent with a simple time shift even at these frequencies. However, the slope of the "best" line is different in

Figures 7 and 8, implying that (significantly) different time shifts are appropriate. Within the estimated confidence limits, the cross spectra are consistent with those produced using complex demodulation and presented in Table 4.

Table 4: Models for the BTS Series 100 with the Corresponding BTS -300 Variable as Explanatory Variable.
Frequency Band .15 - .45 c/y.
95% confidence limits.

	Series	Gain	Phase lag(°)[6]	Coherence
Volume of production	B101 vs B301	1.21 ± .14	15 ± 06	.97
Production capacity	B102 vs B302	0.92 ± .17	23 ± 10	.94
Prices (domestic)	B103 vs B303	1.31 ± .24	13 ± 10	.62
Prices (export)	B104 vs B304	1.15 ± .17	13 ± 09	.95
Orders received (domestic market)	B105 vs B305	1.43 ± .22	9 ± 08	.95
Orders received (export market)	B106 vs B306	1.49 ± .38	-5 ± 15	.89
Purchases of raw materials	B107 vs B307	1.40 ± .19	14 ± 09	.96
Time of deliveries	B108 vs B308	1.57 ± .21	8 ± 07	.97

The conclusion is that there is a clear and significant delay between the B100 series and the corresponding B300 series. This time delay varies from 0 to about 3 months (0 - 23 degrees) for the different series (see Table 4) with the B100 series *leading* (but recall that the B300 series are known one quarter earlier). This is not due to any kind of "random" error in the data, and implies a *systematic* difference in the two series. This difference must be due either to the way in which the data is generated, or to some idiosyncrasy in the way in which the respondents answer the questions.

[6]see footnote 2

Because of the very high coherence between the B100 and B300 series in the relevant frequency band, we can be fairly confident about the reliability of this result.

A comparison of our results with those from a time domain analysis is illuminating, and provides a nice example of why we should routinely consider frequency-domain analyses as a complement to analysis in the time domain:

Bergström (1991) explained B301 with B101 at lags 0 to 4 and seasonal dummies. He obtained an R^2 of 0.89 with lags zero, one and two significant. This is a good deal lower than our estimate of 0.97 (Table 4), a consequence of the lack of coherency at higher frequencies. Bergström observed that several lags were required to describe the relationship, the "mean delay" being 0.98 quarters. According to our analysis, a single delay of 1.6 months is sufficient to describe essentially the whole relationship between the data series, with a minor zero-lag component at seasonal frequencies. While these results appear to be inconsistent, we believe that this is simply due to the difficulty of interpreting the time domain results when the correct lag does not correspond to a multiple of the sampling interval, and the relationships between the series are frequency dependent.

4.2.4 MODELS WITH TWO EXPLANATORY VARIABLES (B101 and another one)

We tried every other variable from the first group (B102 - B108) in a multiple model, one at a time, together with B101 in the frequency band 0.15 to 0.45 c/y. None of the multiple models were successful. In most cases the gain was significant for both B101 and the added variable, but the phase was insignificant for the added variable in most cases, while the phase for B101 was significant.

That such multiple models do not work is simply a reflection of the high degree of similarity between the B101 variable and the other B100 variables (within the relevant frequency band).

5. SUMMARY

Frequency and complex demodulate methods were used to illuminate the relationship between manufacturing and the various BTS-series. The BTS series are intended to measure quarterly change but our analysis shows that it is more likely that they measure annual change. In addition they do contain significant seasonal components. We found that all the (B100 and B300) BTS series used had high coherence with the series of manufacturing production for frequencies between 0.15 and 0.45 c/y corresponding to the frequency band most likely to be dominated by the business cycle. The phase lag between the percentage annual change in manufacturing production was found to be negative indicating a lead for the BTS series B101, B105 and B106.

At other frequencies we found little coherence (other than that due to imperfectly removed seasonal effects - see below). This has important implications for the type of causal model which it is sensible to use for this type of data. For example, at higher frequencies either the data is dominated by "noise" or there is a non-linear relationship between the variables. Either way, it is not optimal to combine analysis of this data with that at lower frequencies. Furthermore, as high frequency ("rapid", "short term") variations seem to be uncorrelated, it seems that the data series are unsuitable for the prediction of rapid variations, only the more slowly varying (lower frequency) part can be predicted with a reasonable degree of success.

When working with traditional econometric methodology the series used must be comparable, so the dependent series should be transformed into a series describing production changes, since this is what the BTS series measures. Frequency and complex demodulate domain methods have a distinct advantage here in that compensation for such effects can be included *after* the actual numerical analysis, whereas in the time domain the entire analysis procedure must be repeated after suitable "adjustment" of the data series.

Comparison of the B300 series with MPI and with the corresponding B100 series showed a consistent and clear time delay between the B100 and B300 series. This time delay can be different for the different series.

All the B100 series had high coherence with the series of manufacturing production, but the cross-correlation between the BTS series is high, so we never can have significant parameter estimates for models with more than one explanatory variable from the BTS.

The purpose of this paper has been to study the **structural relationship** between manufacturing production and the various BTS series which could serve as a basis for making forecasts of the business cycle.
The results indicate that a simple recursive filter (exponential smoothing) applied to B101 or perhaps even better to B301 which is known a quarter earlier would probably give reasonable forecasts of the business cycle (see Öller 1986).

Acknowledgement.

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SVENSK SAMMANFATTNING.

Syftet med denna rapport är att belysa sambandet mellan industriproduktionsindex och ett antal barometerserier för att i ett senare steg utveckla metodik för konjunkturprognoser.

Analys av ekonomiska tidsserier utförs oftast i tidsdomänen. Vi har här valt att i stället arbeta i frekventiell och komplexdemodulerad domän. Eftersom det råder ett entydigt samband mellan tids- och frekvensdomän innehåller de samma information fast i olika form. Vissa strukturer framträder tydligare i frekvensdomänen, andra i tidsdomänen. Komplexdemodulerad tidsdomän är en hybrid mellan de två andra och är särskilt lämpad för analys av förlopp där strukturen varierar över tid.

De dataserier som analyserats är produktionsindex för verkstadsproduktion (aggregerad till kvartalsnivå) och barometerserierna B101 - B108 och B301 - B308. De första serierna (B100) avser att mäta säsongrensad förändring innevarande kvartal jämfört med föregående, medan B300 serierna avser en prognos av kommande kvartal jämfört med innevarande. Våra resultat visar att denna säsongrensning har varierande kvalitet samt att barometerserierna mäter förändring på års- snarare än kvartalsbasis. Vissa serier har kraftiga säsongkomponenter medan det för andra skett en överkompensering av säsong-effekterna. Figur 4 visar amplitudspektrum för produktionsindex (procentuell förändring på årsbasis), D4LOGMPI och barometerserie B101 vilken mäter total produktion. De tunna prickade kurvorna överst på figuren visar konjunkturcykelkomponenten för de två serierna. Av figuren ser vi att spektra är praktiskt taget identiska för frekvenser upp till ca 0,5 cykler/år. Vi ser också att tidsförskjutningen mellan dataserierna är liten, något mindre än ett halvt kvartal. Denna tidsförskjutning beror troligen av att barometerserierna mäts under senare delen av kvartalet. Huruvida barometerserien mäter kvartals- eller årsvisa förändringar är av stor betydelse när den används för att förutse vändpunkter i konjunkturen eftersom tidsförskjutningen mellan konjunktur och kvartalvis förändring är större än mellan konjunkturell och årsvis förändring.

En sammanfattning av resultaten beträffande relationen mellan årlig förändring av produktionsindex och de olika barometerserierna presenteras i tabell 1 och 3. Vid konjunkturcykelfrekvenser visar samtliga barometerserier mycket hög korrelation med produktionsindex. Störst tidsförskjutning visar B106 och B306 vilka mäter orderingång på exportmarknaden. Dessa barometerserier ligger som förväntat ca ett halvt år före produktionsförändringen på årsbasis.

Analysen visar vidare att praktiskt taget all samvariation (förutom säsong) mellan produktionsindex och barometerserierna hänför sig till konjunkturcyklerna, dvs. cykler med en längd mellan 2 och 7 år, samt att denna samvariation är mycket hög (se figurerna 5A-F). Detta innebär att ett enkelt rekursivt filter (exponentiell utjämning) av B101, eller kanske hellre B301 vilken är känd ett kvartal tidigare, förmodligen skulle ge en acceptabel konjunkturprognos.

REFERENCES

Banks R.J. 1975. Complex demodulation of Geomagnetic data and the estimation of transfer functions. *Geophys. J. R. Astr. Soc. 43 87-101*

Bergström, R. (1991) The Relationship Between Manufacturing Production and Different Business Survey Series in Sweden, *Department of Statistics, Uppsala University*

Bingam C.,Godfrey M.D. and Tukey J.W. 1967. Modern techniques of power spectrum estimation. *IEEE Trans. Audio and Electroacoustics AU-15 56-66*

Burley S.P. 1969 A spectral analysis of the Australian business cycle. *Australian Econ. Papers VIII. 193-218*

Böhme J.F. 1986 Separated estimation of wave parameters and spectral parameters by Maximum Likelihood. Proc. *IEEE-ICASSP, Tokyo 2819-2822*

Goodman N.R. 1963 Statistical analysis based on a certain multivariate complex Gaussian distribution (an introduction). *Ann. Math. Statist. 34 152-177*

Granger C.W.T.and Engle R. 1983 Applications of Spectral Analysis in Econometrics. *In Handbook of Statistics, Vol. 3. Ed. Brillinger D.R. and Krishnaiah P.R. Elsevier Science Publishers. 125-156*

Granger C.W.T. and Hatanaka M. 1964 Spectral Analysis of Economic Time Series. *Princeton University Press, Princeton*

Harvey A.C. 1978 Linear regression in the frequency domain. *International Economic Review 19 507-512*

Hasan T. 1983 Complex Demodulation: Some Theory and Applications. *In Handbook of Statistics, Vol. 3. Ed. Brillinger D.R. and Krishnaiah P.R. Elsevier Science Publishers. 125-156*

Knudsen, R. and Norlin, J. (1990) Barometern som Konjunkturmätare,. In *Konjunkturläget, maj 1990. Konjunkturinstitutet*

Öller L-E. 1986. A note on exponentially smoothed seasonal differences. *J. Business and economic statistics. Vol 4, 485-489*

Öller L-E 1990. Forecasting the business cycle using survey data. *International Journal of Forecasting. Vol 6, 453-461*

Roberts R.G. 1984 The long period electromagnetic response of the Earth. *Geophys. J. Roy. Astr. Soc. Vol. 78, 547-572*

Roberts R.G. and Christoffersson A. 1990 Decomposition of complex single-station three-component seismograms. *Geophys. J. Int. 103 55-74.*

Roberts R.G. and Dahl-Jensen T. 1989 Seismic reflection processing in the complex demodulate domain: Basic theory and application to residual static estimation. *Geophys. J. 98 543-552*

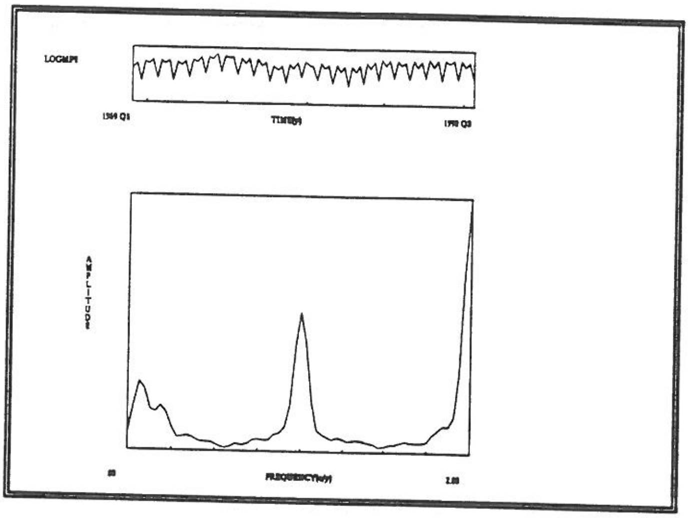

Figure 1. Amplitude spectrum of the logarithm of the manufacturing production index (LOGMPI).

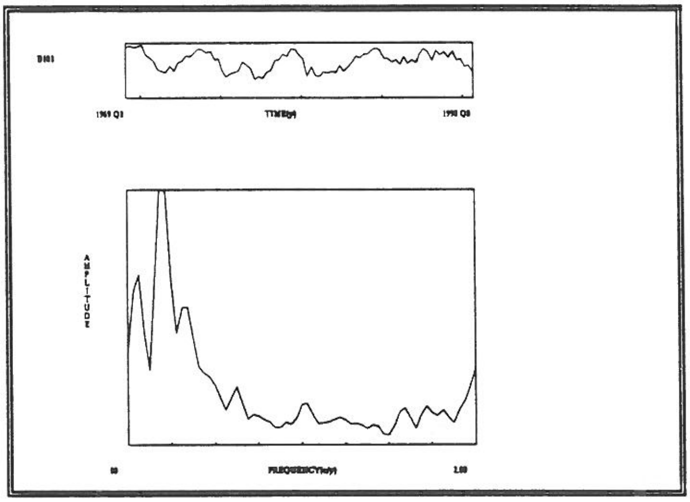

Figure 2. Amplitude spectrum of BTS series B101.

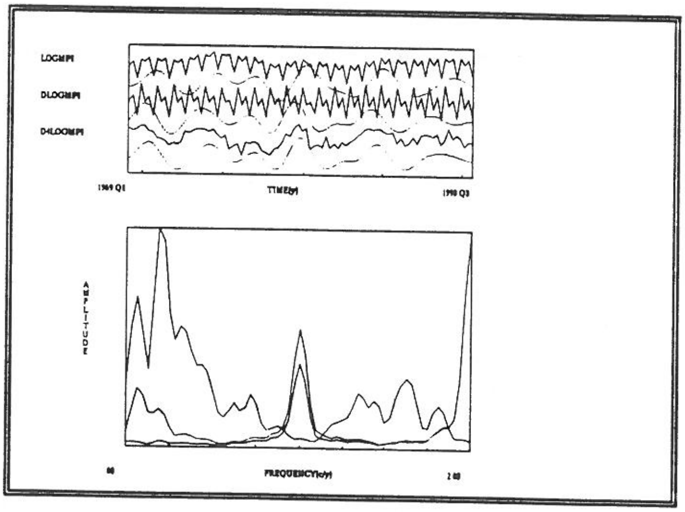

Figure 3. Amplitude spectrum of
(1) the logarithm of the manufacturing production index (LOGMPI)
(2) the first difference (DLOGMPI)
(3) the 4th difference (D4LOGMPI).
The smooth dotted curve below each index series is the corresponding series band-pass (zero phase) filtered from .15 c/y to .45 c/y.

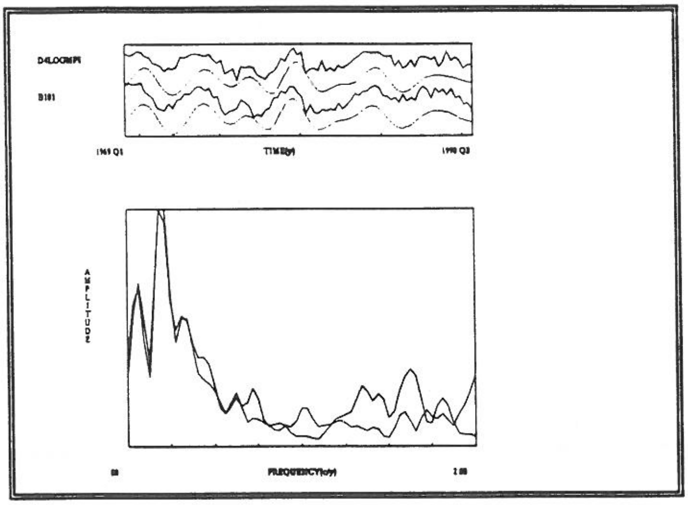

Figure 4. Amplitude spectrum of the logarithm of the 4th difference of the manufacturing production index (D4LOGMPI) and the BTS series B101. The smooth dotted curve below each index series is the corresponding series band-pass (zero phase) filtered from .15 c/y to .45 c/y.

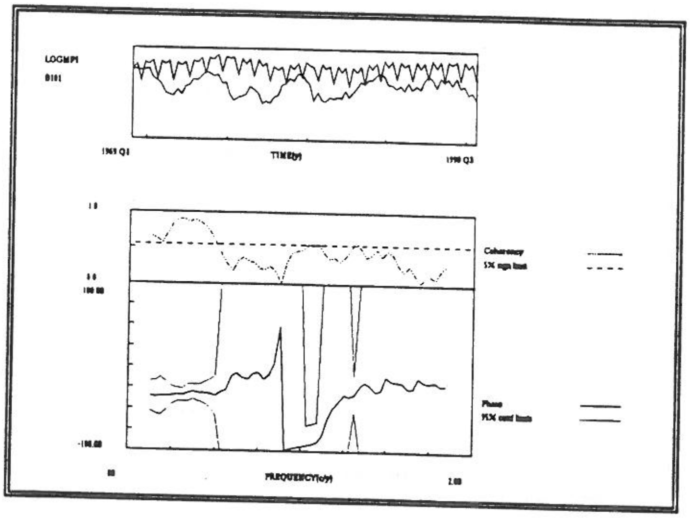

Figure 5A. Phase of the transfer function between the BTS series B101 and the logarithm of the manufacturing production index (LOGMPI).

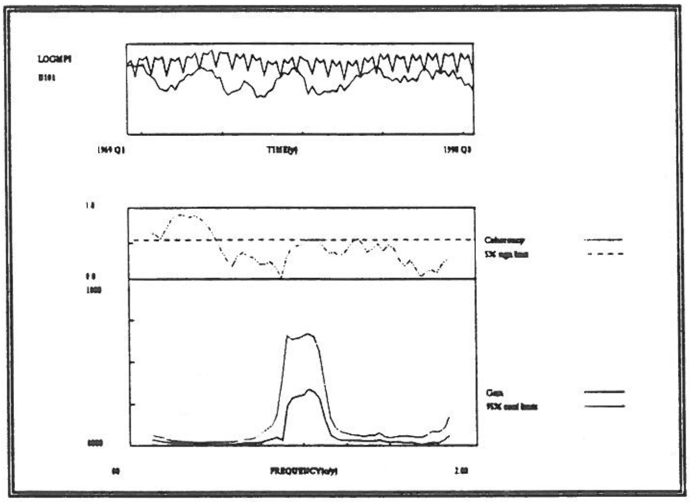

Figure 5B. Gain of the transfer function between the BTS series B101 and the logarithm of the manufacturing production index (LOGMPI).

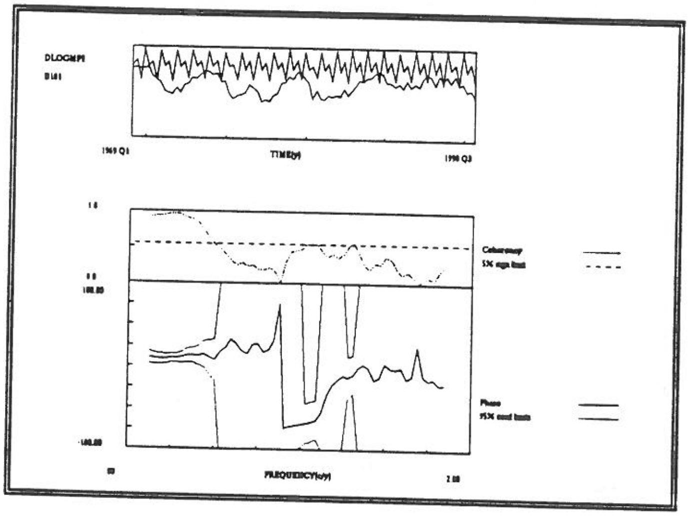

Figure 5C. Phase of the transfer function between the BTS series B101 and the first difference of the logarithm of the manufacturing production index (DLOGMPI).

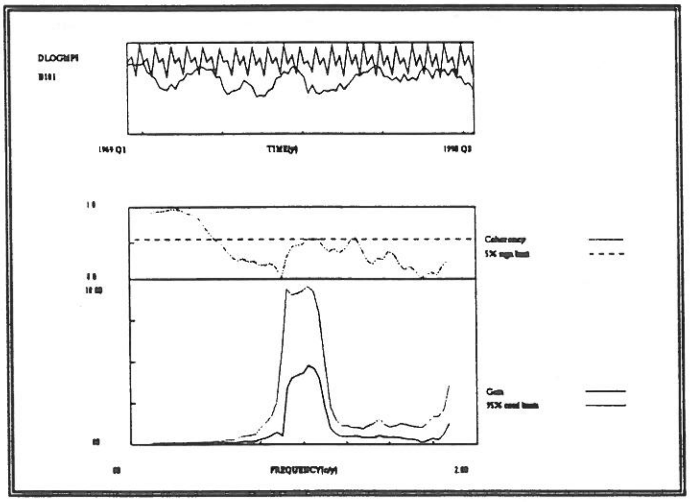

Figure 5D. Gain of the transfer function between the BTS series B101 and the first difference of the logarithm of the manufacturing production index (DLOGMPI).

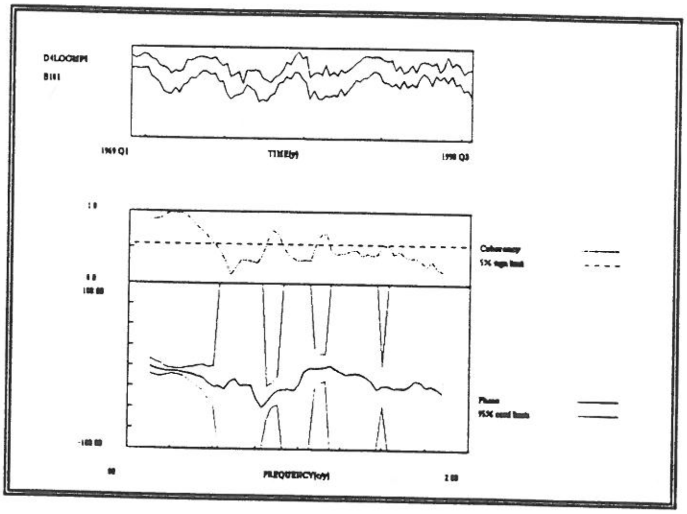

Figure 5E. Phase of the transfer function between the BTS series B101 and the 4th difference of the logarithm of the manufacturing production index (D4LOGMPI).

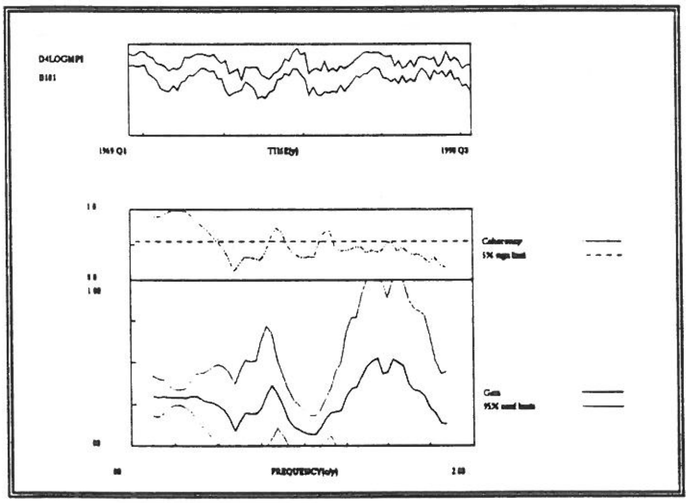

Figure 5F. Gain of the transfer function between the BTS series B101 and the 4th difference of the logarithm of the manufacturing production index (D4LOGMPI).

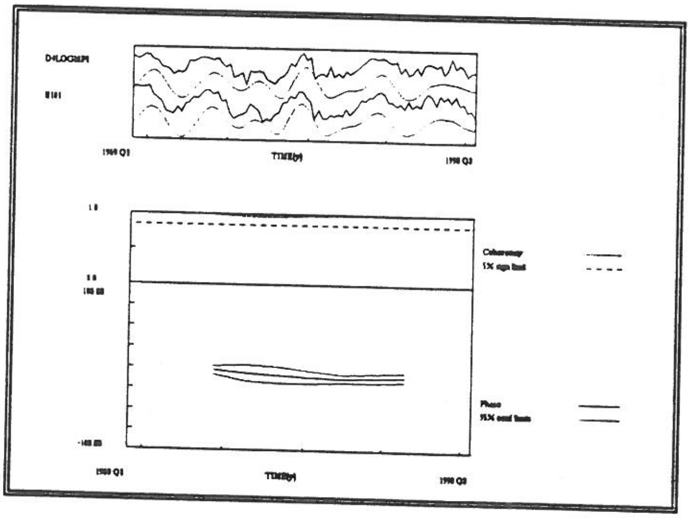

Figure 6A. Phase of the complex demodulate transfer function between the BTS series B101 and the 4th difference of the logarithm of the manufacturing production index (D4LOGMPI). Frequency band .15 c/y - .45 c/y.

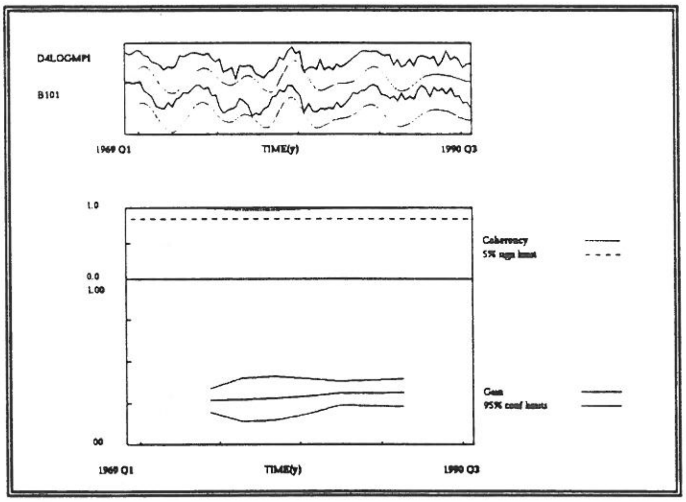

Figure 6B. Gain of the complex demodulate transfer function between the BTS series B101 and the 4th difference of the logarithm of the manufacturing production index (D4LOGMPI). Frequency band .15 c/y - .45 c/y.

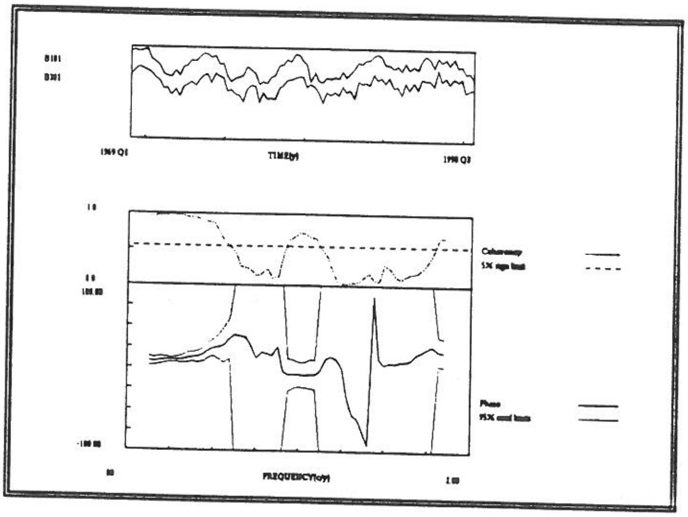

Figure 7. Phase of the transfer function between the BTS series B301 and B101.

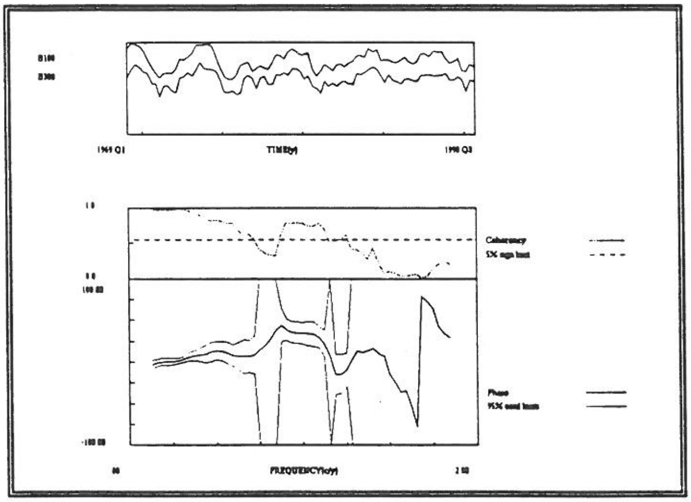

Figure 8. Phase of the transfer function between the BTS series B308 and B108.

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