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1. Introduction

Recent empirical studies of business cycles have focused on establishing robust stylized facts. Such stylized facts are typically based on detrended time series for major economic aggregates, and are presented in the form of variances and autocorrelations of the different series and contemporaneous and lagged correlation coefficients between a reference series (typically GDP) and other series.

This study aims at presenting corresponding stylized facts for the Swedish business cycle. It uses data from 1861 to 1988. The scope of the database may well be unique in an international comparison; it includes not only GDP and its components, but also labor market variables like employment and wages. The quality of the data base can be considered high by international standards. We present the sources for these data in section 2 of the paper.

In contrast to many other studies, we focus specifically on the business cycle, by which we mean cyclical comovements between macroeconomic variables with periods of around 5 years. Defining the business cycle by frequency of fluctuations, it becomes natural to exploit spectral analysis. In section 3 we look at spectra of series which first have been detrended according to two methods: first-differencing and the Hodrick-Prescott filter. We find a considerable amount of spectral mass for periods of between 3 and 8 years, which we interpret as evidence of a business cycle in our data.

Since our aim is to look at the stylized facts of the business cycles rather than of the time series in general, it is natural to treat the data in such a way so that all variation outside business cycle frequencies is filtered out. To do that we use a so-called band-pass filter. The filter is described in section 4, where we also compare the resulting filtered business-cycle series with the original detrended series.

Our results based on the filtered data are presented in the last two sections of the paper. In section 5 we report stylized facts based on the whole period. Overall, they are pretty conventional. GDP and consumption show the lowest standard deviation, whereas investment, exports and imports show the highest standard deviation. Most correlation coefficients with GDP are positive. GDP is contemporaneously uncorrelated with wages and productivity, but positively correlated with GDP lagged one year.

Lucas (1977) advanced the hypothesis that business cycles are "all alike". To investigate this issue we look in section 6 at the stability of our stylized facts over time. We do this by computing all statistics for moving 41-year periods from 1861-1901 to 1948-1988. The results are striking. First, the variance of most series increases, from the pre-war towards the inter-war period, and then it decreases again towards the post-war period. Nevertheless, the relative variances of the different series remain remarkably stable. This is the case in particular when comparing the inter-war and post-war periods. Indeed, the ratio between the standard deviations for the 41 years centered on 1930 and 1968, respectively, is close to 2 for all variables. Likewise, most correlation coefficients remain stable across subperiods. In this sense the Swedish business cycle seems to be uniform ("all alike") across seemingly very different epochs of Swedish economic history.

2. Data

Our purpose is to establish stylized facts of the Swedish business cycle using data beginning in the 1860's. We limit ourselves to the main real variables without including any nominal magnitudes. More specifically, our study covers the items on the destination account of the national accounts, and production, productivity, employment and wages in the manufacturing sector of the Swedish economy. The (logarithms of) our nine time series are depicted in *Figure 1*: gross domestic product (GDP), manufacturing production (Q), private consumption (C), investment (I), exports (X), imports (M), employment (L), real wages (W), and productivity (Q/L). See *Appendix* 1 for details on definitions and sources.

Our basic data sources stem from a major project undertaken in the 1930's at the Institute for Social Sciences at the University of Stockholm. The project covered the period from 1860 to 1930, and the results were published in Myrdal (1933), in Bagge, Lundberg and Svennilson (1933, 1935) and in Lindahl, Dahlgren and Kock (1937). Dahlgren (1936, 1941) and O. Lindahl (1956) subsequently updated the *national accounts* data. Johansson (1967) presented consistent time series for the period 1861-1955. In 1950 the National Institute of Economic Research (konjunkturinstitutet) started publishing a modern national accounts series. Later on the Central Bureau of Statistics assumed responsibility for the national accounts.

The quality of the Swedish historical national accounts is generally regarded to be high in an international comparison. Backus and Kehoe (1989), for instance, regard it to be generally on par with that of Canada and Australia and better than that of the U.S. and the other Scandinavian countries, although not quite reaching the same standard as U.K. data. A number of aspects merit comment. Obviously data quality is not uniform across the whole period. The introduction of local crop investigations in 1870 and the more systematic collection of production data from the manufacturing sector in two rounds 1896 and 1913 substantially improved quality. A fundamental improvement occurred in 1950 when the Central Bureau of Statistics started publishing the modern national accounts. These are basically constructed from the demand side with data from the production, destination and income side being used to calibrate the estimates. By contrast, the earlier series rely almost exclusively on production data.

The original historical national accounts were only given in current prices. Early work on price indices is reported in Åmark (1913) and in Myrdal (1933). Johansson (1967) computed fixed-price series for various sub-aggregates, drawing on these sources but still using the cost of living index from Myrdal to deflate GDP to fixed prices. More recently Krantz and Nilsson (1975) extended Johansson's work considerably and constructed price deflators for the demand components of GDP, by going back to the original quantity series that were used when constructing the historical accounts. They also used these price indices to give a consistent GDP series at fixed prices from 1861 to 1970.

Romers (1989) recent work has pointed out that in many countries the historical data provide a poor measure of value added in various service industries, particularly in commerce. The typical procedure—which Kuznets used for the US—has been to identify value added in commerce by multiplying commodity output by a constant mark–up factor, which relates consumer prices to producer prices. This procedure does not take into account that the mark–up factor may be variable because service output may not vary in constant proportions with commodity output. Romer uses econometric methods to allow for such variations and constructs a new series for pre–WWI GDP, which turns out to be considerably less volatile than that compiled by Kuznets.

In principle, the corresponding Swedish data have the same problem as the US data in that they are based on constant mark–up factors from 1861 to 1930. However, separate mark–up factors are applied for 8 classes of agricultural products and 16 classes of industrial products (see Lindahl et al. (1937) appendix G). It turns out that this procedure introduces considerable variations in the ratio of private services to GDP. The average of this ratio goes from 20.0 per cent for the period 1861–1870 to a high of 26.2 for 1921–1930 and down to 19.1 per cent for 1961–1970. The corresponding 10 year standard deviations are 0.93, 1.81, and 0.43. Since the variance post–WWII—when data are presumably more accurate—lies below that of the 1920's and 1860's, the problem tackled by Romer may not be too serious in the Swedish data.

Our study uses data from Krantz and Nilsson linked in 1950 with the modern national accounts. Apart from the general change in quality at this break point in the data series, two problems should be emphasized. The first problem is how to treat inventory investments. Because the original historical data are basically constructed from the production side, they contain no information on inventories. In order to construct series for investment and consumption, the various production sectors are classified as producers of consumption goods, investment goods and/or intermediary goods. And aggregate consumption and investment is simply total production of consumption and investment goods minus the balance of trade in those goods. This means that inventory investments are split in unknown proportions between the series for consumption and investment. The modern national accounts from 1950, on the other hand, include inventory investments as a separate item. This means that there is a problem in linking the consumption and investment series. Note, however, that the GDP aggregate consistently includes inventories before 1950, as well as after 1950. Absent any particular information on where inventory investments are hidden before 1950 we simply splice all series in 1950.[1]

The second problem is that the Krantz–Nilsson fixed-price series apply to GDP at factor cost, whereas the official national accounts only give GDP at market value in fixed prices. We handle this by deflating GDP at factor cost in current prices post 1950 by the implicit GDP deflator for GDP at market value. Given the relatively small share of indirect taxes in GDP, the resulting error is small.[2]

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1 Note that this procedure differs from that used by Krantz and Nilsson in their linking of pre– and post–1950 data. They start the linking on the destination side of the national product. There it is carried out for public consumption, for the private consumption categories of goods and services, and for the investment categories for machinery and buildings, respectively. These items are subsequently aggregated to form sub–totals for consumption and investment and a total for national product." (p.38). This means that pre–1950 items, which sum to GDP, are linked with post–1950 items, which do not sum to GDP.

2 The way one handles both of these problems is of some quantitative importance. For the period 1950–1970 the Krantz and Nilsson data (table 3.1) show an average growth rate of 3.37 per cent (with a standard deviation of 2.12 per cent). For the national accounts at market value in fixed

From the national accounts we take data for gross domestic product, value added in manufacturing and mining, private consumption, investment, exports and imports. With the exception of imports we deflate all series by the implicit GDP deflator, while we use the import price index to deflate imports.

The basic source for historical data on wages is Bagge et al. (1933, 1935). From 1913 these data derive from official wage statistics published by the Central Bureau of Statistics. For earlier years they combine information from a wide array of sources, largely wage records from a large number of individual companies. These data cover a broad range of industries and the resulting aggregate wage series should be of relatively high quality. We use hourly earnings for workers in manufacturing taken from this source and link it in 1920 with modern data from The Central Bureau of Statistics. We transform this series to real wages by deflating with the implicit deflator for manufacturing production. Employment is measured by total hours worked in manufacturing. We construct this series by dividing the total wage bill to workers in manufacturing taken from Jungenfelt (1966) by our series for hourly earnings.[3] Jungenfelt constructed the wage bill data by multiplying average yearly earnings, taken from Bagge et al., by total number of employed in manufacturing. Employment data are from official industrial statistics and should be of high quality. Finally, our series for productivity is value added in manufacturing over employment.

1968 prices the corresponding figures are 3.77 (1.55), and for our constructed series at factor cost 3.63 (1.42). We see that the Krantz and Nilsson procedure which pretends that there are no inventory investments leads to a considerable underestimation of the variability of GDP. The difference between the market value and factor cost series are minor for this period.

For the period 1970—1987 the official national accounts at fixed market values show an average growth of 2.00 per cent with standard deviation 1.46. Our series at factor cost show a slightly lower growth rate of 1.93 per cent but a considerably higher standard deviation of 1.96.

3 Jungenfeldts (1966) and Johanssons (1967) studies were part of the same research project, carried out at Uppsala university in the 1960's. As a result the wage bill data and the production data rely on identical definitions for the manufacturing sector.

3. Spectral Analysis

We choose a traditional definition of business cycles, namely *cyclical comovements of important macroeconomic variables with periods of around 5 years.* In this section we use spectral analysis to examine the pattern of Swedish business cycles: that is, we examine patterns in our time series with periods of around 5 years (see for instance Koopmans (1974), Priestley (1981) or Sargent (1987) for a description of spectral analysis).

Using a Fourier transform, one can express a stationary time series as a sum of cyclical components of different frequencies. This yields the spectrum of the time series which decomposes the series's total variance into variance attributed to different frequencies. One can interpret the spectrum as a density function. The area under the spectrum for an interval between two frequencies equals the proportion of total variance attributed to components with frequencies within that interval. We are particularly interested in the part of the spectra that corresponds to cyclical components with periods of around 5 years, since the density at these frequencies indicates the relative importance of business cycle fluctuations as we have defined them.

We will also consider the coherence between the GDP series and each of the other series. The coherence between two series at a particular frequency may be interpreted as a correlation coefficient between the two series' cyclical components of that frequency. Coherence squared for a given frequency is the proportion of either series's total variance at that frequency that can be explained by linear regression of one series on the other. Again, we are particularly interested in the coherence between GDP and the other series at business cycle frequencies.

It is not meaningful to consider spectra and coherences for series that are not stationary. When deciding how to detrend the data, one should ideally rely either on a particular theoretical model, or on statistical tests. Given that we do not have a particular theoretical model in mind, and given the weak power of most tests for stochastic versus deterministic trends, we prefer to take an agnostic view towards detrending. Therefore we transform the raw series into stationary series in two different ways.

One way we use to remove a trend from the data is to take first differences. The other way is to use the filter previously used by Hodrick and Prescott (1980) and many others, known as the Whittaker–Henderson type A filter. To apply this filter, one chooses a smoothing coefficient λ. The value of this coefficient reflects the relative variance of the "growth component," which is filtered out from the data, and the remaining stationary component. We choose $\lambda = 400$, which is lower than the value of 1600 used in several studies of quarterly data. Our motivation is that the relative variability of the growth component should be expected to be larger in annual than in quarterly data; results are not sensitive to the value of λ though.[4]

We apply both detrending methods to the logs of each series. Given that we are interested in establishing robust stylized facts and given the well-known difficulties in judging a priori what kind of trend governs macroeconomic time series, we report results from both ways of detrending our raw time series. We have actually used a third method of detrending, namely just removing a linear time trend; the results of the spectral analysis in this case are similar to those reported below (except at the very lowest frequencies). To shorten the following presentation, let us introduce the label "λ-series" for those series that are detrended by applying the Hodrick-Prescott filter and the label "Δ-series" for the series that are detrended by taking first differences.

The spectra (in logs) and coherences are shown in *Figures 2a* and *2b* for the λ-series and in *Figures 3a* and *3b* for the Δ-series. We plot the spectra and coherences as functions of frequency, from 1 cycle per the whole period of 128 years up to 64 cycles

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4 We are grateful to Paul Söderlind for providing us with his program for implementing the Whittaker—Andersson Filter.

per the whole period. This corresponds to periods of 128 years down to 2 years.[5] We have previously talked about the business cycle as fluctuations with "periods of around 5 years." We now operationally define this to mean *periods of between 3 and 8 years.* A period of 8 years corresponds to a frequency of 16 cycles per 128 years, and a period of 3 years corresponds to a frequency of about 43 cycles per 128 years. The interval between 3 and 8 years is marked by vertical lines in the spectra and coherences (the line corresponding to 8 years is the left one, since the period (frequency) is decreasing (increasing) to the right). The horizontal dashed line shows the log of the average spectrum, that is, what the spectrum would look like if it was completely flat (and the series generating it is a random walk). The level of the log average spectrum is $\ln(1/64) \approx -4.16$.

Let us first look at the spectra in Figure 2a, for the λ-series. We see that a most of the spectral mass for all the series is to the left of the 8-year period line. That is, most of the variation in the series is attributed to components of periods longer than 8 years. In fact the spectra of all λ–series have a peak at low frequencies, around 10 cycles per 128 years, that is, corresponding to a period of around 13 years. This is similar to what Granger (1966) found to be the typical spectral shape of economic variables, except that our spectra peak at a positive frequency rather than at zero. (Recall that the Hodrick-Prescott filter suppresses low frequencies.) We also see that there is some spectral mass and a small hump in most series for periods in the interval between 3 and 8

5 The spectra and coherences are computed with the Fast Fourier Transform supplied with *GAUSS*. The original series are then automatically padded with zeros so that the number of observations is a power of 2. This is of no consequence for us, since our number of observations, 128, happens to be a power of 2. (The first–differenced time series has 127 observations, so there one zero is added.) The spectra and coherences are smoothed with a tent–shaped window of width equal to 11. Each raw spectrum is normalized by the variance of the series, so that the area under the spectrum is unity. Finally, the natural logarithm of the spectra are plotted against frequency expressed in cycles per 128 years. The means of the original series have been subtracted before the use of the Fourier Transform, so the spectra for frequency zero (not plotted) equal zero. See Koopmans (1974), especially chapter 9, for details and recommendations on practical spectral analysis.

Alternatively, we can measure frequency as cycles per year, in which case frequency runs from 1/128 cycle per year to 1/2 cycle per year.

years, although the peak reaches above the average spectrum only for imports.

Looking at the coherences in Figure 2b, we note that there is relatively high coherence between GDP and most series for periods longer than 8 years. The coherence between GDP and several series is also relatively high for periods between 3 and 8 years. It is only for private consumption that the coherence is high for all business cycle frequencies. For the other series the coherence varies unsystematically with the frequency.

Let us look next at the spectra in Figure 3a for the Δ-series. First-differencing suppresses cyclical components of longer periods (lower frequencies). Consequently, we see that—compared to the spectra in Figure 2a—there is less spectral mass for periods longer than 8 years and relatively more spectral mass for periods in the interval between 3 and 8 years. In that interval, the spectral mass is now considerably above the average. The coherences for the Δ-series in Figure 3b look similar to the coherences for the λ-series in Figure 2b.

As an alternative reference series to GDP we have also considered manufacturing production. We note that the coherence between manufacturing production and GDP at business cycle frequencies is quite low except for a peak around a period of about 5 years. Hence, one would expect a different pattern of coherences with the other series. It turns out that the coherences between manufacturing production and the other series are indeed relatively low except for a period of around 10-12 years. No clear pattern arises for shorter periods. The lack of a consistent pattern may be natural in view of the sharp relative increase in the size of the manufacturing sector over the period. In what follows we only report results with GDP as the reference series.

We conclude that there is indeed some empirical support for a Swedish business cycle with period between 3 and 8 years: most of the macroeconomic variables have both considerable spectral mass and fairly high GDP in the corresponding frequency band.

4. Filtering

One reason why one may want to eliminate a trend from a macroeconomic time series is technical: one wants to carry out statistical operations—such as the spectral analysis of Section 3—which require a stationary series. In the following, we refer to this as *detrending.* Another reason is conceptual: one wants to separate the series into a "growth component" and a "cyclical component." In the following, we refer to this as *filtering.* As we noted in Section 3 we are agnostic about the proper way of detrending and we report results for different methods—both for the λ-series and for the Δ-series, as defined above—and look for results that seem robust relative to the method of detrending.

But when deciding how to filter out the cyclical component, one cannot escape an a priori judgment: to study business cycle fluctuations, it is necessary to be clear about what one means by business cycles. We have already declared that we subscribe to a traditional view of business cycles, namely "cyclical comovements of important macro variables with a period of around 5 years." And we want to filter in a way that corresponds as closely as possible to this view.

For our purposes it is therefore natural to use a filter that operates in the frequency domain, rather than in the time domain. We will primarily rely on a band–pass filter (see Priestley (1981) p. 274–5). The filter works roughly like this: (1) transform a given detrended time series to the frequency domain by the Fourier transform, (2) filter out all the components, except for those in a particular frequency band, and (3) transform the remaining components back to the time domain by the inverse Fourier transform. The result of these three operations is our measure of the cyclical part of the series. *Appendix 2* gives a formal definition of the band–pass filter.

In line with our previous discussion, we choose a band between 3 and 8 years. The rationale for shutting out frequencies corresponding to cycles above 8 years is clear:

according to our definition such cycles are "growth cycles" rather than business cycles. But what is the rationale for shutting out the highest frequencies, corresponding to cycles with periods between 2 and 3 years? We have two in mind. One is that specific events—such as the large strikes that have taken place during this historical period—may just reshuffle production between two adjacent years, which will show up as a 2–year cycle in the data. Another is that (temporary) measurement error will introduce a lot of noise at the highest frequencies. We have actually experimented with moving the boundaries of our frequency band a bit in each direction, but this does not produce any major changes in the results.

Qualitatively, application of our band–pass filter has a similar effect for all time series. *Figure 4* illustrates the effects on a few selected time series: the λ-series for GDP, exports and hours and the Δ-series for GDP. A first effect is to reduce the fluctuations in all four series. This is obvious, since we are filtering out frequency components that are associated with significant spectral mass. A second effect is to induce a more regular cyclical pattern. This is also an obvious, and desired, result. Counting the number of peaks and troughs, we end up with close to 25 cycles over 128 (127) years, which corresponds well to our notion of business cycles having a period of around 5 years. A third effect is to greatly reduce certain outliers, particularly during the interwar period. While less obvious, this effect is nevertheless understandable. Partly it comes from eliminating temporary large shifts leading to "2–year cycles". But there is also another reason: looking at the detrended series in Figure 4, we see that the sequence of extreme observations in the interwar period actually looks like a cycle with a period of 10 to 12 years. (These outliers are thus a likely explanation for the peaks in the spectra for relatively low frequencies that we noted in Section 3.) Our band–pass filter eliminates fluctuations at these frequencies, and thus extracts the business cycle component from the extreme observations.

We end this section with a technical qualification. For an infinite series such a filter completely shuts out the fluctuations at all other frequencies than those within the chosen pass band. Complete elimination of fluctuations at frequencies outside the band is not feasible for a finite series, however. The problem arises because the Finite Fourier Transform implicitly treats the finite series as periodic with period equal to the sample length: in our case, it treats the observation for 1988 as the observation preceding 1861. This "wrap over" of the data may distort the true cyclical pattern and lead to "leakage", such that fluctuations at frequencies outside the pass band are not completely filtered out.

We do two things that hopefully diminish this potential problem. First, we apply the band–pass filter to series that have been detrended either by taking first differences or by the Hodrick–Prescott filter. As a result the observations at the beginning and at the end of the sample are close to zero, something which should limit the distortions induced by the wrap over. Second, before applying the band–pass filter we pad the data by adding a large number of observations to the beginning and the end of each series.[6]

As a check on our results, we also occasionally used a different filter, namely a so called Butterworth filter. This filter operates in the time domain, but it is optimally designed to filter out frequencies above and below a chosen pass band: in our case the band is the same as the one used above, namely (43/128, 16/128).[7] Before applying the Butterworth filter, we removed the very lowest frequencies form the data by a slow–moving Hodrick–Prescott filter. When reporting on results below, we refer to the series that have been detrended and filtered in this way as "β–series".

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6 The padding consists of adding the series itself to the beginning and end of each time series. We continue padding in this way until the resulting filtered time series is unaffected by an additional round of padding.

7 Stock and Watson (1990) discuss and use a Butterworth filter in their recent study of the business cycle properties of a large number of US time series. We are grateful to Jim Stock for giving us access to his programs for implementing the Butterworth filter.

5. Stylized Facts

In this section we characterize the Swedish business cycle during the last 130 years by presenting some summary statistics for the nine time series in our data set. Following the tradition established by real-business-cycle analysts, we shall concentrate on the volatility of each series and its comovement with GDP. For the sake of comparison, we present results both for the detrended and the filtered data and for the λ-series as well as for the Δ-series. Given the qualification at the end of Section 4, we also present results for the β–series.

Consider first the volatility of the series, as measured by their standard deviation. *Table 1* displays the standard deviation of all our series, each expressed in percent of its own trend value. As expected, the standard deviation of the filtered series on average falls more relative to the detrended series for the λ-series. This is natural, since the Hodrick-Prescott filter shuts out less of the cyclical components corresponding to the lower frequencies than does the first-difference filter. The volatility of each β–series typically lie in between that of the corresponding detrended and filtered λ–series and Δ–series. This is natural since the detrending before applying the Butterworth filter leaves relatively more spectral mass.

With regard to the *relative* volatility of the series, the results are robust across the five columns in the table. For all series GDP and consumption are least volatile; investment, exports and imports are most volatile; and manufacturing production, hours, wages and productivity lie somewhere in-between. Evidently, the ranking in terms of volatility is not very sensitive, nor to the choice of detrending method, nor to the filtering of the data.

How do these stylized facts correspond to the results in other studies? Let us start by comparing with studies on Swedish historical data. Bergman and Jonung (1990) have analyzed the same set of historical national accounts data included in our study, but starting only in 1873. Their comparable results show some minor differences relative to ours; standard deviations of consumption and investment for log differences are 4.06 and 9.76 rather than 3.39 and 13.33, as we find when extending the data series back to 1861. The ranking of the different series in terms of standard deviations is the same as in our study, though. The greater volatility of investment relative to output and consumption is also confirmed by Backus and Kehoe (1989) using data from Johansson (1967) deflated by the GDP deflator. They also show that the same pattern holds for corresponding historical data from other countries, including Japan, Norway, United Kingdom and the United States. Based on Hodrick–Prescott filtered data, the standard deviation of investment is consistently between two and five times that of output for those countries. The standard deviation of private consumption on the other hand is about the same as that of output in most countries, somewhat lower than for output in the U.S. and considerably higher in Norway during the post–war period. Neither of these studies contain any wage and employment data.

A richer set of studies is available for comparison if we move to the post–war period. Kydland and Prescott (1990) for the United States, Danthine and Girardin (1989) for Switzerland, and Brandner and Neusser (1990) for Austria and Germany all analyze quarterly data and eliminate the trend by the Hodrick–Prescott method (λ=1600).[8] In *Table 2* we compare their results with ours. There are some similarities and some differences. First, the relative volatilities of consumption, investment and output are not radically different across countries. Consumption is about as volatile as output whereas investment is three times as volatile. Second, exports and imports are relatively more volatile in our data than in post–war United States and Switzerland.

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8 Some of the cited results may be sensitive to the detrending method. King, Plosser and Rebelo (1988) present US standard deviations around a log–linear trend for a similar period and report a standard deviation of GDP which is three times that of Kydland and Prescott. This is natural since removing a linear trend, leaves much more spectral mass at low frequencies than does the Hodrick–Prescott filter. For a further discussion about filtering practices, see King and Rebelo (1989).

Third, employment, wages, and productivity appear generally somewhat less volatile than GDP in post–war quarterly data, while we find a standard deviation about twice as high as that of GDP.[9] Like in Switzerland, but unlike the U.S., productivity varies slightly more than employment.

Consider next the comovement of the different variables, as measured by their correlation with GDP. *Table 3a* looks at the λ-series and displays the correlation coefficients between GDP and each of the other variables lagged one year, contemporaneous and leaded one year. As in Table 1 we show results both for the filtered and for the detrended series. *Table 3b* gives the same information for the Δ-series. *Table 3c* shows the correlation coefficients for the β–series.

Again the results are fairly robust across the different series. Most of the correlation coefficients are positive, indicating comovements between the variables. For most variables, the contemporaneous correlation coefficients are the highest. Of these, the correlation coefficients for private consumption are highest followed by those for manufacturing production, investment, and exports. The correlation coefficients for imports are lower, while they are close to zero for wages and productivity (largely as a result of filtering). The latter two variables consistently seem to lead GDP, however. There is no particular sign of any variable lagging GDP. We note that for some variables, the contemporaneous correlation coefficients are indeed higher for the filtered series than for the detrended series. Among the λ-series this is true for investment and hours, and among the Δ-series it is true for investment, hours, exports, and imports. A possible interpretation is that the business cycle component is relatively more pronounced for these series.

The comovements are generally similar to those for other countries and other time periods. Backus and Kehoe confirm that consumption and investment are strongly

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9 Recall, however, that our employment data do not refer to the economy as a whole, but only to the manufacturing and mining sector.

positively related to GDP in the historical data from other countries.[10] In *Table 4* we compare the Swedish historical patterns with those for other countries during the post–war period. The correlation coefficients for all components of GDP are of the same magnitude across the countries included. On the other hand the labor market variables—at least employment and productivity—are not as strongly correlated with GDP in our Swedish data as they are for the other countries. The finding of a lead in wages and productivity in relation to GDP is consistent with results for the United States and Germany but not with Austria.

6. Stability Over Time

The stylized facts in the previous section are statistics for the whole period 1861-1988. This period encompasses different stages in Sweden's development from a primitive agrarian economy to a modern industrialized economy. It is therefore legitimate to ask whether the stylized facts are stable across different subperiods.

Other authors have asked the closely related question of whether business cycles have been more volatile in the period after World War II than in earlier periods. The U.S. evidence is in dispute, largely due to the relatively poor quality of data for earlier periods. Romer (1989) and Balke and Gordon (1989) revised the pre–war data in various ways. They looked at the ratio between the standard deviation of the deviations of GDP from trend pre–WWI and post–WWII, employing different methods. Romer found the ratio to be 1.3, while Balke and Gordon arrived at numbers around 1.7.

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10 Again, the results may be sensitive to how trends are handled. Warne and Vredin (1991) analyze the joint properties of four time series from the same data set that we study: GDP, investment, savings and the terms of trade. They use a multivariate detrending technique based on a time series model with joint stochastic trends and find the correlation between innovations to investment and GDP to be negative (though not significantly different from zero).

Sheffrin (1988) investigated the same issue for five countries believed to have historical data of particularly high quality. For four of these (the U.K., Norway, Italy and Denmark) the standard deviations of pre–WWI growth rates are only slightly higher than the corresponding standard deviation after WWII with ratios around 1.3. Only Sweden is an exception with a ratio of 2.5. For all countries the inter–war period stands out as more volatile than other periods.

For Sweden Sheffrin relied on the work by Johansson (1967), which used the consumer price index from Myrdal (1933) to deflate GDP. Bergman and Jonung (1990) noted that data based on the improved deflators of Krantz and Nilson (1975) give rise to a much lower pre–war volatility bringing the same ratio down to around 1.5. They also investigated relative volatility for a number of other macroeconomic time series.

Backus and Kehoe (1989) expanded the perspective by looking at the major GDP components for a larger sample of 10 countries. They confirmed the picture of rather small decreases in GDP volatility between the pre– and post–war periods for most countries.

Let us now look at the development of our stylized business cycle facts over time. Rather than committing to comparison of specific subperiods, as other authors have done, we prefer to leave the partition of our data a bit more open, so we use a window of 41 years and compute moving statistics (standard deviations and correlations with GDP) over time. *Figure 5* shows the results for the filtered λ-series (the results for the Δ-series and for the β–series are qualitatively similar and not shown here.) When reading the figure, note that it is the center of the window that is displayed on the horizontal axis. The last observation, which is dated 1968, is thus the standard deviation for the subperiod 1948-1988.

What emerges from the figure is a very clear hump-shaped pattern for all the variables with the exception of investments and productivity. This pattern confirms that business cycles were distinctly less volatile in the pre-World War I period *and* in the post-World War II period than they were in the intermediate period including the wars and the depression. Most variables also exhibit more stability after WWII than before WWI. The difference is small for GDP but larger for consumption and even larger for investment, productivity, and employment.[11]

In the middle of all this instability over time, there is nevertheless a striking symmetry. This is so particularly if one compares the inter-war period and the post-war period, periods which are comparable in terms of data quality but very different in terms of volatility. Look at the standard deviations for the 41 years centered on 1930 and 1968, respectively. The ratio between them is close to 2 for all of the nine variables in our data set (GDP: 1.89, manufacturing production: 2.14, private consumption 2.46, investments 2.16, exports: 1.81, imports: 2.84, hours: 2.13, wage: 2.10, and productivity: 2.55). This relative stability also holds for the Δ-series. Even though volatility has changed a great deal in absolute terms, it has hardly changed at all in relative terms.

We have also computed moving contemporaneous correlation coefficients between all variables and GDP for our filtered series. *Figure 6* shows the results for the λ-series. (The results for the Δ-series again are similar.) Although there are some big changes over time—particularly for manufacturing production, productivity, imports and wages—many of the correlation coefficients are surprisingly stable over time. Most interesting is perhaps that the correlation coefficients do not seem to change systematically with the volatility of the series. Again, look at the 41 years centered on 1930 and 1968. Despite the difference in volatility during these two subperiods, there is a great deal of stability in the corresponding correlation coefficients. Manufacturing production remains most highly correlated with the coefficient decreasing slightly

11 The careful reader may wonder whether this instability over time makes the spectral analysis in Section 3 meaningless. The answer is: not necessarily. In particular, if we make the assumption that the periodic pattern of fluctuations has been stable across time—so that the instability across subperiods is due to different amplitudes in the cycles—the spectra and coherences computed in Section 3 can be interpreted as appropriate averages over the entire time period. See Granger and Hatanaka (1964, ch.9).

from .88 to .82. The only major change relates to wages where the correlation coefficient goes from .24 to –.46. For all the other variables the coefficients fluctuate around .5 (private consumption goes from .65 to .45, investments from .58 to .56, exports from .54 to .64, imports from .34 to .54, hours from .43 to .50, and productivity from .54 to .50).

Taken together, we find these results very interesting. On one hand, business cycles in Sweden since the 1860's have been quite different in the sense of different subperiods showing much variation in the joint volatility of all variables. On the other hand, business cycles have been quite similar in the sense of different subperiods showing little variation in the relative volatility of and comovements between different variables.[12]

The filtered time series for different variables thus seem to have a lot in common. We have tried to take that observation a step further using the "common features" idea outlined in Engle and Kozicki (1990). The general idea of common features can be looked upon as a generalization of the idea of common trends: in the same way as a linear combination of some time series may not have a trend, even though each individual series has a trend, a linear combination of some time series may not have some other statistical feature, even though each individual time series has that feature. Engle and Kozicki explain how to carry out regression tests for a number of such common features.

Following their approach, we have carried out a number of tests for *common autoregressive conditional hetroskedasticity* (*FACTOR ARCH*), focusing on the apparent common volatility in the different time series. We tested for pairwise *FACTOR ARCH* between *GDP* and each other variable y in our data set. The test is a Lagrange–multiplier test, which was constructed as follows: First, estimate by two–stage non–linear least squares the δ that minimizes the vector

$$\boldsymbol{u} = [(y_t - \delta GDP_t)^2]_1^T,$$

12 A similar stability is noted by Backus and Kehoe (1989) in their study of fixed subperiods for several countries, but for a more narrow set of variables.

using $z_t = [(GDP_{t-p})^2, (y_{t-p})^2, (GDP_{t-p}y_{t-p})]_1^P$ as instruments. Second, regress the residuals u_t on z_t. The test–statistic for the null hypothesis of no common hetroskedasticity is R^2 of the second regression times the number of observations and has a χ^2–distribution with 3P–1 degrees of freedom.

The results are mixed and depend on the filtering method and on P, the number of lags included. For most variables the hypothesis of common hetroskedasticity cannot be rejected in the λ–series and in the Δ–series when P = 1. But for higher values of P and for the β–series, the hypothesis is decisively rejected.

Nevertheless, we see the results as a preliminary confirmation of a common volatility pattern in the data. Of course, the hypothesis of *FACTOR ARCH* is very strong, and it would have been very surprising if we had not been able to reject it for a data set that spans such along timed period. In future research, we hope to do more work on common features in our data set.

7. Conclusions

An important research program in macroeconomics aims at establishing stylized macroeconomic facts based on the properties of long time series. Most of the "facts" that researchers actually use, e.g. when calibrating and judging the performance of numerical equilibrium models of business cycles, are based on quarterly post–war data [Plosser (1989), Prescott (1986)]. This practice is somewhat doubtful for two reasons. First, these models are typically stochastic growth models, where the very long run properties are an important integral part of the performance of the model. Second, even disregarding the long–run dynamics it is of considerable interest to know whether the stylized facts are stable over time. Indeed, many of the models that are being calibrated abstract from economic policies and other institutional factors which have changed over time.

The issue of stability over long time periods is difficult to address for the U.S. economy due to the shortage of appropriate data. It is in this perspective we want to view our study of Swedish data based on a combination of labor market and national accounts data for 128 years. We have chosen to filter our data in such a way as to concentrate on the intermediate frequencies typically associated with the term "business cycle." Our conclusions with regard to the stability of the business cycle facts are somewhat mixed. On one hand we reestablish the well known fact that the post–war period in general is much less volatile than the inter–war period and slightly less volatile than the pre–war period. On the other hand we show that there is a great deal of stability in relative variances of different variables and in correlations between different variables and GDP. We believe that these findings are very suggestive for subsequent theoretical and empirical modeling of business cycle fluctuations. They suggest that a natural candidate for a business cycle model that would fit the data well, should have stable propagation mechanisms driven by a set of forcing variables with hetroskedastic innovations.

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Appendix 1

Data Sources and Definitions

GDP:
GDP at fixed factor prices. For the period after 1950 GDP at fixed prices (millions of SEK) is constructed by dividing GDP at current prices by an implicit GDP deflator. The deflator is constructed by taking GDP at current market prices over GDP at fixed market prices.
1861—1949: Krantz and Nilsson (1975), Table 3.1.
1950—1979: Statistics Sweden, N10 SM 8901, Appendix 2—3, Tables 3:1 and 3:2.
1980—1988: Statistics Sweden, N14 SM8901, Tables 1 and 2.

Manufacturing production (Q):
Value added in manufacturing and mining at fixed producer prices.
1861—1949: Krantz and Nilsson (1975), Table 3.2.1, Column 2.
1950—1962: Statistics Sweden, SM N 1975:98, Table 2A.
1963—1969: Statistics Sweden, SM N 1981:2.5, Appendix 4, Table 2A.
1970—1988: Statistics Sweden, N 10 SM8901, Table H:4.

Consumption: (C)
Private consumption of goods and services at current prices deflated by the implicit GDP deflator.
1861—1949: Krantz and Nilsson (1975), Table 1:1.
1950—1979: Statistics Sweden, N10 SM 8901, Appendix 2—3, Table 3:1.
1980—1988: Statistics Sweden, , N14 SM8901, Table 1.

Investments: (I)
Domestic investments in current prices divided by the implicit GDP deflator.
1861—1949: Krantz and Nilsson (1975), Table 1:1.
1950—1969: Statistics Sweden, N10 SM8801, Appendix 2—3, Table 3:1.
1970—1979: Statistics Sweden, N10 SM8801, Table H:4.
1980—1988: Statistics Sweden, N14 SM8901, Table 1.

Exports: (X)
Exports of goods and services in current prices divided by the GDP deflator.
1861—1949: Johansson (1967), Table 49, Column 14.
1950—1979: Statistics Sweden, N10 SM8901, Appendix 2—3, Table 3:1.
1980—1988: Statistics Sweden, N14 SM8901, Table 1.

Imports: (M)
Imports of goods and services at fixed prices.
1861—1949: Johansson (1967), table 52, Column 12.
1950—1979: Statistics Sweden, N10 SM8901, Appendix 2—3, Table 3:1.
1980—1988: Statistics Sweden, N14 SM8901, Table 1.

Hours: (L)
Hours worked in manufacturing and mining.
1870—1949: Total wages paid to workers in manufacturing [from Jungenfelt (1959), p. 122, col 5—col 2] divided by wage (see below).
1950—1969: N 1975:98 Appendix 5, Tables 92 and 98.
1970—1979: N 1981:2.5 Appendix 5, Table 92.
1980—1988: N 10 SM 8901 Appendix 5, Table 5:9.

Wage: (W)
Wage (in SEK/100 hours) per hour for workers in manufacturing and mining deflated by the implicit

deflator for manufacturing production.
1861—1913: Bagge et al. (1935), Table 26, Column "Social Science Institute."
1914—1919: Bagge et al. (1935), Table 26, Column "Social Board."
1920—1929: Statistics Sweden, *Lönestatistisk årsbok 1929*, Table 8.
1930—1934: Statistics Sweden, *Lönestatistisk årsbok 1938*, Table 24.
1935—1938: Statistics Sweden, *Lönestatistisk årsbok 1940*, Table 28.
1939—1984: Statistics Sweden, *Löner 1984*, Page 58, Table D.
1985—1986: Statistics Sweden, *Löner och sysselsättning inom privat sektor 1988*, Page 44, Table D.

Productivity: (Q/L)
Manufacturing production divided by hours.

Appendix 2

Description of the Filtering Procedure

We filter the detrended time series x(t) into the filtered series $\bar{x}(t)$, t=1,....,T, in three steps. First, we apply the Fourier transform

$$z(\omega(j)) = \sum_{t=1}^{T} \exp(-i\omega(j)t)\, x(t); \quad \omega(j) \equiv 2\pi j/T; \quad j = -T/2, \ldots\ldots, T/2.$$

Second, we choose a specific frequency band $[(\underline{j}, \bar{j})]$ to define an indicator function

$$I(j) = \begin{cases} 1 \text{ if } j \in [-\bar{j}, -\underline{j}] \cup [\underline{j}, \bar{j}] \\ 0 \text{ otherwise} \end{cases}.$$

Third, we apply the inverse Fourier transform to that band,

$$\bar{x}(t) = \frac{1}{2\pi} \sum_{j=-T/2}^{T/2} I(j) \exp(i\omega(j)t)\, z(\omega(j)); \quad t = 1,\ldots\ldots,T.$$

The GAUSS programs that were used in the filtering procedure are available upon request from the authors.

Notes to the Figures

Figure 1 shows the natural logarithm of the series described in Appendix 1.

Figure 2a and 3a show the natural logarithm of the spectra for the λ—series and the Δ—series, respectively, plotted against frequency, defined as cycles per whole period of 128 years (127 for the Δ—series). The spectra are normalized, that is, the area under the spectra equals equal unity.

Figure 2b and 3b show the coherence between GDP and each of the other variables, for the λ—series and Δ—series, plotted against frequency.

Figure 4 shows a few of the detrended and the filtered series.

Figure 5 shows moving standard deviations of the λ—series, with a window of 41 years.

Figure 6 shows moving correlations coefficients between GDP and other variables for the λ—series, with a window of 41 years.

Table 1

Standard deviations 1861 – 1988

	λ—series Detrended	Filtered	Δ—series Detrended	Filtered	β—series
GDP	3.55	1.84	3.00	2.22	2.60
Manufact Production	8.30	3.83	7.00	4.35	6.30
Private Consumption	3.86	2.14	3.39	2.57	2.72
Investment	12.84	7.56	13.33	9.19	9.18
Exports	15.68	6.93	13.58	9.21	11.79
Imports	16.87	10.61	17.53	14.06	11.45
Employment	6.07	3.45	5.49	3.93	5.00
Wages	8.59	3.23	6.34	3.75	6.44
Productivity	8.39	4.03	7.63	4.91	5.96

Table 2

Standard deviations relative to GDP

	Sweden (λ—series) Detrended	Filtered	Switzerland	Austria	Germany	U.S
Private Consumption	1.09	1.16	0.71	1.24	0.92	0.73
Investment	3.62	4.11	3.95	3.08	2.83	3.15
Exports	4.42	3.71	1.45	n.a.	n.a.	3.23
Imports	4.75	5.71	2.26	n.a.	n.a.	2.88
Employment	1.71	1.87	0.58	1.48	0.81	0.96
Wages	2.42	1.70	0.86	0.93	0.97	0.53
Productivity	2.36	2.19	0.66	1.39	0.69	0.49

Sources: Danthine and Girardin (1989), Brandner and Neusser (1990), and Kydland and Prescott (1990).

Table 3

Cross–correlations with GDP 1861 – 1988

a) λ – series

	Detrended			Filtered		
	–1	0	+1	–1	0	+1
Manufact Production	0.625	0.761	0.575	0.358	0.571	0.136
Private Consumption	0.634	0.791	0.468	0.230	0.683	0.174
Investment	0.330	0.558	0.400	0.237	0.614	0.163
Exports	0.431	0.630	0.461	0.179	0.573	–0.032
Imports	0.408	0.552	0.417	0.091	0.364	0.066
Employment	0.077	0.330	0.325	0.083	0.421	0.080
Wages	0.562	0.395	0.176	0.341	0.069	–0.047
Productivity	0.538	0.499	0.332	0.234	0.224	0.131

b) Δ – series

	Detrended			Filtered		
	–1	0	+1	–1	0	+1
Manufact Production	0.265	0.511	0.167	0.275	0.491	0.020
Private Consumption	0.113	0.709	0.055	0.025	0.679	0.035
Investment	0.064	0.481	0.105	0.022	0.578	0.063
Exports	0.170	0.538	0.072	0.096	0.640	–0.147
Imports	0.151	0.355	0.108	0.001	0.363	–0.001
Employment	–0.029	0.349	0.146	–0.090	0.518	0.065
Wages	0.376	0.150	–0.014	0.365	–0.013	–0.147
Productivity	0.254	0.222	0.064	0.280	0.053	0.002

c) β – series

	–1	0	+1
Manufact Production	0.695	0.861	0.751
Private Consumption	0.743	0.778	0.523
Investment	0.452	0.652	0.594
Exports	0.573	0.772	0.631
Imports	0.511	0.657	0.576
Employment	0.169	0.392	0.489
Wages	0.509	0.339	0.061
Productivity	0.530	0.528	0.364

Table 4

Contemporaneous correlations with GDP

	Sweden (λ–series) Detrended	Filtered	Switzerland	Austria	Germany	U.S
Private Consumption	0.79	0.68	0.67	0.54	0.69	0.82
Investment	0.56	0.61	0.89	0.74	0.83	0.91
Exports	0.63	0.57	0.64	n.a.	n.a.	0.34
Imports	0.55	0.36	0.75	n.a.	n.a.	0.71
Employment	0.33	0.42	0.78	0.40	0.69	0.88
Wages	0.40	0.07	–0.12	–0.07	0.55	0.35
Productivity	0.50	0.22	0.84	0.29	0.64	0.31

Sources: Same as for Table 2.

Figure 1. Data

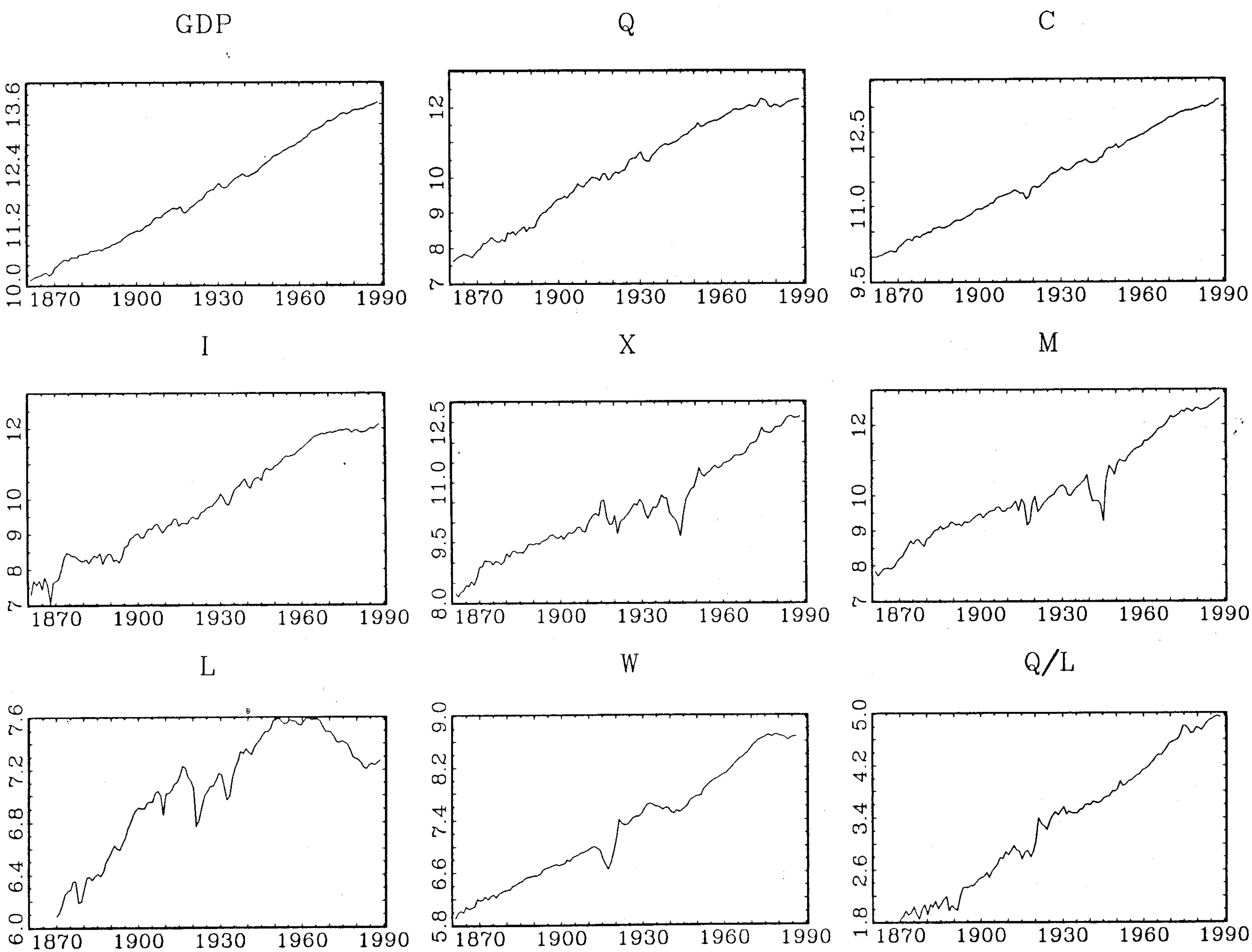

Figure 2a. Spectra, λ-series

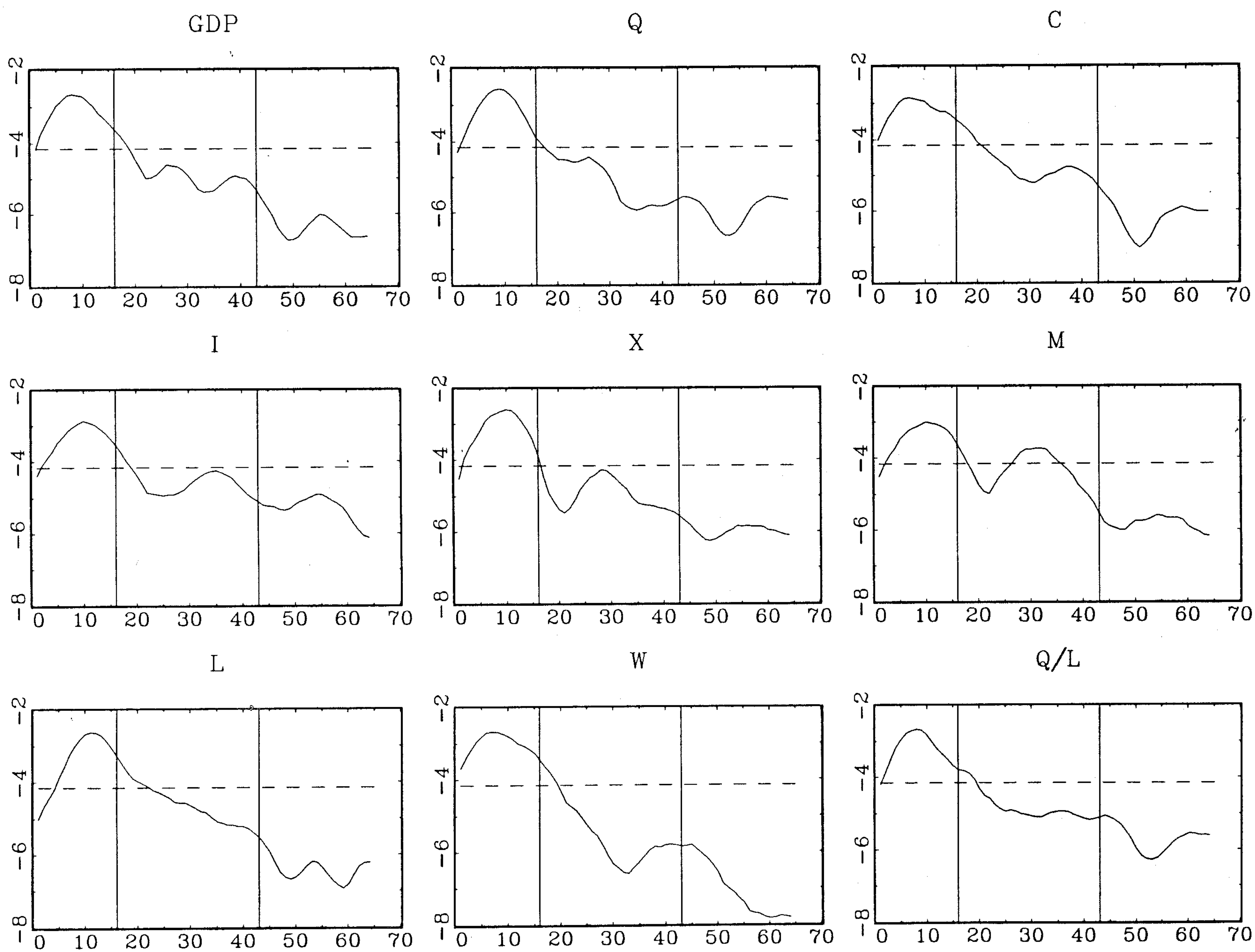

Figure 2b. Coherences with GDP, λ-series

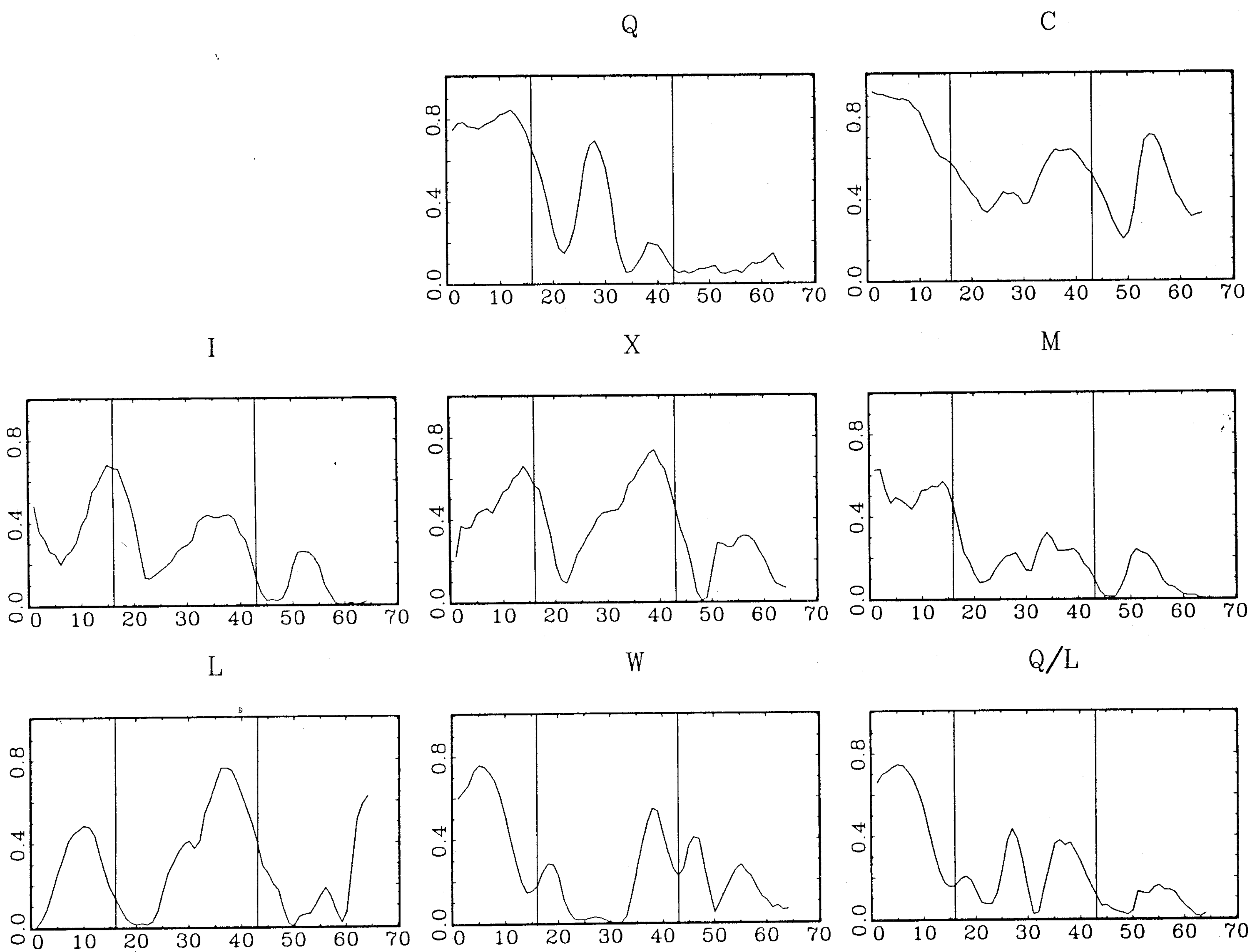

Figure 3a. Spectra, Δ-series

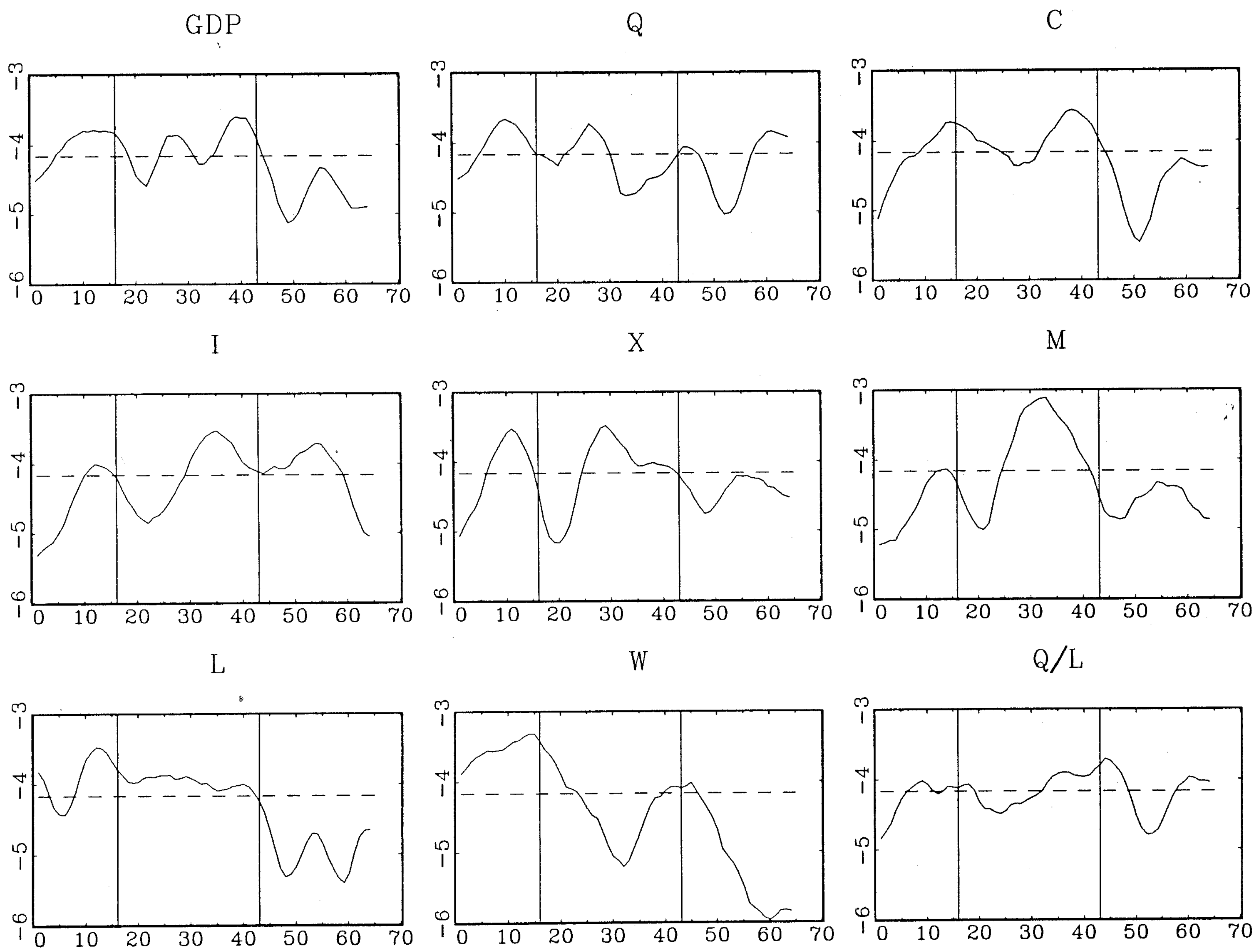

Figure 3b. Coherences with GDP, Δ-series

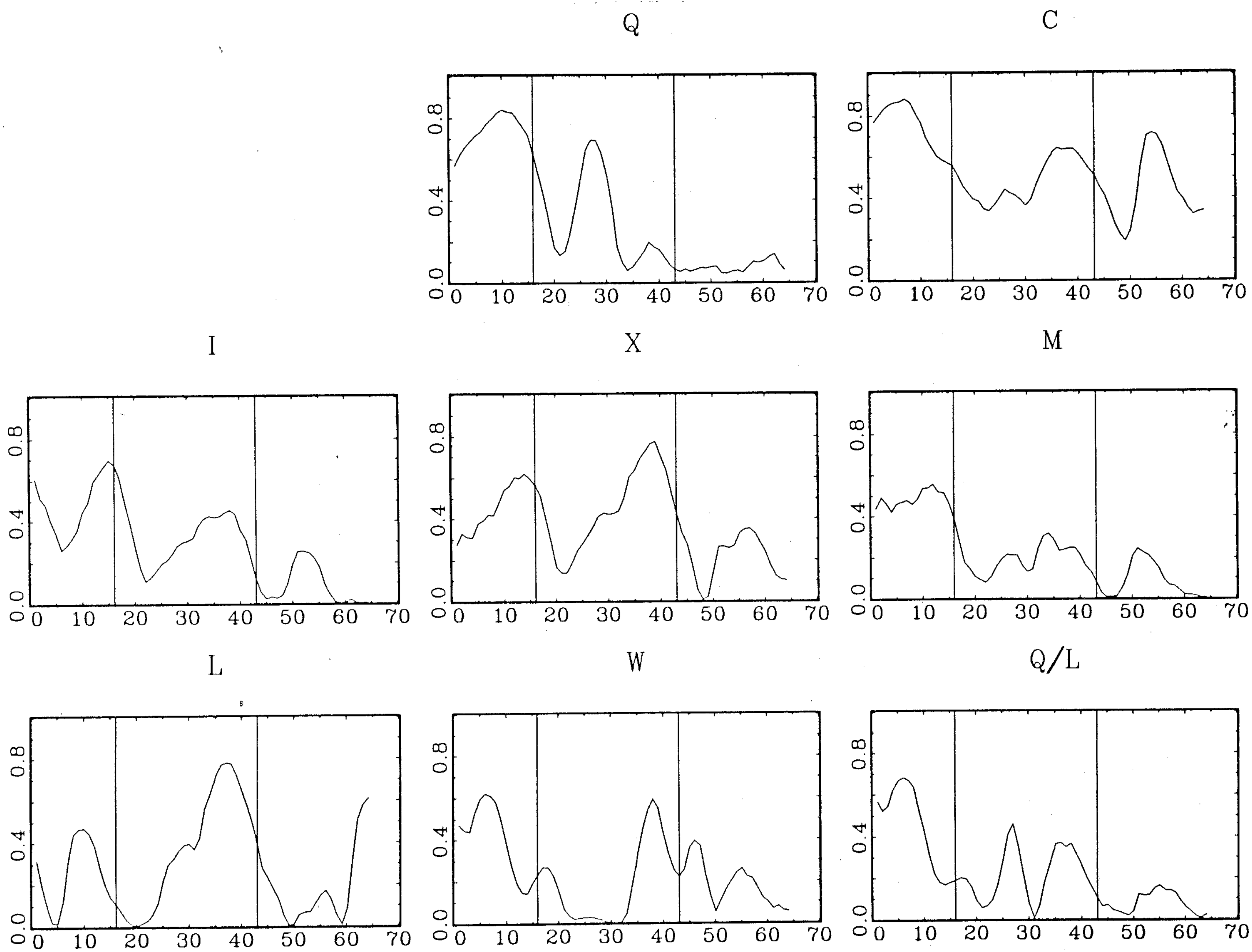

Figure 4. Detrended and filtered series

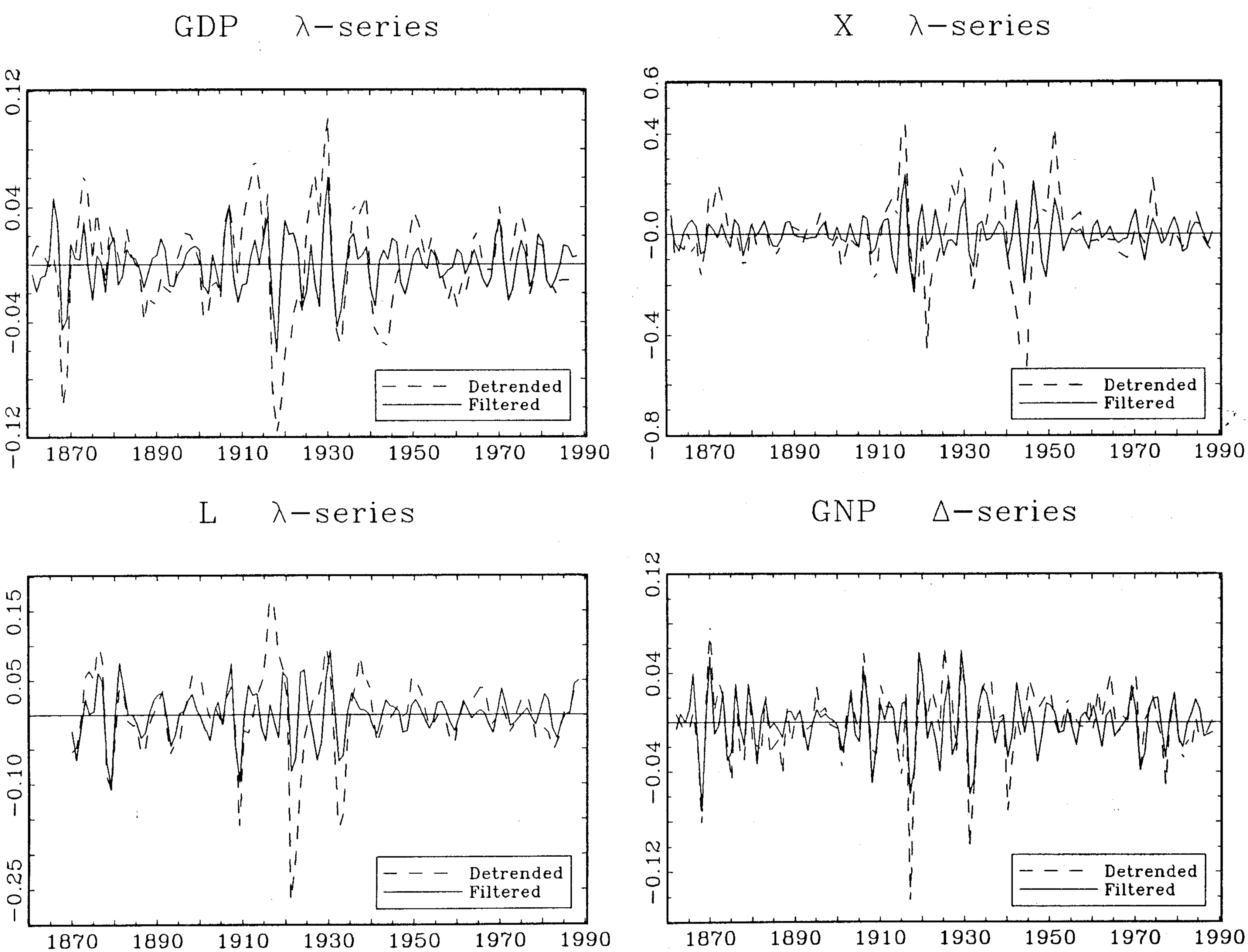

Figure 5. Moving standard deviations, λ-series

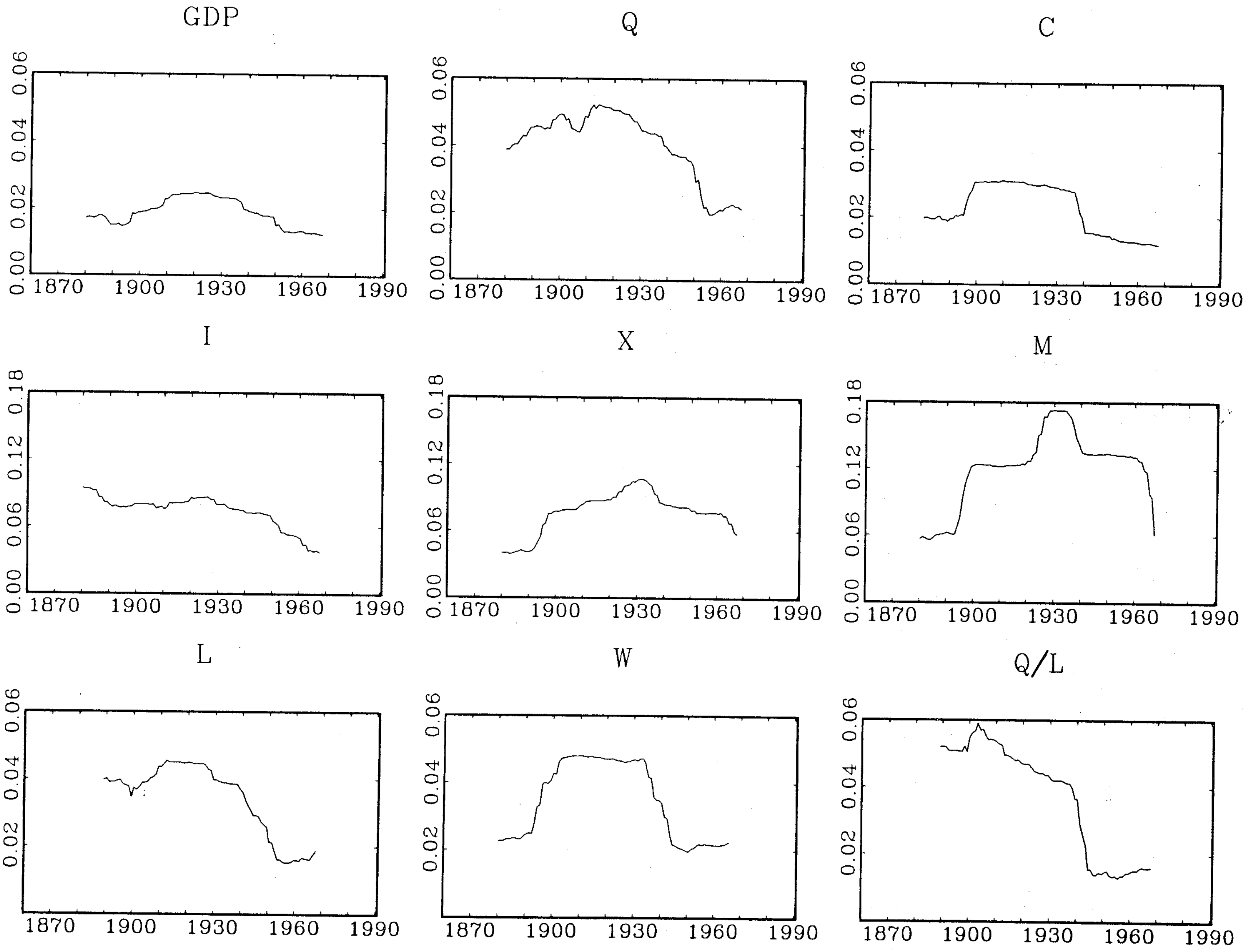

Figure 6. Moving correlations with GDP, λ-series