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When did the 2001 recession *really* start?

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Abstract

The paper develops a non-parametric, non-stationary framework for business-cycle dating based on an innovative statistical methodology known as Adaptive Weights Smoothing (AWS). The methodology is used both for the study of the individual macroeconomic time series relevant to the dating of the business cycle as well as for the estimation of their joint dynamic.

Since the business cycle is defined as the common dynamic of *some* set of macroeconomic indicators, its estimation depends fundamentally on the group of series monitored. We apply our dating approach to two sets of US economic indicators including the monthly series of industrial production, nonfarm payroll employment, real income, wholesale-retail trade and gross domestic product (GDP).

We find evidence of a change in the methodology of the NBER's Business-Cycle Dating Committee: an extended set of five monthly macroeconomic indicators replaced in the dating of the last recession the set of indicators emphasized by the NBER's Business-Cycle Dating Committee in recent decades. This change seems to seriously affect the continuity in the outcome of the dating of business cycle. Had the dating been done on the traditional set of indicators, the last recession would have lasted one year and a half longer.

We find that, independent of the set of coincident indicators monitored, the last economic contraction began in November 2000, four months before the date of the NBER's Business-Cycle Dating Committee.

1 Introduction

The paper develops a non-parametric, non-stationary framework for business-cycle dating based on an innovative statistical methodology known as Adaptive Weights Smoothing (AWS). The methodology is used both for the study of the individual macroeconomic time series relevant to the dating of the business cycle: employment, real personal income, sales, industrial production and gross domestic product (GDP) as well as for the estimation of their joint dynamic.

In our approach the macroeconomic indicators are modelled as stochastic variations around a time-varying trend[1]. Moreover, the movements of the level of individual indicators are assumed to have as common source the dynamic of the economy as a whole. Periods of economic expansion translate into increasing levels (positive trends) of the individual indicators or, equivalently, into a positive first derivative of the trend. Similarly, a shrinking economy is seen in decreasing levels (negative trends) or, equivalently, a negative first derivative of the trend.

The individual series analysis we perform yields the turning points in the level of the macroeconomic indicators highlighting their non-stationary nature. It shows that the indicators peak and attain their trough in different months. This makes finding the turning points of the economy particularly challenging and calls for pooling of information from all the individual indicators. We complement the analysis of individual macroeconomic series with an estimation of the business cycle defined as the common dynamic of a group of relevant economic indicators. This is done through a non-stationary factor analysis which is one of the main contributions of the paper.

Since the business cycle is defined as the common dynamic of *some* set of macroeconomic indicators, its estimation depends fundamentally on the group of series monitored. We apply our dating approach to two groups of US economic indicators: the four monthly economic indicators of industrial production, payroll employment, wholesale-retail trade, and real income emphasized by the NBER's Business-Cycle Dating Committee in recent decades and an extended group with the GDP as the fifth series[2].

When the series under scrutiny are the four mentioned monthly economic indicators, our statistical methodology seems to find the same pattern in the data as the unknown dating approach of the NBER's Business-Cycle Dating Committee for *all but the last* recession. The two methods produce very different results when it comes to the last episode of economic contraction. The recession seems to have lasted from November 2000, four months before the NBER start date, until May 2003 (the last month of negative growth), i.e. one year and six months after the date announced by the NBER's Business-Cycle

[1] The volatility of the stochastic variations is also time-varying.

[2] A monthly series of the GDP seems to have been used lately by the dating committee to supplement the information on the business cycle.

Dating Committee.

We argue that a possible explanation of this finding could be the inclusion of the monthly GDP data in the set of indicators closely monitored for the dating of the last economic contraction episode[3]. When the set of macroeconomic indicators from which the common dynamic is extracted is extended to include the monthly GDP, the month of November 2000 is again individuated as the beginning of the recession. However, in this set-up, the first derivative of the trend of the economy becomes significantly positive in November 2001, the date of the end of the recession according to the NBER's Business-Cycle Dating Committee. Hence, the common dynamic of the five monthly indicators is consistent with the NBER dating of the recession's end in November 2001. The growth rate of the economy in the months that followed was extremely small (0.2 of a percent) and seems to have stayed at this level until the end of the sample[4].

Our findings support the hypothesis of a change in the methodology of the NBER's Business-Cycle Dating Committee. They also bring evidence of the existence of a break in the outcome of the business-cycle dating: had the dating been done based on the traditional set of indicators, the last recession would have lasted one year and a half longer becoming the longest contraction episode in the postwar economic history.

While the date of the end of the last recession depends on the set of macroeconomic indicators (and, in the case of the extended set of five indicators, is consistent with the NBER's Business-Cycle Dating Committee dating), we find that, independent of the set of coincident indicators monitored, the last economic contraction began in November 2000, four months before the date of the NBER's Business-Cycle Dating Committee.

The non-parametric approach we propose is of particular relevance because dating the business cycle as well as assessing in real-time the current health level of the economy are, primary, data summaries. The use of a *parametric* model is, hence, questionable from a

[3]The change in the emphasis on the GDP series is visible in the official announcements of the NBER's Business-Cycle Dating Committee (see Section 6). Despite claims of continuity in the outcome of the dating, this change could possibly introduce a strong discontinuity in the practice of NBER's Business-Cycle Dating Committee.

[4]While from a strictly statistical point of view, the month of November marks the end of the recession (the growth rate becomes then statistically significant positive), the economic relevance of a rate of growth as small as 0.2 of a percent during the period until August 2003 might still be a matter of debate. The answer to the question 'When did the 2001 recession really end?' depends on assigning the period of (practically) flat economic activity after November 2001 either to the past contraction or to the future expansion. To solve this dilemma one needs not look any further than the practice of the NBER's Business-Cycle Dating Committee which specifies that 'if economic activity is *roughly flat* at the end of a recession or expansion, *the turning point is placed at the end of the flat period*'. Hence, if the statistical rigor is complemented by the established practice and experience, one could further argue that, even when the monthly GDP series is included in the set of monthly indicators, the recession which started in November 2000 extended at least until the summer of 2003, i.e. at least eighteen months after the ending date of the NBER announcement.

methodological point of view. The situation can be compared with that in which one who is interested in the mean and the variance of a time series, instead of computing sample moments, would fit at AR(1) and then infer the desired quantities[5].

By treating the business cycle as a succession of structurally different periods our approach takes an 'intrinsic ' view, the same as Hamilton [8], Diebold and Rudebush [6], Chauvet [3], Kim and Nelson [11], Otrok and Whiteman [12] among others. By contrast, the 'extrinsic' view assumes that recessions and expansions are generated by certain configuration of random shocks to a stationary (usually linear) time series model. For example, Stock and Watson [21], [22] and [23] model the co-movements among many economic series by means of a single, common, linear, unobserved index.

Our approach belongs to the so-called 'classical cycle' methodology that focuses on the cyclical characteristics of the *level* of the macroeconomic series, such as their peaks and troughs. In another strand of literature known as *growth cycle* or *deviation cycle*, business cycle patterns are explored assuming that the relevant series can be decomposed as the sum of a trend and a cycle[6].

What distinguishes our contribution from the rest of the large business cycle literature is the non-stationary, non-parametric approach[7] we are advocating. Besides being intuitively appealing, our non-parametric approach requires only few assumptions on the nature of the dynamics of the data. The changes of the expected level as well as those in the volatility function can be smooth or marked by discontinuities. Last, a solid body of theoretical results and methodological recommendations on the estimation of the model is

[5]Following the plastic formulation in Harding and Pagan [9] the situation can be compared with that in which one who is interested in the mean μ and the variance σ^2 of a time series, instead of computing sample moments, would fit at AR(1) with μ as intercept, ρ as the AR(1) parameter and σ^2 as the variance of the innovations and then infer the desired quantities from $\mu/(1-\rho)$ and $\sigma^2/(1-\rho^2)$. If the data generating process is an AR(1), this would work well; otherwise the parametric approach would not be very sensible.

[6]Much of the effort in this field of research is devoted to studying the properties of trend-removing filters, see Hodrick and Prescott [10], Christiano and Fitzgerald [4], Corbae, Ouliaris and Phillips [5], Baxten and King [1]. See Harding and Pagan [9] for a discussion on the relevance of this approach to the literature of business cycle.

[7]Despite the fact that broad evidence of instability in macroeconomic variables and relations has been gathering (Stock and Watson [24], [25], Sichel [19], Boldin [2]), the dating of the business cycle is done mostly by estimating *stationary, parametric* models on the growth rates of the macroeconomic series modelled as random variables. Even recent models that treat the phases of the business cycle as structurally different and that grew from the seminal paper of Hamilton [8] (see Chauvet [3], Kim and Nelson [11], Otrok and Whiteman [12]) enforce stationarity by the assumption of changes in the level of growth governed by an unobserved, *stationary*, Markov switching state variable. This supposes a constant pattern of change between various phases of the business cycle. To put it more directly, despite the various important changes that affected the US economy through the decades, these models assume that the dynamic recession/expansion has not changed over the years. Moreover, all phases of the same type (all recessions, all recovery periods, all expansions, etc.) are characterized by the same level of growth. In other words, all recessions look the same. This assumption is in strong contradiction with the empirical evidence (Sichel [19], Boldin [2], Stock and Watson [25]).

already available. Moreover, these results yield rigorous measures of the estimation error providing the frame for testing hypotheses on expected mean and variance of the growth rate.

2 Stylized facts of macroeconomic time series

The first order differences of the logarithm of the four monthly US macroeconomic indicators of industrial production (IP), nonfarm payroll employment (E), sales (S), and real personal income (PI) as well as the quarterly series of the US GDP are plotted in Figure 2.1. It is instructive to summarize the most important common features of these time series which should be captured by a relevant data analysis[8].

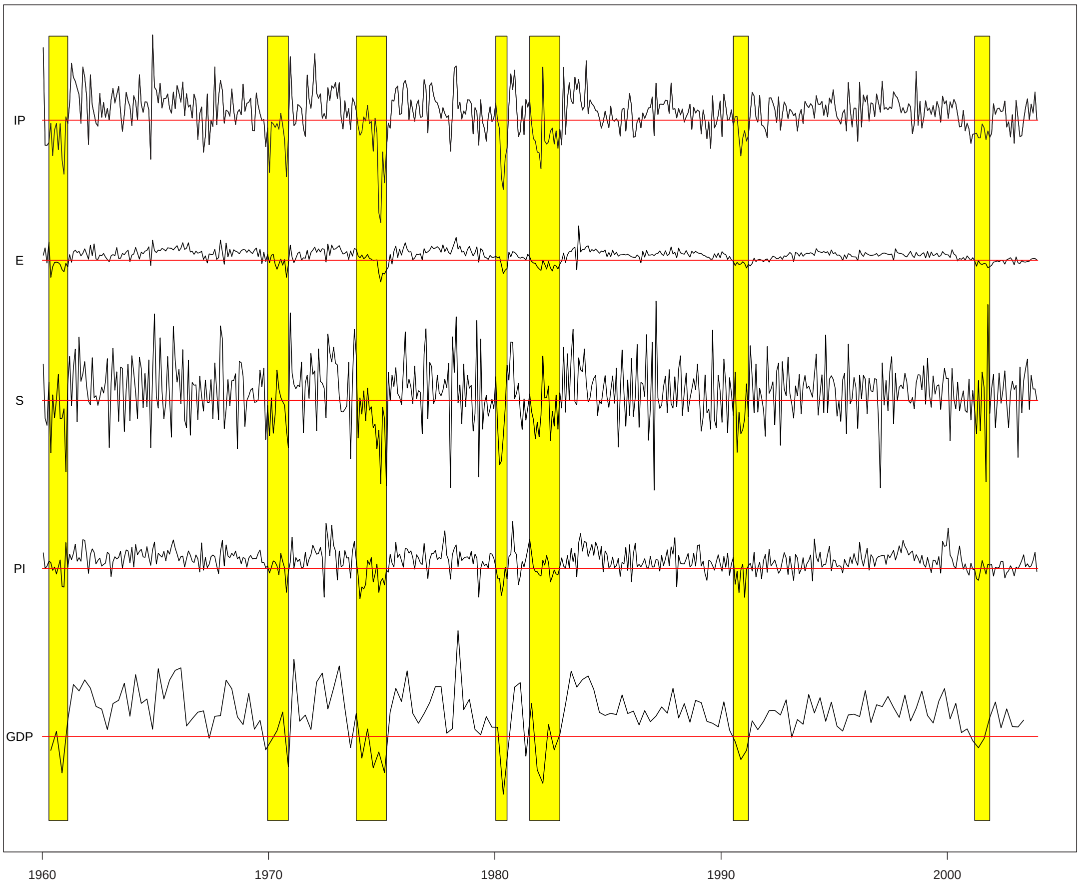

Figure 2.1: The first order differences of the logarithm of the NBER monthly indicators: IP, E, S, PI and of the quarterly GDP .

[8]Although for the sake of clarity the discussion of the common features of the coincident economic indicators focuses on the growth rates, the modeling of the individual series and the estimation of the common dynamic will be done starting from the *level* series.

Non-stationarity

Most approaches to the analysis of macroeconomic and financial time series are based on the assumption of stationarity: the growth rates of economic variables are modelled as stationary when ARMA or VAR processes are fitted, the financial log-returns, interest rates, foreign exchange rates are assumed to be stationary when modelled by the ARCH-type or stochastic volatility processes.

Stationarity is a non-trivial and in some cases misleading assumption which imposes serious restrictions on modeling itself and on the interpretation of the fitted model. More concretely, under the assumption of stationarity of the data, a stationary model should be estimated on the *whole* data set, one would try always to use as much data as possible in order to support any statistical statement or to make forecasts. On the other hand, when in doubt about the time-invariant character of the data, a stationary process could possibly become at most an useful local approximation of the true data generating process. The parameters of the model should then be re-estimated periodically on a moving window. One would shy away from making statistical statements based on long samples and in forecasting one would prefer to use the most recent past for the calibration of the model. However, were the unconditional features of the data time-varying, it is not clear of what help a stationary model would then be in describing the future dynamic of the data. Assuming data stationarity, stationary models for economic or financial variables ignores the evolving nature of the economic processes, the dynamic character of the economy. For an illustration of the size of the negative impact of the unjustified assumption of stationarity on modeling and forecasting financial returns, see Stărică [20].

The visual inspection of the series in Figure 2.1 reveals two possible types of non-stationarities: in the mean of the growth rates and in their variance.

Time-varying mean

The growth rates seem to have a negative first moment during the episodes of recession while displaying a positive first moment during most of the expansion phase.

Unconditional heteroscedasticity

Some of the series in Figure 2.1 seem to have a time-varying variance. Different periods are animated by different unconditional variances. This feature is especially presented in IP, E, and GDP data which underwent a reduction of the variance around the mid 1980's (see Section 4 for a discussion on structural changes in the behavior of the considered time series).

Small "signal-to-noise" ratio

Some of the indicators are very noisy with a small 'signal-to-noise' ratio. In the case of the first order differences of the log-levels, the signal [9] is the growth rate or the time-varying first derivative of the trend, while a measure of the noise is given by the variance. The variance of industrial production and sales are particularly large making the recognition of the trend a non-trivial task. As we will see in Section 4, the monthly series of the GDP also displays a particularly large variance second only to that of sales.

Presence of common dynamic

By marking the NBER-defined recession periods in Figure 2.1 we tried to emphasize one of the most important features of the indicators under discussion: their common dynamic. However, as we will soon see, the comparison of the estimated turning points of individual series with the turning points of the economy as specified by the NBER's Business-Cycle Dating Committee reveals that none of the indicators delivers precise information about all the episodes of the business cycles. So, the major requirement to be fulfilled by any analytic approach to business-cycle dating is that of capturing *the common dynamic* of the macroeconomic indicators monitored.

3 Adaptive Weights Smoothing (AWS) methodology

In this section we describe the statistical methodology which lies at the core of both the analysis of individual indicators and of the estimation of the common dynamic of a set of macroeconomic series.

3.1 Nonparametric modeling

Let y_t denote the logarithm of the level of a macroeconomic variable. The features of the data we discussed above lead naturally to the following model for individual macroeconomic time series.

$$y_t = \mu(t) + \sigma(t)\,\varepsilon_t, \quad t = 1, 2, ..., n, \tag{3.1}$$

where the time-varying trend μ and volatility σ could be continuous or display jumps; the noise (ε_t) is assumed i.i.d. with zero mean and unit variance, non-necessarily Gaussian. In words, the macroeconomic indicators are modelled as stochastic variations around a *time-varying trend* or expected level μ. The volatility of the variations is also time-varying.

[9] In the case of the log-series, the signal is the time-varying trend while a measure of the noise is the variance of the stochastic variations of the series around its trend.

Periods of economic expansion correspond to a positive trend or increasing expected level μ or, equivalently a positive first derivative of the trend, μ' (positive expected growth rates). Similarly, a shrinking economy will manifest in a negative trend (decreasing expected levels) μ or, equivalently, a negative first derivative of the trend μ' (negative expected growth rates).

The main goal of our analysis is estimation of the time-varying trend function μ and its first derivative and identification of the intervals in which μ' is significantly negative (positive).

3.2 Local linear estimation

Our approach does not impose any global structural (parametric) assumption on the functions μ and σ. Instead we impose the following assumption of a *local parametric structure*: for every time point t there exists a time interval around t in which these two functions can be well approximated by a simple parametric model. In this paper we locally approximate the volatility σ by a constant and the trend μ by a linear function which corresponds to a local constant approximation of the derivative μ'. Under the mentioned hypothesis, the main question concerns the construction of the intervals where a parametric, stationary model provides a good approximation to the true data generating process and on which the parameters of the model can be consistently estimated. The size of these intervals is sometimes referred to as *degree of locality.* One classical approach suggests to select a *bandwidth* h and to estimate the functions μ and σ from the time window $[t-h, t+h]$ using the approximating model equation

$$y_s = \mu_0(t) + (s-t)\mu_1(t) + \sigma(t)\varepsilon_s, \qquad s \in [t-h, t+h].$$

This is a classical linear parametric model with three unknown coefficients $\mu_0(t), \mu_1(t)$ and $\sigma(t)$ which can be estimated using the standard least squares approach.

The degree of locality is given by the bandwidth h and its choice is crucial for many applications. On one hand, the choice of a small h leads to insufficient noise reduction because too few points are used for estimating the unknown parameters. On the other hand, selection of a large bandwidth h may lead to a substantial bias due to the insufficient approximation of the true function μ on the whole window by a linear function. It is intuitively clear that the choice of the optimal bandwidth depends on the unknown geometry of the function to estimate and that a choice of a fixed bandwidth can be restrictive for the analysis we aim to perform.

In what follows we apply the Adaptive Weights Smoothing (AWS) approach introduced in Polzehl and Spokoiny [16] in the context of image denoising and extended in Polzehl and Spokoiny [17] to a large class of statistical models. The AWS method has a number of features which make it well-suited for the problem at hand. Firstly, it is completely data-driven and it adapts automatically to the unknown structure of the signal function μ in the model. It particular, it is very sensitive to structural changes and can identify the location of the break point with high precision. Secondly, it can be applied to a situation where the noise is heteroscedastic. In the case of a heteroscedastic regression, it can be also used to estimation the time-varying variance of the noise. Finally, in many special cases it provides nearly optimal noise reduction, see Polzehl and Spokoiny ([17], [18]).

The idea behind the approach is to describe the local neighborhood of every time point t by a set of nonnegative weights $w_{t,s}$ satisfying $w_{t,s} \in [0,1]$. For the case of the known variance $\sigma^2(s)$, this leads to the estimates $\mu_0(t)$ and $\mu_1(t)$ defined by the weighted least squares:

$$(\widehat{\mu}_0(t), \widehat{\mu}_1(t))^\top = \operatorname*{argmin}_{(\mu_0,\mu_1)} \sum_s (y_s - \mu_0 - \mu_1(s-t))^2 \sigma^{-2}(s) w_{t,s}.$$

This is a quadratic optimization problem with the closed form solution

$$(3.2) \qquad (\widehat{\mu}_0(t), \widehat{\mu}_1(t))^\top = \left(\sum_s Z_{s,t} Z_{s,t}^\top \sigma^{-2}(s) w_{t,s} \right)^{-1} \sum_s Z_{s,t} y_s \sigma^{-2}(s) w_{t,s}.$$

Here $Z_{s,t} = (1, s-t)^\top$.

If the variance $\sigma^2(s)$ is unknown, it should be replaced by its estimate $\widehat{\sigma}^2(s)$. The weights $w_{t,s}$ are constructed from the data using the following iterative procedure. Start with the usual kernel weights $w_{t,s} = K(|t-s|^2/h_0^2)$ for some kernel K and a small bandwidth h_0. Then compute the estimates $\widehat{\mu}_0(t), \widehat{\mu}_1(t)$ according to (3.2). Recompute the weights $w_{t,s}$ by comparing $(\widehat{\mu}_0(t), \widehat{\mu}_1(t))$ and $(\widehat{\mu}_0(s), \widehat{\mu}_1(s))$ for every $s \in [t-h_1, t+h_1]$, where h_1 is a larger bandwidth than h_0. These two steps, i.e. recomputing the weights and the estimates, are repeated increasing at every step k the bandwidth parameter h_k. The details of the procedure can be found in Polzehl and Spokoiny [17], [18].

For estimating the time varying variance $\sigma^2(t)$ we build the differences $\widehat{\varepsilon}_s = 2^{-1/2}(y_t - y_{t-1})$. Since every $\widehat{\varepsilon}_s$ is approximatively normal zero mean with the variance equal to σ_t^2, we apply the AWS procedure for the local constant volatility model to $\widehat{\varepsilon}_s$, see Polzehl and Spokoiny [17].

The expression (3.2) helps to bound the standard deviation of the estimate $\widehat{\mu}(t)$, $\widehat{\mu}'(t)$ and therefore, to construct the α-percent symmetric or one-sided confidence intervals for these estimates. Since we are mostly interested in the sign of the growth rate (or derivative $\mu'(t)$), we use one-sided intervals which assess the significance of the movements of the level of the economy. For instance, if $\widehat{\mu}'(t) < 0$ and if $\widehat{v}(t)$ is its estimated standard deviation then, the one sided α-interval of interest is of the form $I_\alpha = [\widehat{\mu}'(t), \widehat{\mu}'(t) + t_\alpha \widehat{v}(t)]$ where t_α is the corresponding one-sided quantile of the normal distribution. If I_α belongs to the negative semiaxis, the growth rate is significantly negative at level α.

4 A non-stationary analysis of the individual macroeconomic indicators

In this section, the non-parametric, non-stationary set-up introduced previously is used to perform an analysis of the dynamics of the individual monthly macroeconomic indicators US industrial production, payroll employment, sales and real personal income as well as of the monthly and quarterly series of US GDP. Our non-stationary analysis yields estimates of the time-varying trend and its first derivative (corresponding to the growth rate) for each of the five coincident macroeconomic series. It produces series-specific cycle turning points[10]. It also yields a precise picture of the dynamic of the variance of the stochastic variations around the trend for each of the five indicators.

Figures 4.1 and 4.2 display the time-varying first derivative of the estimated level of the individual series and yield a number of interesting conclusions.

First, the second graph in Figure 4.1 shows clearly that the behavior of the nonfarm payroll employment series in the initial period of economic recovery that follows a recession has changed during the last two recessions. For all the recessions but the last two, the employment series recovered strongly immediately after the trough. Statistically, this phenomena is seen in the significantly positive (at the 90% level we used through the paper) growth rates that used to accompany the beginning of the expansion. The 1991 recovery (which according to the NBER's Business-Cycle Dating Committee started in March 1991) saw the estimated employment growth rate remain statistically equal to zero until December 1992, i.e. one year and nine month beyond the official end of the recession, while for the current expansion (that according to the NBER's Business-Cycle Dating Committee starter in November 2001), the estimated payroll employment growth rate remained significantly negative until the end of the data set (December 2003), i.e. at least two years and a month beyond the official end date of the recession. These differences could possibly be due to the structural changes in the economy which in the past two recessions were more pronounced than the cyclical downturn changes. In other words, the economy was changing rather than just going through a temporary slowdown[11].

[10] Classical cycle peaks (troughs) are points at which a series moves from positive (negative) expected growth rates to negative (positive) expected growth rates.

[11] The job losses in cyclical downturns are largely temporary. At the end of the recession, industries rebound and laid-off workers are readily find employment in similar industries. Job losses from structural changes are permanent. As industries decline or change, workers are forced to switch industries, sectors, locations or skills in order to find a new job. Numerous studies indicate that many of the several million jobs, particularly the factory jobs, lost in the past three years are permanently gone. Groshen and Potter [7] suggest that 79% of employees who have lost their jobs in the recent recession (and recovery) worked in industries more affected by structural shifts than by cyclical shifts. Job losses that stem from structural changes are permanent: as industries decline, jobs are eliminated, compelling workers to switch industries, sectors, locations, or skills in order to find a new job.

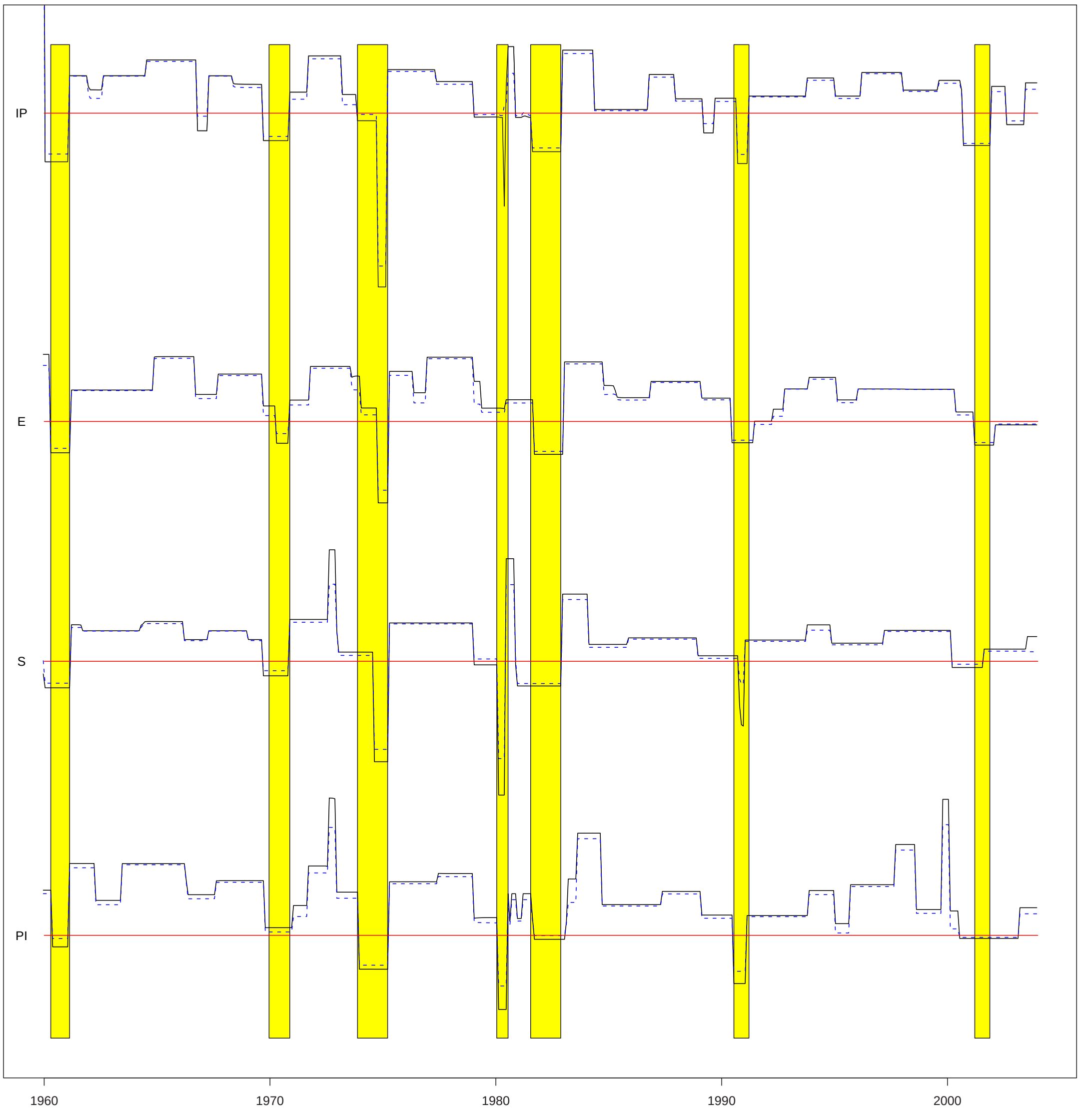

Figure 4.1: Estimated first derivative of the trend, μ' (growth rate) of the NBER monthly indicators: IP, E, S, PI.

Second, the graph on the bottom of Figure 4.1 shows clearly that the personal income has not fallen significantly during three of the past seven recessions (in 1960, 1969 and 1981). The decline during the last recession seems significant (at the 90% level).

Third, it emphasizes the fact that determination of the date of the turning points in economic activity is a challenging task. In every episode, the indicators peak or attain their trough in different months. Tables 4.1 and 4.2 show the number of months earlier (minus sign) or later (plus sign) that the peak, trough respectively, occurred relative to the NBER's business-cycle peak date. The differences are based on the graphs in Figure 4.1. In Table 4.1 the second column under every indicator contains the differences (in

Peak	Industrial Production		Employment		Real Sales		Real Income	
1960	-10	-3	0	0	-3	-3	+1	+1
1969	-3	-2	+4	+3	-3	-2	No peak	+8
1973	0	0	+11	+11	+9	0	+1	0
1980	-12	-7	No peak	+2	+1	-10	+1	-1
1981	-8	0	+2	0	-7	-6	+2	+1
1990	+2	+2	-1	-1	+3	+1	0	0
2001	-6	-6	0	0	-12	-7	-8	No peak

Table 4.1: Differences between individual turning points and the turning points of the economy as defined by NBER's Business-Cycle Dating Committee. The table displays the number of months earlier (minus sign) or later (plus sign) that the peak occurred relative to the NBER's business-cycle peak date. The first column is based on the estimates displayed in Figure 4.1. The second column are NBER's Business-Cycle Dating Committee values.

months) as they appear in the report of the NBER's Business-Cycle Dating Committee announcing the peak of March 2001, [13].

Trough	Industrial Production	Employment	Real Sales	Real Income
1960	-1	0	0	-1
1969	-1	-1	-1	No trough
1973	-1	0	0	0
1980	-2	No trough	-2	0
1981	0	+1	0	+2
1990	-1	+12	-3	-2
2001	0	No trough	-4	+15

Table 4.2: Differences between individual turning points and the turning points of the economy as defined by NBER's Business-Cycle Dating Committee. The table displays the number of months earlier (minus sign) or later (plus sign) that the trough occurred relative to the NBER's business-cycle trough date. The values are based on the estimates displayed in Figure 4.1.

A look at the behavior of the four monthly indicators during the last recession reveals that the expected growth of employment was negative in March 2001 and has remained negative until the end of the sample (December 2003). The expected growth rate of personal income became negative in July 2000 and turned positive in March 2003. The expected growth rate of sales was negative between March 2000 and July 2001, while the industrial production went through two periods of negative growth between September 2000 and November 2001 and between August 2002 and May 2003. The monthly GDP's period of negative growth was July 2000 - July 2001.

Figure 4.2 displays the estimated growth rate of the quarterly GDP. It shows a poor

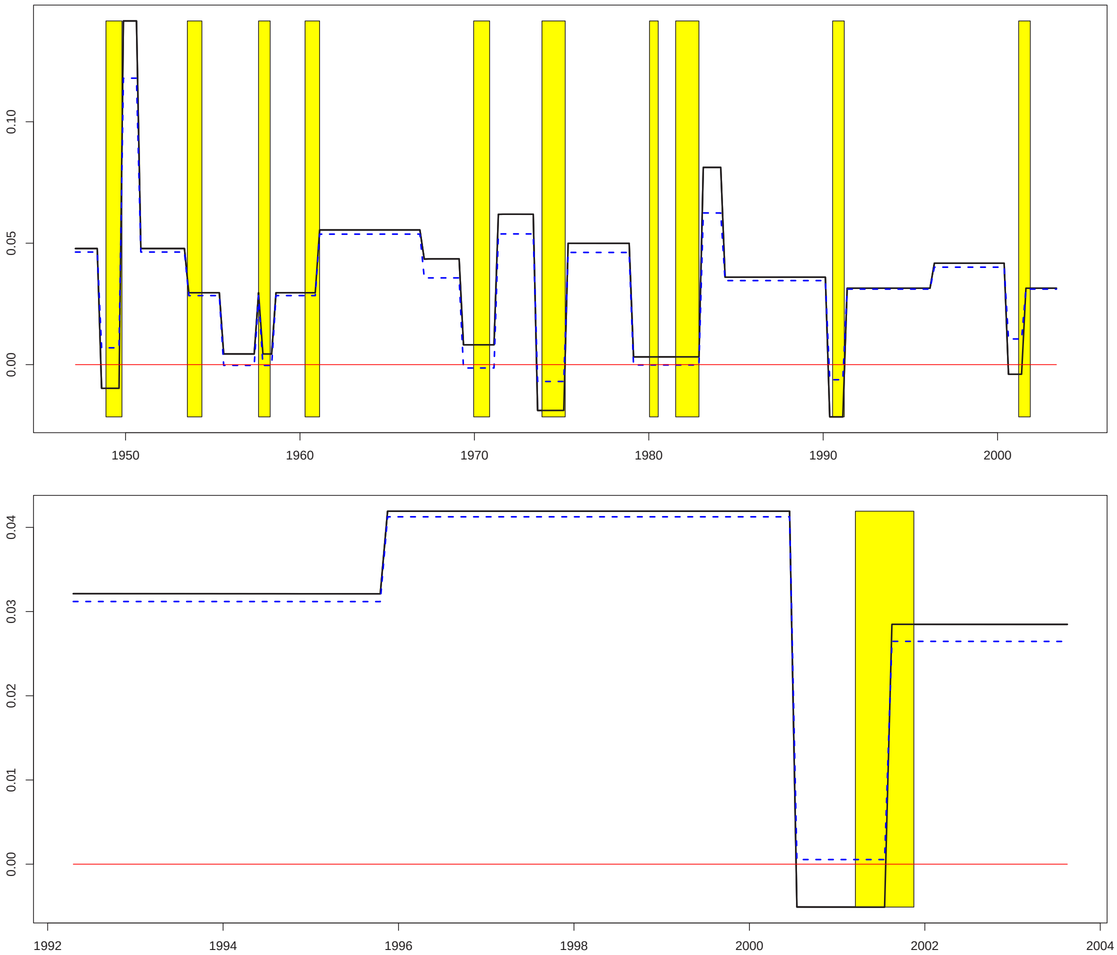

Figure 4.2: Turning points in the GDP. Estimated growth rate (μ') of the GDP, quarterly data (top and middle), monthly data (bottom). The dash-dotted line is the 10% one-sided confidence interval. The quarterly data suggest negative (although statistically not significant) growth between III 2000 - II 2001 while The monthly data yield July 2000 - July 2001 as the period of negative (and almost significant at the 90% level) growth.

correspondence between the pattern in the estimated growth rate and that of the recessions/expansions particularly for the period anterior to the pronounced variance reduction of the series in the middle of the '80s. For example, the period 1980-1983 is statistically consistent with a period of positive but low growth rate for the GDP although the NBER dating would decompose it into a quick succession of two negative growth periods interrupted by one of short positive growth. The impact the sampling frequency has on the estimation of the turning points is highlighted in Figure 4.2. While based on quarterly data, the negative estimate of the growth in the GDP in the end of 2000 and beginning of 2001 is close to zero and not significant at 90% level, the estimation based on monthly data yields a smaller point estimate that is close to being significant at the 90% level. As a conclusion, the large volatility as well as the low sampling frequency make dating the business cycle using *only* the GDP quarterly series impossible.

The results of the volatility estimation by the AWS procedure are shown in Figure 4.3. One can observe significant time variation of the volatility in some of the four monthly indicators as well as in the variance of the quarterly GDP. The industrial production displays two breaks in the volatility process, the first in the summer of 1961, the second in the end of 1984, the employment displays a sharper reduction in variance towards the beginning of 1987 while the volatility of the sales and personal income does not seem to have changed much over the last 4 decades. The relative size of the volatilities does not practically change through time. The payroll employment series has the lowest variance followed by the personal income, industrial production and the sales series. In particular the sales series has a variance more than nine times bigger than the employment.

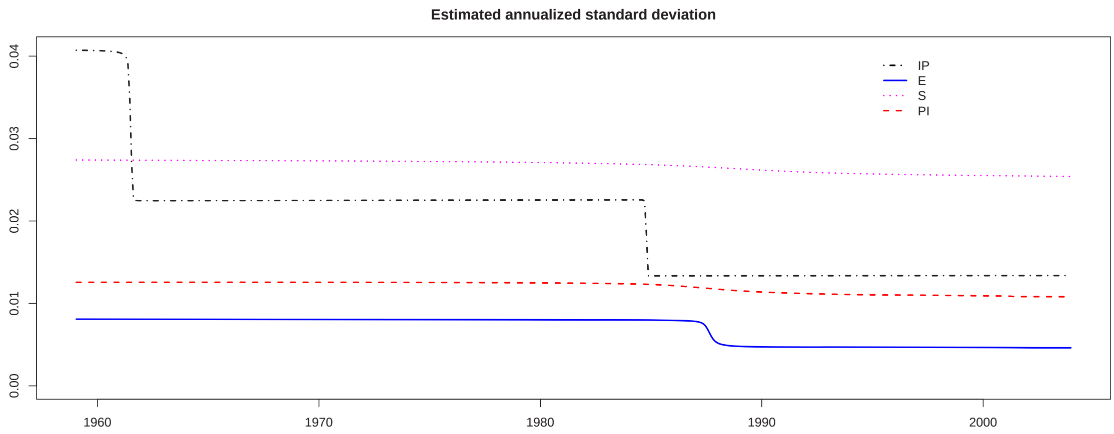

Figure 4.3: Volatility of the monthly NBER indicators: IP black dash-dotted, E blue solid, S magenta dotted, PI red dashed, GDP green dash-dotted.

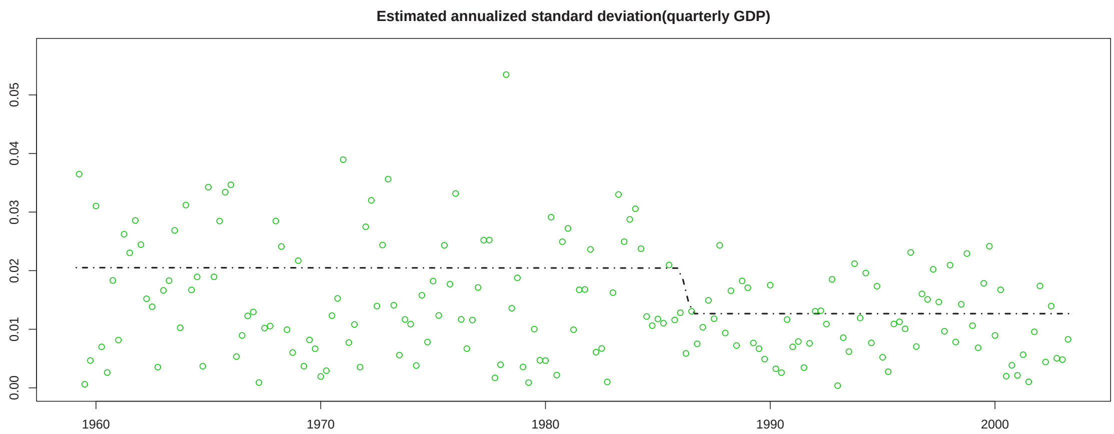

Figure 4.4: Volatility of the quarterly GDP data series.

The variance of the quarterly GDP decreased significantly (2.4 times) between the first and the second quarter of 1986.

5 Dating the business cycle: the methodology

In the sequel, following the NBER's Business Cycle Dating Committee, we define a recession as a significant decline in activity spread across the economy, lasting more than a few months normally visible in a set of relevant macroeconomic indicators. In other words, the business cycle is defined as the common dynamic of a group of economic variables. While in the previous section we individually analyzed a number of macroeconomic series, in this section we propose a methodology of estimating their common dynamic.

Besides the assumptions that formed the basis of the individual analysis in previous section, here we hypothesize, consistently with the above definition of recession, that the time-varying means of relevant macroeconomic series have a common dynamic. More concretely, if we denote by $y_t^{(i)}$ the logarithm of the i-th macroeconomic variable (like the industrial production, employment, etc.), this assumption can be expressed in the following form:

$$y_t^{(i)} = m^{(i)} + \alpha^{(i)} f(t) + \sigma^{(i)}(t)\, \varepsilon_t^{(i)}, \quad t = 1, 2, \ldots, n, \quad i = 1, 2, \ldots, p, \tag{5.1}$$

where the (deterministic) functions f and $\sigma^{(i)}$ are possibly discontinuous. The quantities $m^{(i)}$ and $\alpha^{(i)}$ are unknown positive coefficients.

The noise $(\varepsilon_t^{(1)}, \ldots, \varepsilon_t^{(p)})$ for every indicator is assumed i.i.d. with zero mean and unit variance, non-necessarily Gaussian. The model allows correlations between errors $\varepsilon^{(i)}$ for different indicators i. The estimation of the correlation structure of the errors is discussed in the next section.

In words, we assume that the levels of relevant macroeconomic time series fall or rise together as an expression of the changes in the state of the economy which is modelled by the trend function $f(t)$. Increasing f corresponds to expansions while a decreasing f identifies the recessions. Alternatively, a positive first derivative of f signals an expanding economy, a negative fist derivative is associated with a contracting economy. Concisely, f is the time-varying trend of the economy as a whole.

The relation (5.1) can be too restrictive if too many series and a long time period are considered. A standard way to tackle this problem is to allow the coefficients $m^{(i)}$ and $\alpha^{(i)}$ to change slowly with time. This leads to the equation

$$y_t^{(i)} = m^{(i)}(t) + \alpha^{(i)}(t) f(t) + \sigma^{(i)}(t)\, \varepsilon_t^{(i)}, \quad t = 1, 2, \ldots, n, \quad i = 1, 2, \ldots, p. \tag{5.2}$$

The time dependent coefficients $m^{(i)}(t)$ and $\alpha^{(i)}(t)$ are assumed to vary smoothly and more slowly than function f.

The aim of this section is to introduce a methodology to estimate the economy's driving function f.

5.1 Estimation of the correlation structure

The first step in our analysis consists in estimating the covariance matrix $\Sigma(t) = \mathrm{Var}(\boldsymbol{y}_t)$. Similarly to the univariate case, for every $i = 1, \ldots, p$, we first estimate the standard deviations $\widehat{\sigma}^{(i)}(t)$ from the differences $(y_t^{(i)} - y_{t-1}^{(i)})$ using the volatility AWS-algorithm (see Section 3). Denote $\widehat{\varepsilon}_t^{(i)} = (y_t^{(i)} - y_{t-1}^{(i)})/\widehat{\sigma}^{(i)}(t)$ for $i = 1, \ldots, p$; $\widehat{\boldsymbol{\varepsilon}}(t) = (\widehat{\varepsilon}^{(1)}(t), \ldots, \widehat{\varepsilon}^{(p)}(t))^\top$ and $\widehat{\boldsymbol{\sigma}}(t) = \mathrm{diag}(\widehat{\sigma}^{(1)}(t), \ldots, \widehat{\sigma}^{(p)}(t))$. Next, we locally estimate the correlation matrix $C_t = \boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_t^\top$ as $\widehat{C}_t = (2h)^{-1} \sum_{s=t-h}^{t+h} \widehat{\boldsymbol{\varepsilon}}_s \widehat{\boldsymbol{\varepsilon}}_s^\top$. Since our results do not indicate a strong correlation structure between different time series, we further proceed assuming no correlation and $\Sigma(t) = \widehat{\boldsymbol{\sigma}}(t)^2$. However, the procedure presented below applies for any time varying correlation structure between the individual time series.

5.2 Estimation of the common dynamics

In the first step we estimate the coefficient functions $m^{(i)}(t)$ and $\alpha^{(i)}(t)$. Note that these functions are only identifiable up to a shift and scaling factor. We can therefore set one of the $m^{(i)}$ equal to zero and one of the $\alpha^{(i)}$ equal to one. We select the indicator that has the largest signal-to-noise ratio (say, the i_0-th series), that is, we set $m^{(i_0)}(t) \equiv 0$ and $\alpha^{(i_0)}(t) \equiv 1$.

For estimating the other coefficients we note that for every $i \neq i_0$ and for every point t, $\mu^{(i)}(s) \approx m^{(i)}(t) + \alpha^{(i)}(t) f(s)$ for s in some neighborhood of t, $s \in [t-h, t+h]$. Therefore, the coefficients $m^{(i)}(t)$ and $\alpha^{(i)}(t)$ can be estimated from the observations $y_s^{(i)}$ by ordinary least square regression. If $\omega_{ts} = K((t-s)/h)$ then

$$
\begin{aligned}
(\widehat{m}^{(i)}(t), \widehat{\alpha}^{(i)}(t))^\top &= \operatorname*{arginf}_{(m,\alpha)} \sum_s \left(y_s^{(i)} - m - \alpha y_s^{(i_0)} \right)^2 \omega_{ts} \\
&= \begin{pmatrix} \sum_s \omega_{ts} & \sum_s y_s^{(i_0)} \omega_{ts} \\ \sum_s y_s^{(i_0)} \omega_{ts} & \sum_s |y_s^{(i_0)}|^2 \omega_{ts} \end{pmatrix}^{-1} \begin{pmatrix} \sum_s y_s^{(i)} \omega_{ts} \\ \sum_s y_s^{(i)} y_s^{(i_0)} \omega_{ts} \end{pmatrix}.
\end{aligned}
$$

A value of $h = 90$ (which corresponds to a window of fifteen years) and the Epanechnicov kernel $K(u) = (1 - u^2)_+$ are used in our analysis. This choice ensures a small estimation error of the parameters $m^{(i)}$ and $\alpha^{(i)}$ and justifies the use of the estimates $\widehat{m}^{(i)}(t)$ and $\widehat{\alpha}^{(i)}(t)$ in place of the true values.

The estimation of the function f is based on the observation that for all i the variables $z_t^{(i)} = (y_t^{(i)} - m^{(i)}(t))/\alpha^{(i)}(t)$ have same mean $f(t)$ and variance $|\sigma^{(i)}(t)/\alpha^{(i)}(t)|^2$. The covariance of the vector $\boldsymbol{z}(t) = (z^{(1)}(t), \ldots, z^{(p)}(t))$ is given by $\mathrm{Var}\, \boldsymbol{z}(t) = A^{-1}(t)\Sigma(t)A^{-1}(t)$

where $A(t) = \operatorname{diag}(\alpha^{(1)}(t), \dots, \alpha^{(p)}(t))$ is the diagonal matrix with the diagonal entries $\alpha^{(i)}(t)$ and $\Sigma(t) = \operatorname{Var} \boldsymbol{y}_t$.

In a next step, we produce the convex combination of the p series in $\boldsymbol{z}_t$

$$X_t = \boldsymbol{\beta}^\top(t)\boldsymbol{z}_t, \tag{5.3}$$

that has expectation $f(t)$ and the smallest variance. In other words, the vector of coefficients $\boldsymbol{\beta}(t)$ is chosen to minimize the variance of X_t in the class $\mathcal{B}_+$ of all vectors $\boldsymbol{\beta} = (\beta^{(1)}, \dots, \beta^{(p)})$ satisfying $\sum_{i=1}^p \beta^{(i)} = 1$ and $\beta^{(i)} \ge 0$

$$\begin{aligned} \boldsymbol{\beta}(t) &= \operatorname*{argmin}_{\boldsymbol{\beta}\in\mathcal{B}_+} \operatorname{Var}(\boldsymbol{\beta}^\top \boldsymbol{z}_t) = \operatorname*{argmin}_{\boldsymbol{\beta}\in\mathcal{B}_+} \boldsymbol{\beta}^\top \operatorname{Var}(\boldsymbol{z}_t)\boldsymbol{\beta} \\ &= \operatorname*{argmin}_{\boldsymbol{\beta}\in\mathcal{B}_+} \boldsymbol{\beta}^\top A^{-1}(t)\Sigma(t)A^{-1}(t)\boldsymbol{\beta}. \end{aligned} \tag{5.4}$$

If $f(t)$ is the signal we are interested in, the series X_t has the best signal-to-noise ratio among all linear combinations of the coordinates of $\boldsymbol{z}_t$. Given the matrices $A(t)$ and $\Sigma(t)$, this is a standard quadratic optimization problem with cone constraints. If the condition $\beta^{(i)} \ge 0$ is disregarded, an application of the Lagrange multipliers approach leads to the following solution

$$\begin{aligned} \boldsymbol{\beta}^*(t) &= \frac{1}{\mathbf{1}^\top A(t)\Sigma^{-1}(t)A(t)\mathbf{1}} A(t)\Sigma^{-1}(t)A(t)\mathbf{1}, \\ \operatorname{Var} X(t) &= \operatorname{Var}(\boldsymbol{z}^\top(t)\boldsymbol{\beta}^*(t)) = \frac{1}{\mathbf{1}^\top A(t)\Sigma^{-1}(t)A(t)\mathbf{1}}, \end{aligned}$$

where $\mathbf{1}$ is a vector with the entries equal to one.

Often, the vector $\boldsymbol{\beta}^*(t)$ belongs to the set $\mathcal{B}_+$. If some entries of the vector $\boldsymbol{\beta}^*(t)$ are negative, the corresponding components are excluded from the optimization and the procedure is repeated.

In applications the true covariance matrix $\Sigma(t)$ and true coefficients $m^{(i)}(t), \alpha^{(i)}(t)$ are not known and we replace them with the corresponding estimates. This leads to the following definition

$$\begin{aligned} \widehat{z}_t^{(i)} &= \frac{y_t^{(i)} - \widehat{m}^{(i)}(t)}{\widehat{\alpha}^{(i)}(t)}, \qquad \widehat{\boldsymbol{z}}_t = (\widehat{z}_t^{(1)}, \dots, \widehat{z}_t^{(p)}), \\ \widehat{\boldsymbol{\beta}}(t) &= \frac{1}{\mathbf{1}^\top \widehat{A}(t)\widehat{\Sigma}^{-1}(t)\widehat{A}(t)\mathbf{1}} \widehat{A}(t)\widehat{\Sigma}^{-1}(t)\widehat{A}(t)\mathbf{1}, \\ \widehat{X}_t &= \widehat{\boldsymbol{\beta}}^\top(t)\widehat{\boldsymbol{z}}_t. \end{aligned}$$

As a final step, the series $\widehat{X}_t$ is smoothed with the AWS methodology (Section 3), using the variance estimate $\operatorname{Var} \widehat{X}(t) \approx \left(\mathbf{1}^\top \widehat{A}(t)\widehat{\Sigma}^{-1}(t)\widehat{A}(t)\mathbf{1}\right)^{-1}$ to obtain an estimate of the function $f(t)$ and of its first derivative. Recall that the function $f(t)$ is a proxy for the level of the economy while the first derivative measures the growth rate of the economy.

6 Dating the business cycle: the practice

Defining recession as a significant decline in activity spread *across* the economy, assigns an important role to the choice of measures of economic activity that reflect this decline[12]. During the last decades, the NBER's Business Cycle Dating Committee has emphasized a group of four monthly economic indicators consisting of industrial production (IP), nonfarm payroll employment (E), real personal income (PI), and wholesale-retail trade (S) as defined in the note 'The Business-Cycle Peak of March 2001' [13] (2001 Announcement) .

Recently, according to the note of July 17, 2003 [14] (2003 Announcement) as well as in the most recent description of the NBER's Business-Cycle dating procedure issued on October 21, 2003 [15] (2003 Description), the Committee seems to have extended the set of indicators to include a monthly series of GDP estimates issued by Macroeconomic Advisers, a private consulting firm.

This section investigates the impact the choice of the set of macroeconomic variables has on the results of the dating in the context of the possible recent changes of the methodology of the NBER's Business-Cycle Dating Committee [13].

6.1 Business-cycle dating based on the four traditional NBER's Business-Cycle Dating Committee coincident indicators

In the sequel we apply the dating methodology described in Section 5 to the set of the four monthly economic indicators of industrial production, nonfarm payroll employment, wholesale-retail trade, and real income, emphasized by the NBER's Business-Cycle Dating Committee in recent decades. The results of the estimation are displayed in Figures 6.1 through 6.3.

The top-left graph shows the four indicators minus their value in January 1959 while the

[12]Monitoring different groups of macroeconomic indicators can possibly yield different business-cycle dating outcomes.

[13]The existence of a break in the dating approach of the NBER's Business-Cycle Dating Committee is further supported by the contrasting statements on the role of the GDP series. The 2001 Announcement [13] states that 'the committee gives relatively little weight to real GDP because it is only measured quarterly and it is subject to continuing, large revisions.' Quite differently, the 2003 Announcement [14] stresses the importance of 'the real GDP as the single best measure of economic activity' and frases most of the explanation about the dating of the trough as November 2001 around the dynamic of a *monthly* real GDP time series issued by Macroeconomic Advisers. Evidence of continuing falling employment and industrial production at the date of the announcement of the trough is waived by 'the fact that the broadest, most comprehensive measure of economic activity (i.e. the GDP, n.n.) is well above its pre-recession levels' (2003 Announcement [14]). Moreover, in contrast with the 2001 Announcement, the 2003 Description [15] clearly states that 'the committee places considerable weight on the estimates of real GDP issued by the Bureau of Economic Analysis of the U.S. Department of Commerce'.

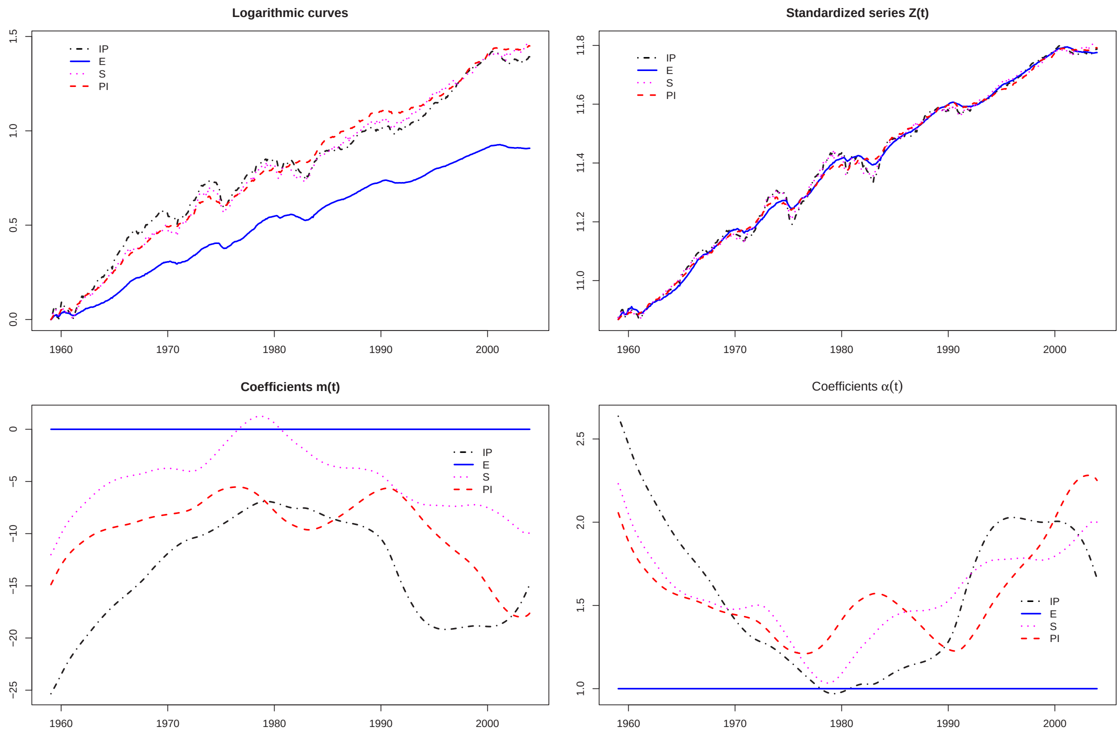

Figure 6.1: *Top* The log NBER series minus their value in Jan 1959 and the same series centered and scaled with corresponding estimated $m^{(\cdot)}$ and $\alpha^{(\cdot)}$. *Bottom* The coefficients m (left) and α (right). IP black dash-dotted, E blue solid, S magenta dotted, PI red dashed.

top-right graph shows the estimated $\widehat{\boldsymbol{z}}_t$ series, i.e. the original series centered and scaled with corresponding estimated $m^{(\cdot)}$ and $\alpha^{(\cdot)}$. The graphs indicate that our methodology succeeds in highlighting the common dynamic of the four series. The bottom graphs display the coefficients m (left) and α(right). The displayed changes in values of the parameters m and α seem to confirm the correctness of the assumption that they are slowly time-varying. The coefficients β are plotted in Figure 6.2.

It is worth noticing that the series that contribute most to building $\widehat{X}_t$, the convex combination of the z-series, are the employment and personal income indicators. During the first three decades, employment series contribution varied between 30% and 55%, the personal income series contributed with 35 to 50% while the participation of the industrial production series decreased from 20% in the begining of the 60's to less than 10% in the middle of the 80's. Sales contributed roughly 10% during the whole period. Employment accounting for as much as 65% around 1990. In the last decade, the personal income series considerably increased its contribution from 20% to 40%, employment's impact decreased from 65% to 40% while industrial production accounted for 15-25%. To put it shortly, our methodology finds that the dynamic of the economy is strongly expressed in the payroll employment and personal income series, with the employment being the most

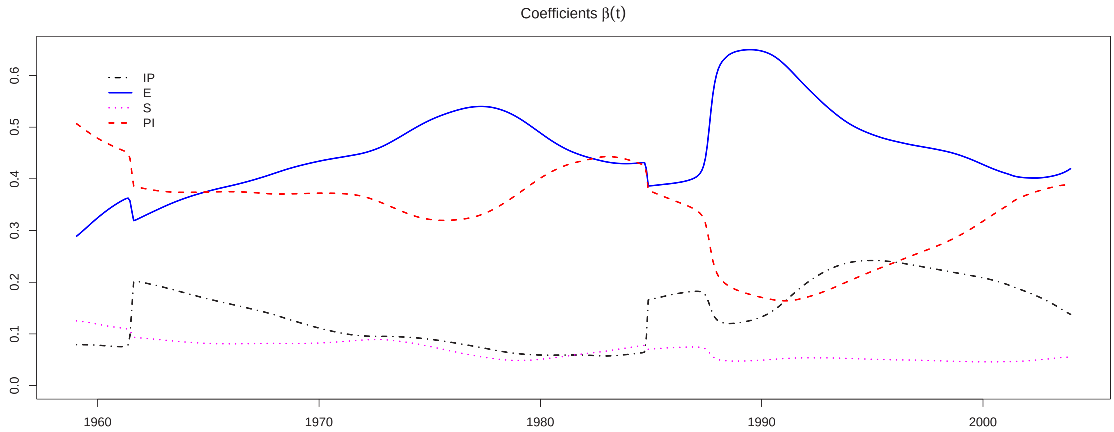

Figure 6.2: The estimated coefficients β. IP black dash-dotted, E blue solid, S magenta dotted, PI red dashed.

important single series. This is in line with the practice of the NBER's Business-Cycle Dating Committee that emphasizes the two series as the main coincident indicators.

Figure 6.3 displays the first derivative of the estimated level of the minimum-variance series $\widehat{X}_t$. The information about the dating is summarized in Table 6.1. For all the recessions but the last one we see a very good correspondence between the periods when the estimated growth rate f' of the economy is significantly negative and the intervals defined by the NBER Business-Cycle Dating Committee as recessions. We interpret this as evidence that our reproducible statistical method and the unknown NBER Business-Cycle Dating Committee procedure produce the same measure of data's features of interest.

Recession	peak	trough
1960	-3	-1
1969	-2	-1
1973	+1	0
1980	+2	-1
1981	+2	+2
1990	0	0
2001	-4	+18

Table 6.1: Differences between turning points of the economy defined by our procedure and those defined by NBER's Business-Cycle Dating Committee. The table displays the number of months earlier (minus sign) or later (plus sign) that the turn (measured by our methodology) occurred relative to the NBER's business-cycle turn date. The values are based on the estimates displayed in Figure 6.3.

The two methods give a very different overall picture of the last episode of economic contraction. Our method dates the beginning of the economic contraction during the month of November 2000, four months before the NBER dating. We find a significant

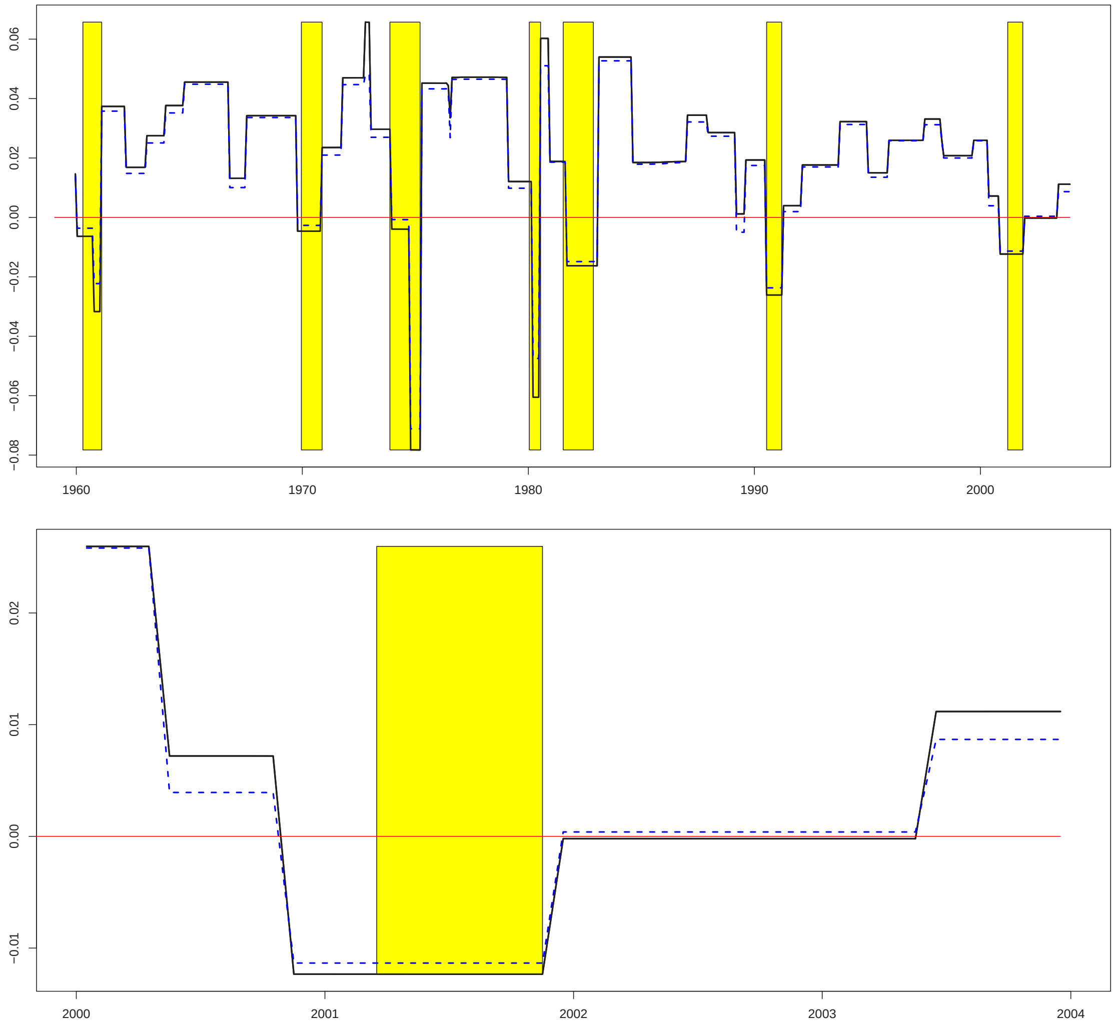

Figure 6.3: The estimated growth rate f' of the economy. The doted line corresponds to the 90% one-sided confidence intervals.

increase in the growth rate of the economy in December 2001 to a level that is still negative (although close to zero). The growth level does not become significantly positive until June 2003. Our approach indicates that, based on the traditional four coincident macroeconomic indicators, the recession ended in May 2003 (June being the first month with significant positive economic growth), eighteen months beyond the date NBER's Business-Cycle Dating Committee specified as the end of the recession (November 2001).

Could it be that the strong discrepancy between the two end dates of the last recession could be explained by augmenting the set of monthly indicators to include the monthly GDP series?

6.2 Business-cycle dating based on a set of indicators extended to include the monthly GDP series

In order to answer this question we applied our methodology to the extended set of economic indicators which includes also the monthly series of the GDP. The data cover the interval May 1992 to August 2003.

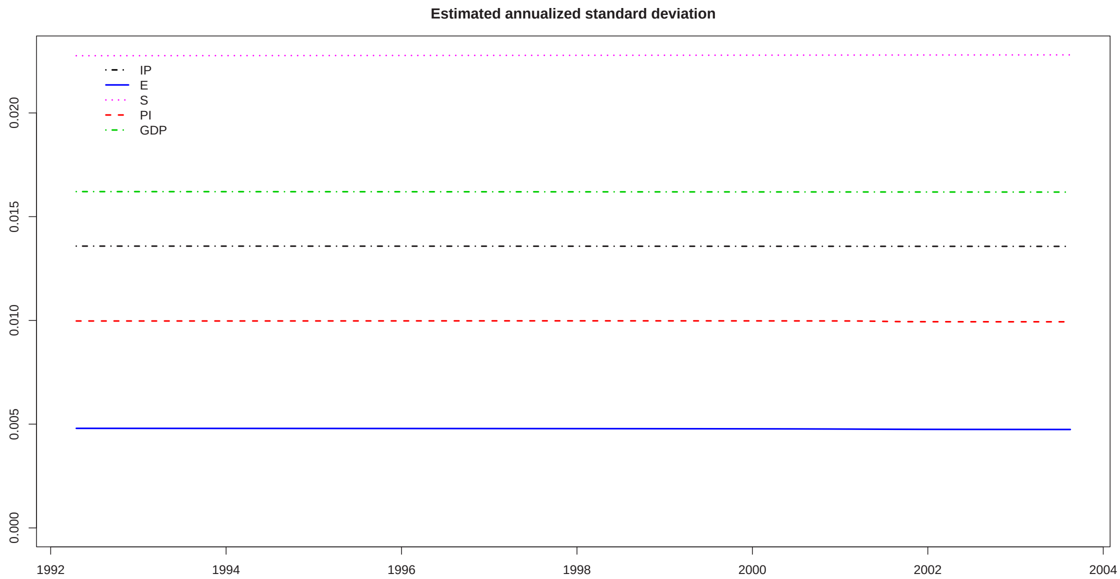

Figure 6.4: Volatility of the NBER data series together with the monthly GDP: IP black dash-dotted, E blue solid, S magenta dotted, PI red dashed, GDP green bold-dotted. The variance of the GDP series is second only to sales.

Figure 6.4 displays the volatility estimates of the five monthly series. The relative size of the volatilities does not practically change through time. The payroll employment series has the lowest variance followed by the personal income, industrial production, the GDP and the sales series. In particular the GDP series has a standard deviation more than four times bigger than the employment while the factor is six for the sales. In this application, we took i_0 to be 2.

The top left graph in Figure 6.5 displays the five indicators minus their value in May 1992 (the first month the monthly GDP series is available). The top-right graph shows the estimated $\widehat{\boldsymbol{z}}_t$ series, i.e. the original series centered and scaled with corresponding estimated m and α. The bottom graphs display the coefficients m (left) and α (right).

The corresponding β-coefficient are plotted in Figure 6.6. Similarly to the previous analysis of Section 5, the resulting series $\widehat{X}_t$ is mainly a combination between employment and personal income. The payroll employment coefficient β decreases from 0.57 to 0.43 while the weight of the personal income increases from 0.23 to 0.46. The industrial produc-

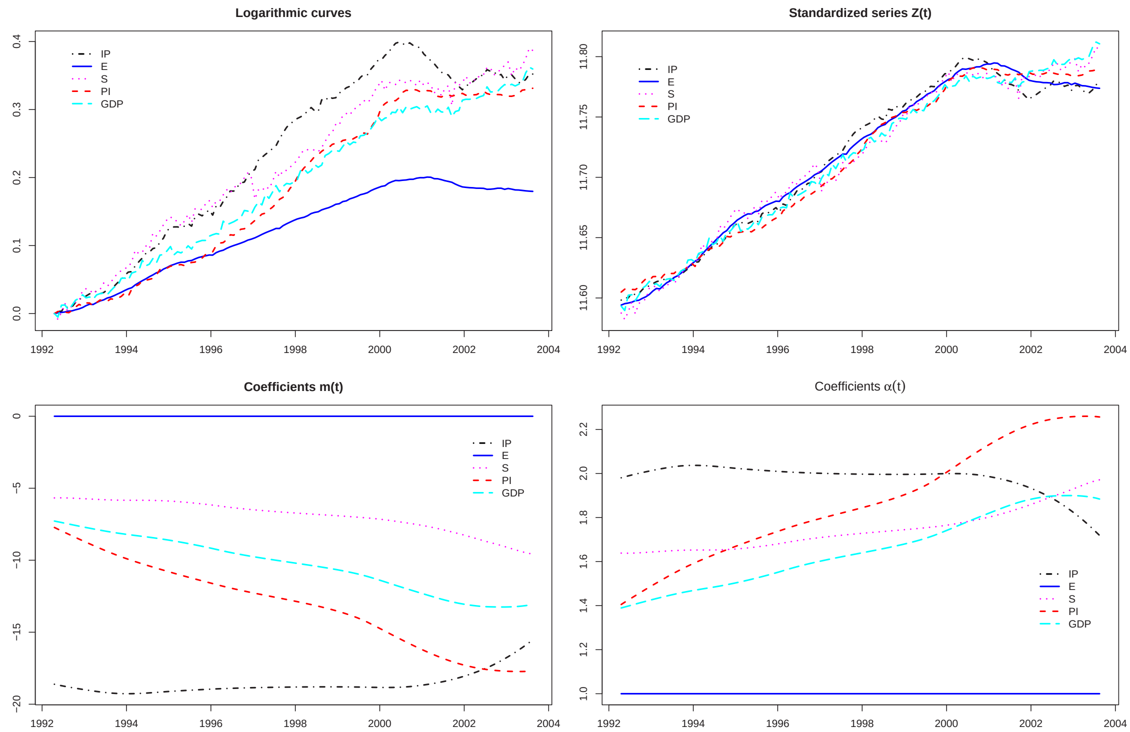

Figure 6.5: The log NBER series together with the monthly GDP minus their value in May 1992 and the same series centered and scaled with corresponding estimated $m^{(\cdot)}$ and $\alpha^{(\cdot)}$. *Bottom* The coefficients m (left) and α (right). IP black dash-dotted, E blue solid, S magenta dotted, PI red dashed, GDP black cross-dotted.

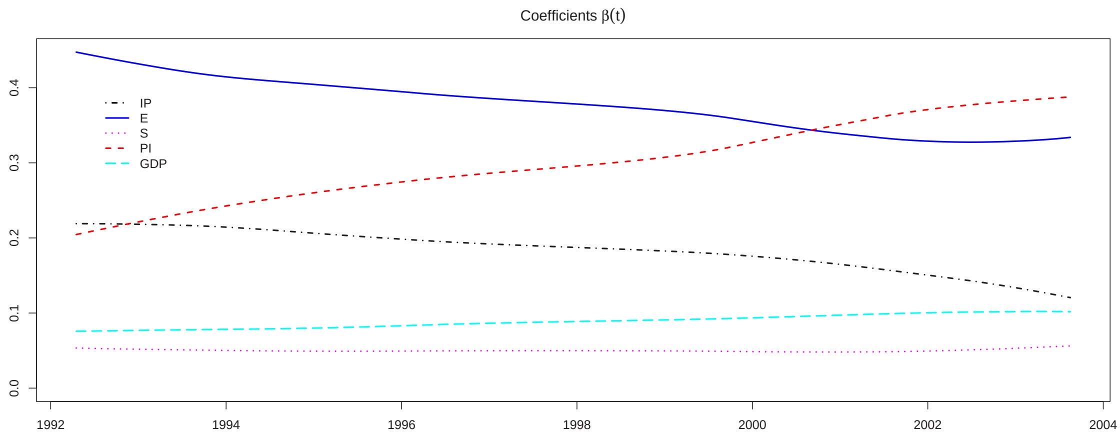

Figure 6.6: The estimated coefficients β. IP black dash-dotted, E blue solid, S magenta dotted, PI red dashed, GDP black cross-dotted.

tion's weight decreases from about 0.22 to 0.12. The GDP series has an almost constant contribution with $\beta \leq 0.09$ while the β of the sales series is about 0.05.

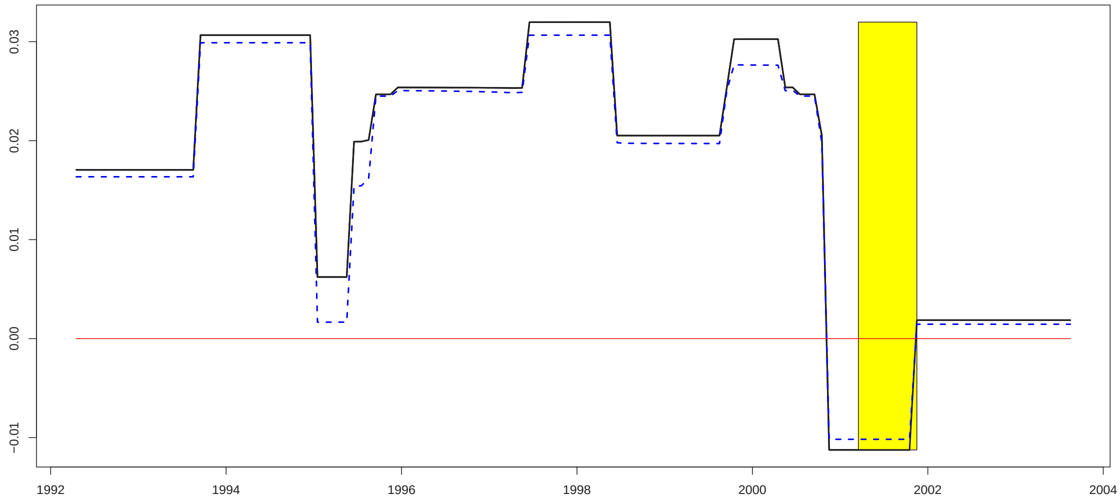

Figure 6.7: Estimated first derivative of f, the trend of the economy. Negative/positive values correspond to periods of negative/positive growth of the economy.

The results of the dating analysis are displayed in Figure 6.7. The graph shows the estimated growth rate of the economy, i.e. the first derivative of the estimated function f, together with a 90% one-sided confidence interval.

Consistently with the previous dating, our methodology finds that the growth rate of the economy became negative in November 2000, placing the start of the recession four months before the NBER date. In contrast with the dating based only on four macroeconomic indicators, we find that between October and November 2001, the first derivative made a significant jump upwards to a *small, but statistically significant positive value* (0.2 of a percent). (The first derivative seems to have stayed at this level until the end of the sample.)[14]. From a strictly statistical point of view, we find that the month of November 2001 marks the end of the recession that started in November 2000.

To summarize, for all recessions where the monthly GDP series was not directly used

[14] While from a strictly statistical point of view, the month of November marks the end of the recession, the economic relevance of such a small rate of growth that animates the following months might still be a matter of debate. Should a period at the end of a recession that is characterized by such a small growth, barely-significantly different from zero be considered the beginning of a new expansion as the Dating Committee seems to have done it? Or should it be treated as a continuation of the recession until the growth becomes significantly stronger? A possible answer exists already in the practice of the Dating Committee. The 2003 Announcement emphasized that 'if economic activity is *roughly flat* at the end of a recession or expansion, the turning point is placed at the end of the flat period'. Hence, if the statistical rigor is complemented by the established practice and experience, one could further argue that, even when the monthly GDP series is included in the set of monthly indicators, the recession which started in November 2000 extended at least until the summer of 2003, i.e. at least eighteen months after the ending date of the NBER announcement. However, since our competence is mainly statistical, we leave the economic interpretation of our findings to the economists.

in dating[15], our statistical methodology yields a dating that closely matches that of the NBER's Business-Cycle Dating Committee (the biggest difference is of 3 months and concerns the beginning of the 1960 recession[16]). The two methods (i.e. the method of the NBER's Business-Cycle Dating Committee and ours) produce very different results when it comes to the last episode of recession. First, our methodology finds that *the recession started in November 2000*, four months before the NBER date. Second, *it dates the end of the recession in May 2003*, one year and six months after the date announced by the Committee.

When the methodology developed in Section 5 is applied to a set macroeconomic indicators extended to include the monthly GDP series, we confirm the month of November 2000 as the beginning of the recession. We also find that, from a statistical point of view, the recession ended in November 2001, consistent with the NBER's Business-Cycle Dating Committee dating.

7 Conclusions

In this paper we introduced a non-parametric, non-stationary approach to business-cycle dating. The main ingredient is the innovative statistical methodology known as Adaptive Weights Smoothing (AWS) which is used both for the study of the individual macroeconomic time series relevant to the dating of the business cycle as well as for the estimation of their joint dynamic. The estimation of the business cycle is done through a non-stationary factor analysis which is one of the main contributions of the paper.

The main conclusion of the paper is that the dating of the business cycle *fundamentally* depends on the group of series monitored. When our dating approach is applied to the set of US economic indicators emphasized by the NBER's Business-Cycle Dating Committee in recent decades consisting of the monthly series of industrial production, payroll employment, real income, and wholesale-retail trade, we find that the 2001 recession lasted between November 2000 and May 2003. Extracting the business-cycle common dynamic from an extended group of coincident indicators with the GDP as the fifth series yields different results, dating the end of the last economic contraction in November 2001, consistent with the NBER's Business-Cycle Dating Committee date.

These findings support the hypothesis of a change in the methodology of the NBER's Business-Cycle Dating Committee: in the dating of the last recession, an extended set of five monthly macroeconomic indicators replaced the set of indicators emphasized by the NBER's Business-Cycle Dating Committee in recent decades. They also bring evidence

[15] The monthly GDP series on the NBER site is available from 1992.

[16] Note that our analysis is based on current, revised data. This fact could very well be responsible for some of the minor mismatches between the official NBER dates and the results of our procedure.

of the existence of a continuity break in the outcome of NBER's Business-Cycle Dating Committee output: had the dating been done based on the traditional set of indicators, the last recession would have lasted one year and a half longer becoming the longest contraction episode in the postwar economic history.

While the date of the end of the last recession depends on the set of macroeconomic indicators (and, in the case of the extended set of five indicators, is consistent with the NBER's Business-Cycle Dating Committee dating), we find that, independent of the set of coincident indicators monitored, *the last economic contraction began in November 2000*, four months before the date of the NBER's Business-Cycle Dating Committee.

References

[1] Baxter, M and King, R. (1999), Measuring Business Cycle: Approximate Band-Pass Filters for Economic Time Series, Review of Economics and Statistics, 81, pp. 575-593

[2] Boldin, M. D. (1996), A check on the robustness of Hamiltons Markov Switching model approach to the economic analysis of the business cycle. Studies in Nonlinear Dynamics and Econometrics, 1, 35–46.

[3] Chauvet, M., (1998), An Econometric Characterization of Business Cycle Dynamics with Factor Structure and Regime Switches, International Economic Review, 39, 969-96

[4] Christiano, L. and Fitzgerald, T. (1998), The Business Cycle: It's still a Puzzle, Federal Reserve Bank of Chicago Economic Perspectives, 4th Quarter, 56-83

[5] Corbae, D. Ouliaris, S. and Phillips, P. C. B. (2001), A new Approach to Extracting Business Cycles, mimeo, Yale.

[6] Diebold, F. X. and Rudebusch G. D., (1996), Measuring Business Cycles: A Modern Perspective, The Review of Economics and Statistics 78, 67–77.

[7] Groshen E. and Potter, S. (2003), Has Structural Change Contributed to a Jobless Recovery? Current Issues in Economics and Finance, Federal Reserve Bank of New York, 9.

[8] Hamilton, J., (1989), A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle, Econometrica, 57 (2), 357-384

[9] Harding D. and Pagan A., (2001), Extracting, Analysing and Using Cyclical Information, CEPR Conference on Monitoring the Euro Area Business Cycle.

[10] Hodrick, R. J. and Prescott, E. C. (1997), Post-War U.S business cycles: A descriptive empirical investigation, Journal of Money Credit and Banking, 29, 1-26

[11] Kim, M-J. and Nelson, C. R., (1998), Business Cycle Turning Points, a New Coincident Index and Tests of Duration Dependence Based on A Dynamic Factor Model with Regime Switching, Review of Economics and Economic Statistics, 80, 188-201

[12] Otrok, C. and Whiteman, C.H., (1998), Bayesian Leading Indicators: Measuring and Predicting Economic Conditions in Iowa, forthcoming: International Economic Review.

[13] NBER, The Business Cycle Dating Committee (2001), The business-cycle peak of March 2001 (November 26, 2001 announcement of business cycle peak/beginning of last recession). Available at http://www.nber.org/cycles/november2001/

[14] NBER, The Business Cycle Dating Committee (2003), July 17, 2003 announcement of business cycle trough/end of last recession. Available at http://www.nber.org/cycles/july2003.html

[15] NBER, The Business Cycle Dating Committee (2003), The NBERs Recession Dating Procedure (October 21, 2003 Memo from the Business Cycle Dating Committee). Available at http://www.nber.org/cycles/recessions.html

[16] Polzehl, J. and Spokoiny, V. (2000). Adaptive weights smoothing with applications to image segmentation. J. of Royal Stat. Soc., 62, Series B, 335–354.

[17] Polzehl, J. and Spokoiny, V. (2002). Local likelihood modeling by adaptive weights smoothing. Preprint 787. WIAS 2002. `http://www.wias-berlin.de/publications/preprints/787`.

[18] Polzehl, J. and Spokoiny, V. (2002). Varying coefficient regression modeling by adaptive weights smoothing. Preprint 818, WIAS, 2003.

[19] Sichel, D. E. (1994), Inventories and the three phases of the business cycle. Journal of Business and Economic Statistics, 12, 269–277.

[20] Stărică C., (2003), Is GARCH(1,1) as good a model as the Nobel prize accolades would imply? Working paper. Available at http://www.math.chalmers.se/ starica

[21] Stock, J. and Watson, M. (1989), New Indexes of Coincident and Leading Economic Indicators, Macroeconomics Annual, Vol. 4, M.I.T. Press.

[22] Stock, J. and Watson, M. (1991), A Probability Model of the Coincident Economic Indicators, in Leading Economic Indicators: New Approaches and Forecasting Records, edited by K. Lahiri and G. Moore, Cambridge University Press.

[23] Stock, J. and Watson, M. (1993), A Procedure for Predicting Recessions with Leading Indicators: Econometric Issues and Recent Experience, in New Research on Business

Cycles, Indicators and Forecasting, James Stock and Mark Watson (editors), University of Chicago Press.

[24] Stock, J. and Watson, M. (1996), Evidence on Structural Instability in Macroeconomic Time Series Relations, (with James H. Stock), Journal of Business and Economic Statistics, 14, 11-30.

[25] Stock, J. and Watson, M. (2003), Has the Business Cycle Changed? Evidence and Explanations, Prepared for the FRB Kansas City symposium, Jackson Hole, Wyoming, August 28-30.