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Detrending and turning points

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Abstract

This paper examines the sensitivity of turning points classification to different detrending methods and the ability of each method to replicate NBER dating. We use two different turning point rules and a variety of detrending methods to compute the cyclical component of output. We show that while differences are minor with the first rule, the results are extremely sensitive to detrending with the second rule. Many detrending procedures generate false alarms and many miss several commonly classified turning points. The output series detrended with the Hodrick and Prescott filter and with a frequency domain masking of the low frequency components of the series reproduce all NBER turning points with at most two quarters lead or lag, regardless of the dating rule used.

Key words: Turning point classification; Business cycle; Filtering

JEL classification: B41; E32

Idleness was painful after so many years of wars, bitter governments and trivial loves.

Gabriel Garcia Marquez

1. Introduction

Can we rationalize the turning point dating procedure used by NBER and Department of Commerce (DOC) researchers with the tools of modern time series econometrics? Are results sensitive to the choice of filtering procedure used to extract the cyclical component of the series?

This paper attempts to shed some light on these two issues. There are at

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least two reasons why this exercise may be important. First, the dating procedures employed by NBER and DOC researchers are very elaborate, based on a variety of series and often ad-hoc. It is therefore useful to examine whether simple classification rules based on a single economic indicator (GNP) which involve no judgmental adjustments can approximate sufficiently well more complicated ones and whether among the many rules existing in the literature (see e.g. Zarnowitz and Moore, 1991; McNees, 1991; or Webb, 1991), there is one which is superior for this scope. Second, it has become standard to classify turning points using growth-cycle concepts, i.e. dating turning points using fluctuations around the trend of the series (see Niemera, 1991). In Canova (1992) I showed that different trend removal procedures, all of which are reasonable given existing empirical evidence and available econometric tools, induce different properties in the moments of the cyclical component of macroeconomic time series. It is therefore interesting to check whether the *path* properties induced by different detrending methods are also substantially different. This analysis complements the previous one and provides a more complete perspective of the time series properties implied by different trend-removal procedures. It is important to stress that this paper does not address questions concerning turning point predictions or how to better evaluate the record of turning point forecasts. There is a vast literature on the subject (see e.g. Wecker, 1979, or Zellner and Hong, 1991) pointing out some of the weaknesses of existing approaches. Alternatives to remedy these weaknesses are discussed in Canova (1993).

The paper is organized as follows: the next section describes the various detrending procedures and Section 3 the data, the two dating rules and the summary statistics employed. Section 4 contains the results: we show that turning point classification is not very sensitive to detrending with one rule but with the other it is and that with this second rule many standardly reported turning points are missed and many false alarms appear. Overall, two procedures (Hodrick and Prescott filtering and frequency domain masking) come closest in reproducing standard NBER classification with both rules.

2. Alternative detrending methods

This section briefly describes the 11 procedures used to extract trends from the observable time series. Throughout the paper I denote the natural logarithm of the time series by y_t, its trend by x_t and its cyclical component by c_t. The methods will be classified according to three characteristics: assumptions on the features of the trend, assumptions on the correlation between x_t and c_t and on whether the methods have statistical or economic justifications. Since only trend and cycle are assumed to exist, all the procedures implicitly assume that y_t has previously been seasonally adjusted. Also, throughout the paper I examine only methods which produce stationary c_t, i.e. procedures like Hamilton's (1989) will not be considered.

Linear detrending (LT) and segmented detrending (SEGM) assume that x_t is a deterministic process which can be approximated by polynomial functions of time and that x_t and c_t are uncorrelated. With segmented detrending we also assume that there is a structural break in x_t at a known time $\bar{t}=1973$ 3.

The basic assumptions of a first-order differencing procedure (FOD) are that x_t is a random walk with no drift and c_t is stationary and that the two components are uncorrelated. Similarly, Beveridge and Nelson's (1981) procedure (BN) assumes that y_t has a unit root and that x_t accounts for its nonstationary behavior. In this procedure x_t is the long-run forecast of y_t adjusted for its mean rate of change, so that the trend is the value y_t would have taken if it were on the long-run path. One implication of BN construction is that in this decomposition x_t and c_t are perfectly correlated since they are driven by the same shocks. Since some judgmental decisions need to be made in implementing BN decomposition, I report results for the case where y_t is modelled as an ARIMA(5, 1, 0), the value of y_t at 1955,2 is used as a initial condition and the quick computational approach of Coddington and Winters (1987) is employed.

The identifying assumptions of the Unobservable Components (UC) procedure are that x_t follows a random walk with drift and that c_t is a stationary finite order AR process. Contrary to a FOD procedure, here x_t and c_t may be correlated (see Watson, 1986). Also in this case some judgmental decisions need to be made: here I report results for the case where c_t is an AR(2), parameters are estimated using moment restrictions as in Carvalho et al. (1979) and estimates of the state equations are obtained with the Kalman filter with no smoothing of recursive estimates.

The frequency domain (FREQ) procedure assumes that c_t and x_t are independent, that x_t has most of its power concentrated in a low frequency band of the spectrum and that away from zero the power of the secular component decays very fast (see Sims, 1974). These identification assumptions do not restrict x_t to be either deterministic or stochastic and allow for changes in x_t over time as long as they are not too frequent. Results are presented for the case where c_t includes all the cycles of y_t with length less that 30 quarters.

Detrending using a one dimensional index model (MFREQ) involves the formulation of a multivariate model. In this case I use data on GNP, Consumption, Investment, Real Wage and Capital. The procedure assumes that in the low frequencies of the spectrum of y_t there exists a one dimensional process x_t which is common to all series (see e.g. Stock and Watson, 1989). x_t is characterized by the property that it has all its power at low frequencies and that away from zero it decays very fast. An estimate of c_t is obtained using a multivariate version of the procedure used for the UC model assuming an AR(2) model for each of the six cyclical components.

Contrary to the first seven methods which have been developed in the statistical literature, the last three procedures have economic justifications. King et al. (1988) present a neoclassical model of capital accumulation with labor supply choices where there is deterministic labor augmenting technical progress. In their model all endogenous variables have a common deterministic trend (the growth rate of labor augmenting technical progress), fluctuations around this trend are of a transitory nature and independent of the trend. To extract a common deterministic trend I use the six series used for the index model (MLT).

King et al. (1991) propose a version of King et al.'s (1988) model driven by a nonstationary technological shock. The corresponding statistical common trend representation (see Stock and Watson, 1988) is the multivariate counterpart of the method of Beveridge and Nelson and implies that all the endogenous variables of the model will have a common nonstationary trend (COIN). To produce estimates of c_t for GNP, I use the same six series used for the index model and estimate a vector error correction model with five lags for each variable and one lag of two cointegrating vectors (GNP/consumption, GNP/investment). An estimate of c_t is then obtained summing all the stationary component.

Blanchard and Quah (1989) (BQ) propose a version of Fisher's staggering-wage model in which 'demand' shocks have no long-run effects on output and unemployment and 'supply' shocks have long-run effects on output but not on unemployment. The implied trend–cycle decomposition of GNP has the property that x_t has a unit root, c_t is stationary and the two components are uncorrelated. To estimate c_t, I use the same bivariate VAR specification employed by Blanchard and Quah.

The final procedure, the Hodrick and Prescott (HP) (1980) filter, has two justifications: one intuitive (see Kydland and Prescott, 1990) and one statistical (see e.g. Wabha, 1980; or Harvey and Jaeger, 1993). In the first case the HP filter is a flexible tool which can accommodate the needs of applied researchers while in the second it is an optimal extractor of a trend which is stochastic but moves smoothly over time and is uncorrelated with the c_t. Smoothness is imposed by assuming that the sum of squares of the second differences of x_t is small. In the RBC literature the free parameter λ, which regulates the extent of the penalty imposed for large fluctuations in x_t, is typically fixed a priori to $\lambda = 1600$ for quarterly data. Because Nelson and Plosser (1982) estimated λ to be in the range $[1/6, 1]$ for most of the series they examine, I present results for the standard setting (HP1600) and for a $\lambda = 4$ (HP4), which is closer to Nelson and Plosser's estimates.

The sensitivity of the results to changes in the information set for the BN, UC, BQ and COIN decomposition, to various settings of λ for HP, to different breaking points for SEGM and to different assumptions on the length of the cycles included in c_t for FREQ have been studied in Canova (1992) and Faust and Leeper (1993). More details on the detrending procedures appear in Canova (1993).

3. The data and the dating rules

The data used in the exercise is taken from the Citibase Tape. The results refer to the logarithm of seasonally adjusted quarterly US series for the period 1955,3–1990,1. For all univariate procedures we use real gross national product in 1982 dollars (Citibase name: GNP82). For multivariate procedures we add to GNP consumption expenditure by domestic residents on nondurable and service (Citibase names: GSC82+GCN82), fixed investment in plants and equipment plus consumer durables (Citibase names: GINPD82+GCD82), total number of hours of labor input as reported by establishment survey data (Citibase name: LPMHU), real wage constructed as the ratio of nominal total compensation of nonagricultural employees and the CPI (Citibase names: GCOMP/PUNEW) and a capital stock series constructed using the net capital stock for 1954, the quarterly series for investment and a depreciation rate of 2.5% per quarter.

To examine the properties of each detrending method in dating turning points we focus on the estimates of the cyclical component of GNP and on two dating rules. Although some authors have pointed out that restricting the attention to GNP may be misleading since the effects of certain recessions are not captured in this series (see e.g. Zarnowitz and Moore, 1991), our approach has the advantage of being straightforward and easily reproducible. As a term of comparison we use the turning points classifications reported by the NBER and the Center for International Business Cycle Research (NBER) and by the Department of Commerce using the Higgins and Poole procedure (see Niemera, 1991) (CLI).

The first classification rule is very standard (see e.g. Wecker, 1979; or Zellner and Hong, 1991). It defines a trough as a situation where two consecutive declines in the cyclical component of GNP are followed by an increase, i.e., at time t, $c_{t+1} > c_t < c_{t-1} < c_{t-2}$. Similarly a peak is defined as a situation where two consecutive increases in the cyclical component of GNP are followed by a decline, i.e. at time t, $c_{t+1} < c_t > c_{t-1} > c_{t-2}$. The second classification rule is less standard but it has very appealing features (see e.g. Webb, 1991). It selects quarter t as a trough (peak) when there have been at least two consecutive negative (positive) spells in the cyclical component of GNP over a three-quarter period, i.e. when $c_t < (>) 0$ and $c_{t-1} < (>) 0$ or when $c_{t+1} < (>) 0$ and $c_t < (>) 0$.

Note that with the first classification we may pick up mild contractions and mild recoveries, while this is not the case with the second classification. However, the first rule may provide an earlier signal of the presence of a turning point. Therefore the two rules balance the scope for an early recognition of the phenomena (at the cost of possible false alarms) vs. its more accurate description (at the cost of a later discovery). Although there are variants or combinations of these two classifications which may discount false alarms (see e.g. Hymans, 1973) and more precise dating can be obtained by designing more complex rules (see e.g. McNees, 1991; or Stock and Watson, 1989), we restrict the attention to these two because they are simple and widely used.

While it is common to evaluate the dating record using simple statistics like the mean and variance of the differences (in quarters) between the signal and the NBER turning point, we use a stricter rule based on the timing of the event. The signal is considered false if a turning point does not appear within $\pm$ 2 quarters interval around that date and missing if no signal appears within ± 2 quarters interval around the actual NBER or DOC turning point.

4. The results

Several features of the results, which are contained in Table 1, deserve mention. First, in agreement with McNees (1991) and Zarnowitz and Moore (1991), there is a substantial difference between the two rules. With the first dating rule, there is at most one year difference in the dates selected by various detrending methods while with the second rule there is little agreement on the number of turning points and on their timing. For example, all detrending methods detect at a minimum 8 peaks and 8 troughs with the first rule (with a maximum of 11), but with the second rule, the range is between 3 and 12 peaks and 3 and 11 troughs.

Second, with the first rule the two HP filters produce almost the same dating and the differences with the second rule are small. Hence, even though the moments of the cyclical component of GNP differ with the value of λ (see Canova, 1992), the time paths have similar features when filtered with the two rules we use.

Third, with the first rule, there are two NBER turning points (64,4 and 69,1) which are missed by *all* methods. However, when one uses the CLI chronology (the dating are 63,1 and 67,4), many detrending methods do capture these events, suggesting that measurement errors may be present in the NBER chronology. In addition, all methods record many false peaks and many generate cyclical components whose troughs do not line up with standard classifications. Surprisingly enough, only the HP1600 filter correctly

Table 1
Business cycle chronology: Sample 55,3–90,1[a]

Method	Troughs	Peaks
NBER	58,2; 61,1; 64,4, 67,4, 70,4; 75,1; 82,4	57,2; 60,1; 62,2; 66,2; 69,1; 73,1; 78,4
CLI	58,2; 60,4; 63,1; 67,2; 70,4; 75,2; 82,1; 86,2	59,2; 62,2; 65,4; 67,4; 73,1; 78,2; 84,1
Filter Rule 1		
HP1600	58,2; 60,4; 62,4; 64,4; 67,2; 70,2; 73,3; 76,3; 79,2; 82,4; 85,2*	57,1; 59,2; 62,1; 63,3; 66,1; 68,3; 73,1; 76,1; 77,3; 81,1; 84,2
HP4	58,1; 60,4; 62,4; 64,4; 67,2; 68,4; 73,3; 76,4; 78,1; 82,1; 84,4*	57,1; 58,4; 61,4; 63,3; 66,1; 68,2; 70,2; 76,1; 77,3; 81,1; 84,1
FOD	57,2; 62,4; 66,2; 68,4; 72,3; 73,3; 76,3; 79,2; 82,1; 84,4*	58,4; 63,3; 67,3; 70,3; 73,1; 75,3; 77,3; 81,1; 83,2
BN	58,3; 61,1; 67,3; 70,3; 73,4; 76,4; 79,3; 83,1 85,1*	59,3; 62,4; 68,4; 73,2; 76,2; 77,4; 81,2; 84,3
UC	62,1; 64,1; 66,1; 68,3; 70,1; 76,2; 79,2; 83,2	61,2; 63,3; 64,4; 67,2; 69,3; 74,2; 77,3; 82,2; 85,3(*)
LT	56,3; 58,2; 60,4; 67,2; 70,2; 73,3; 76,3; 79,2; 82,4; 85,2*	57,1; 59,2; 62,3; 68,3; 73,1; 76,1; 77,3; 81,1; 84,2
SEGM	56,3; 59,4; 67,2; 68,4; 73,3; 76,3; 79,2; 82,4; 84,4*	59,2; 62,3; 68,2; 73,1; 76,1; 77,3; 81,1; 84,2
FREQ	58,1; 60,4; 62,4; 64,4; 67,2; 68,4; 73,3; 76,3; 79,2; 82,4	57,1; 59,2; 62,1; 63,3; 66,1; 68,2; 73,1; 76,1; 77,3; 81,1; 84,2*
BQ	57,1; 58,2; 61,2; 64,4; 67,4; 70,4: 78,3; 82,4;	57,3; 59,2; 62,3; 66,3: 69,1: 76,3; 80,3; 84,1(*)
MLT	56,3; 58,2; 60,4; 67,2; 68,4; 73,3; 76,3; 79,2; 82,4; 85,2*	57,1; 59,2; 62,3; 68,2; 73,1; 76,1; 77,3; 81,1; 84,2
MFREQ	58,2; 61,3; 68,4; 73,3; 77,1; 78,1; 79,2; 82,1	57,1; 58,4; 67,3; 73,1; 76,1; 77,3; 78,4; 80,1; 84,2(*)
COIN	58,2; 60,4; 67,2; 68,4; 73,3; 76,3; 79,2; 82,1; 85,2*	59,2; 62,3; 68,2; 73,1; 76,1; 77,3; 81,1; 84,2

Table 1 (continued)

Method	Troughs	Peaks
Filter Rule 2		
HP1600	57,4; 60,3; 62,4; 69,4; 74,3; 80,2 81,4	55,4*; 59,1; 61,4; 65,2; 72,2; 77,3; 80,4; 84,1*
HP4	56,1*; 58,1; 59,3; 60,4; 62,4; 64,4; 66,4; 70,1; 71,4; 75,1; 76,3; 77,4; 79,1; 80,2; 82,3; 84,4*	56,4: 58,4; 60,1; 61,4; 64,1; 65,4; 68,2; 71,1; 73,1; 75,3; 77,2; 78,2; 79,3; 81,1; 84,1
FOD	57,4; 69,4; 74,3; 81,4	56,2; 58,2; 72,1; 75,2; 82,4*
BN	57,3*; 75,1; 80,3*	65,2; 77,2
UC	76,1; 83,2	60,4*; 76,4; 84,3*
LT	56,1; 75,1; 76,3; 80,2*	55,4*; 64,1; 76,1; 77,1
SEGM	57,4; 70,1; 74,3; 81,4	55,4*; 65,1; 73,1; 77,2; 84,1*
FREQ	57,4; 60,4; 62,4; 69,4; 74,4; 80,2; 81,4; 86,1*	54,4*; 58,4; 61,4; 65,3; 72,2; 78,2; 80,4; 83,4
BQ	57,2; 61,1; 63,2; 67,2; 70,2; 74,2; 78,2; 80,1:	55,4*; 60,3; 62,1; 64,3; 68,3; 72,3; 76,2; 78,4; 84,3*;
MLT	56,3; 74,4; 80,2*	55,4*; 64,1; 77,1
MFREQ	58,1*; 74,3	55,4*; 65,2; 81,1*
COIN	57,3*; 70,1; 74,1*	65,4; 72,4

[a] With Filter Rule 1 a trough occurs at t if $c_{t+1} > c_t < c_{t-1} < c_{t-2}$, a peak occurs at t if $c_{t+1} < c_t > c_{t-1} > c_{t-2}$. With Filter Rule 2 a trough occurs at t if $c_t < 0$ and $c_{t-1} < 0$ or if $c_{t+1} < 0$ and $c_t < 0$, a peak occurs at t if $c_{t>0}$ and $c_{t-1} < 0$ or if $c_{t+1} < 0$ and $c_t < 0$. NBER refers to the NBER chronology reported by the Center for International Business Cycle Research at Colombia University. CLI refers to the DOC chronology compiled from the composite index of leading indicators using the Higgins and Poole procedure. Both are taken from Niemera (1991). A '*' indicates that the previous (next) turning point is censored.

identifies all turning points (according to the CLI–Higgins and Poole chronology) within the chosen interval. The closest competitor is a frequency domain masking of the low frequency components of the series, confirming the spectral features of the HP filter highlighted by King and Rebelo (1993).

Finally, with the second rule there is a generalized tendency to miss many turning points of the standard classification and only HP, FREQ and BQ detrended data register at least 7 upturns and 7 downturns over the sample. The reason is that many methods are unable to generate reasonable cycles with this rule since the induced time path of c_t are above or below the trend line for long periods of time. The results obtained with UC, LT and all multivariate methods are very striking in this sense. For example, according to the COIN filter, the US economy experienced only one cyclical trough at 74,1 and no peaks over the last 15 years. Note also that the most frequently missed turning points are those initiating mild and short contractions or expansions (see e.g. 69,4 and 70,4), and that with this second rule only HP4 captures all turning points within the chosen interval and that HP1600 and FREQ filters generate remarkably similar time paths.

In conclusion, the results are extremely sensitive to detrending with the second dating rule, while the differences are minor with the first rule. In addition, many detrending procedures generate cyclical components which do not possess several turning points of the standard US business cycle classification. Overall, the HP and FREQ filters appear to be the most reliable tools to reproduce standard NBER or DOC classifications within the assumed confidence interval, regardless of the dating rule employed.

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