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Using Long-, Medium-, and Short-Term Trends to Forecast Turning Points in the Business Cycle: Some International Evidence

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Abstract. *This paper provides rules for anticipating business-cycle recessions and recoveries for countries showing asymmetric cycle durations. Based on a Schumpeterian framework, we analyze business cycles as sums of short-, medium-, and long-term cycles defined for a particular class of unobserved component models. By associating the trend with the low frequencies of the pseudo-spectrum in the frequency domain, manipulation of the spectral bandwidth allows us to define subjective length trends with specific properties. In this paper, we show how these properties can be exploited to anticipate business-cycle turning points, not only historically, but also in a true ex-ante forecasting exercise. This procedure is applied to U.S. post-World War II GNP quarterly data, as well as to another set of European countries.*

Keywords. unobserved components models; business cycles; turning-point forecast

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1 Introduction

Since the seminal work on the characteristics, length, and prediction of the business cycle by Mitchell and Burns (1938), there has been a permanent debate in theoretical and empirical macroeconomics about the nature of economic fluctuations. More recently, renewed interest in several aspects of cycle modeling has spurred a vast amount of literature with both empirical and theoretical dimensions. Permanent or transitory effects of shocks on output (Clark 1987; Watson 1986; Nelson 1988; among others), average lengths and shapes of cycles (Romer 1989), effects of important exogenous shocks on output (Perron 1989), business-cycle duration and postwar stabilization (Diebold and Rudebusch 1992; Watson 1994), National Bureau of Economic Research (NBER) business-cycle chronology and detrending methods (Canova 1991, 1994), and the developments of new methods for economic turning-point forecasting (Zellner, Hong, and Min

1991; Zellner and Hong 1991; Diebold and Rudebusch 1989; Stock and Watson 1993) are, among others, some of the key issues behind the scene.

This final issue has been recently addressed by a growing literature that approaches the problem of forecasting turning points by finding the probability that a turning point will occur at some future unspecified date. See, for example, the works of Neftci (1982), Diebold and Rudebusch (1989), Hamilton (1989), Lam (1990), Filardo (1994), and Lahiri and Wang (1994), as well as the recent modifications proposed by Boldin (1996). However, in many studies using the leading-indicator probabilistic approach, the several-months-ahead recession probabilities rarely approach one when in fact a recession does occur. In Stock and Watson's work (1991), for instance, the six-month-ahead probability of recession incorrectly drops below 50% during the middle of the 1970 contraction.

One common feature to turning-point characterization is related to the presence of unobserved trends in most economic variables describing the business cycle. Already in the 1920s, some statisticians suggested the decomposition of any observed time series into its unobserved components—basically trend, cycle, seasonality, and irregularity—and since then this view has had a long tradition in the statistics literature. When applied to business-cycle analysis, however, a common attitude shared by many practitioners of this approach has been to consider the trend as a “nuisance” component we should get rid of in order to analyze the cyclical properties of the detrended series that becomes dependent of the particular filtering method that is used. Actually, Mitchell and Burns (1938) felt that although it might be desirable to isolate the components in a time series, the alternatives available at the time were just ad hoc procedures for providing a good solution, so they preferred not to trend adjust the series, a position with which we sympathize today within the present context.

One of the main problems with the unobserved-components approach is related to the fact that although the key concepts of trend, cycle, and seasonality are apparently easy to understand, they are rather difficult to define in an objective way. Kydland and Prescott (1990), for instance, suggest that a good estimate of a time-series trend is the one “. . . that successfully mimics the smooth curves that most business-cycle researchers would draw through plots of the data.” Although their definition is appealing for most of us, the empirical literature on signal extraction is full of examples where large differences in the (unnoticed) researcher's *smoothing priors* are conspicuously flagrant (Ansley 1983). Actually, some empirical results obtained as a by-product of an objective maximum-likelihood estimation procedure confirm the difficulties in picking up precise estimates of unrestricted variances when the likelihood function is very flat (Harvey and Jaeger 1993).

Our approach in this paper follows a different road, by openly recognizing a subjective view (in our personal judgment) on what constitutes a trend. Actually, we rather prefer to pose this question in more pragmatic terms by asking ourselves, What do I need my trend for? When trying to answer this question, we are implicitly imposing certain subjective restrictions that we wish our trend to comply with: smoothness, using a priori information, embedding or not, trend and cycle within a single component, etc. By associating the trend with the low frequencies of the pseudo-spectrum in the frequency domain, manipulation of the spectral bandwidth allows us to define subjective short-, medium-, and long-term trends with specific properties. In particular, we argue that if we decompose an output series into cycles of different lengths by selecting alternative noise-to-variance ratios, calculate their respective trend derivatives, and then combine these trend derivatives, we can obtain a good qualitative anticipation of business-cycle turning points not only historically, but also in a true ex-ante forecasting exercise.

The paper is organized as follows. The next section describes the statistical model. Section 3 presents a detailed discussion of the empirical results obtained in the case of the U.S. business cycle, based on post-World War II U.S. GNP quarterly data. Section 4 analyzes the behavior and predictive performance of the model in the case of three European countries: France, Germany, and Spain, also based on quarterly GNP data. Finally, Section 5 discusses the implications of the results for existing theoretical and empirical work.

2 The Unobserved Components Model

Most alternative detrending methods discussed in the literature of business cycles assume that trend and cycle are unobservable, but use different assumptions to identify the two components.¹ In line with this approach,

¹Also, since only trend and cycle are assumed to exist apart from a perturbation term, all the procedures, including ours, implicitly assume that either the data has previously been seasonally adjusted or that the seasonal and the cyclical components of the series are grouped together (see Canova 1991).

we adopt a stochastic state-space (SS) model that belongs to the class of unobserved components (UC-ARIMA) developed by Engle (1978) and Nerlove, Grether, and Carvalho (1979), which has been popular in both the econometric and control-system literatures for some years (e.g., Harvey 1984; Kitagawa and Gersch 1984; Ng and Young 1990). In the context of SS estimation, Young, Ng, and Armitage (1989) used a novel spectral interpretation of the SS smoothing algorithms to decompose the series into various, quasi-orthogonal components that could be estimated using recursive methods of estimation (Young 1984).

2.1 Models for the components

In the present context, we postulate the appropriate model to be:

$$Y_t = T_t + C_t + \varepsilon_t, \quad t = 1, \dots, N, \quad (1)$$

where Y_t is the observed series, T_t is the low frequency or trend component, C_t is the cycle, and ε_t is a zero mean, serially uncorrelated white-noise component with variance σ_ε^2 . It is assumed that the trend can be represented by a local linear model of the form:

$$T_t = T_{t-1} + D_{t-1} + \eta_t, \quad \eta_t \sim NID(0, \sigma_\eta^2), \quad (2)$$

$$D_t = D_{t-1} + \xi_t, \quad \xi_t \sim NID(0, \sigma_\xi^2), \quad (3)$$

where D_t denotes the local slope (time derivative) of the trend, and η_t and ξ_t are normal white-noise disturbances independent of each other.² Our trend model nests other alternatives frequently found in the literature. In particular, when $\sigma_\eta^2 = 0$ but $\sigma_\xi^2 > 0$, the trend is also an I(2) process with relatively smooth behavior. An important issue is therefore whether or not the constraint $\sigma_\eta^2 = 0$ should be imposed at the outset. Harvey and Jaeger (1993) argue that there are series where it is unreasonable to assume a smooth trend a priori, while Ng and Young (1990) and García-Ferrer et al. (1996) hold that in most cases of interest, σ_η^2 can be safely constrained to zero. Therefore, the question whether or not this variance is set to zero is an empirical one, and should be decided according to the characteristics of each data set.³ In what follows, we will assume that $\sigma_\eta^2 = 0$, so Equations 2 and 3 become an integrated random walk (IRW) model of the type developed by Young (1984). Then the variance of ξ_t (σ_ξ^2) is the only unknown in Equations 2 and 3, and can be fixed through the noise variance ratio (NVR), which is the relation between σ_ξ^2 and the variance of the observational noise, σ_ε^2 :

$$\text{NVR} = \frac{\sigma_\xi^2}{\sigma_\varepsilon^2}. \quad (4)$$

This NVR uniquely defines the IRW model for the trend, since all the parameters in the SS model are constrained to unity or zero. The difficulties associated with the “choice” or estimation of the NVR value, as well as its effects on defining length cycles, are discussed later. Note, however, that contrary to the purposes in most of the existing literature, we do not use the unobserved-component models to isolate a time series of the cycle. Our main interest here is in characterizing the properties of the trend, and in particular, its slope (derivative), because it contains useful information to track and forecast business-cycle turning points.

2.2 Model identification and estimation

Once the different model structures for all the components are defined, we can assemble them into an aggregate SS model. In general, the statistical literature on signal extraction has dealt with the problems of structural identification and subsequent parameter estimation only at the cost of imposing somewhat restrictive assumptions on model specification, the correlation among components, and the frequency-domain

²Although not strictly necessary in this case, C_t can also be modeled either as a general transfer function (GTF) or a dynamic harmonic regression (DHR) model: the former is a more general representation of any stochastic time series (particularly those that are seasonally adjusted), while the latter is restricted primarily to series with strong seasonality and is particularly useful in the context of adaptive seasonal adjustment (see García-Ferrer, del Hoyo, and Martín 1997).

³In particular, for the case of the quarterly U.S. real GNP data in Section 3, the result of Harvey and Jaeger (1993) gives $\hat{\sigma}_\eta^2 = 0$.

representation of the estimated seasonal pattern. Also, proponents of a dynamic economic theory of seasonality criticize the imposition of orthogonality restrictions among components of the series (Ghysels 1988; Hansen and Sargent 1990; García-Ferrer and del Hoyo 1992).

With regard to estimation, several alternatives are available. The most obvious approach is to formulate the problem in maximum-likelihood (ML) terms. Given the usual normality assumptions for the disturbances, the likelihood function for the observations can be obtained from the Kalman filter by “prediction-error decomposition” (Harvey and Peters 1990). However, practical experience with this approach indicates that it can turn out to be complex, even for particularly simple models (García-Ferrer 1992), with the likelihood function tending to be flat and indeterminate around the optimum.⁴

In this paper, however, we utilize a different manual-tuning approach, based on the spectral filtering properties of the fixed-interval smoothing (FIS) algorithms used in the state-space analysis (Young 1994). To explain this approach, let us consider again the simplest version of Equation 1; namely, where Y_t is represented by a simple trend-plus-noise model, i.e.,

$$Y_t = T_t^* + \varepsilon_t, \quad (5)$$

in which $T_t^* = T_t + C_t$ is assumed to evolve as an IRW process. This model can be written in the following transfer-function (TF) form:

$$Y_t = \frac{1}{(1-L)^2} \xi_t + \varepsilon_t, \quad (6)$$

so that the autocovariance-generating function $g(L)$ for the model is defined by:

$$g(L) = g_T(L) + \sigma_\varepsilon^2,$$

where $g_T(L)$ is the autocovariance-generating function for the IRW component alone, i.e.,

$$g_T(L) = \frac{\sigma_\xi^2}{(1-L)^2(1-L^{-1})^2}.$$

Bell (1984) has shown that the classical Kolmogorov-Wiener-Whittle approach to filtering and signal extraction can be applied to nonstationary processes such as Equation 6. Consequently, for large sample size N , the optimal smoothing (signal-extraction) filter for estimating T_t^* is given by the ratio of $g_T(L)$ to $g(L)$. In terms of the NVR, this can be written simply as:

$$\hat{T}_{t/N}^* = \frac{\text{NVR}}{\text{NVR} + (1-L)^2(1-L^{-1})^2} Y_t, \quad (7)$$

where $\hat{T}_{t/N}^*$ is the optimally smoothed estimate of T_t^* for period t based on all N observations. This is a symmetric, two-sided filter requiring only the specification of the NVR value. It is easy to verify that this is a low-pass filter with a sharp cutoff for small values of the NVR and excellent filtering properties of the high-frequency components of the data. The associated fixed-interval smoothing algorithm has been used for many years (see Jakeman and Young 1984), and in terms of the associated spectral density function for various NVR values, Young (1984) has shown how the NVR controls the band pass of the filter, which is progressively reduced as the NVR is reduced in size.

Figure 1a shows the spectral densities associated with different NVR values in the case of the IRW filter, while Figure 1b shows the same information for the case of the stationary “residual” of the trend, that most researchers associate with the cycle. Also shown, for comparison, are the spectral densities of the Hodrick-Prescott filters (the HP lines), which are discussed in Section 3.

⁴Despite its problems, this ML approach has become the standard in recent years, following the work of Harvey (1984), Kitagawa (1981) and others. More recently, Young, Pedregal, and Tych (1998) have optimized the NVR values so that the logarithm of the pseudo-spectrum (“pseudo-” because the IRW model is nonstationary) matches the logarithm of either the AR spectrum or the periodogram of the data, in a least-squares sense.

Figure 1a
Spectral characteristics of the IRWSMOOTH filter for different NVR values

Figure 1b
Spectral characteristics of the IRWSMOOTH filter for different NVR values: Stationary residuals of the trend

How to choose the NVR remains an open question, since there are several ways in which it can be selected. They all can be interpreted as defining the bandwidth of the filter in spectral terms. It has been empirically shown (Young 1987) that the cutoff frequency F_{50} (i.e., the frequency at which the filter attenuates the signal by 50%) is related to the NVR by the empirical equation:

$$F_{50} = 0.158(\text{NVR})^{0.25}. \quad (8)$$

More recently, however, Pedregal (1995) has shown how it is possible to improve the approximation used in Equation 8 by deriving the exact relationship between the bandwidth of the IRW filter and the NVR as

$$F_{\alpha} = \frac{\arccos \left[1 - \sqrt{\frac{\text{NVR}(1-\alpha)}{4\alpha}} \right]}{2\pi}, \quad (9)$$

Table 1a

NVR values and cycles per sample

NVR	Cycles	Quarters	Years
1	0.1580	6.33	1.58
0.1	0.0888	11.26	2.81
0.05	0.0747	13.39	3.35
0.01	0.0500	20.02	5.00
0.005	0.0420	23.80	5.95
0.001	0.0281	35.59	8.90
0.0005	0.0236	42.33	10.58
0.0001	0.0158	63.29	15.82
0.00005	0.0133	75.27	18.82
0.00001	0.0089	112.56	28.14
0.000001	0.0050	200.16	50.04

Table 1b

Cycles (in years and quarters) and NVR values

Years	Quarters	Cycles	NVR
1	4	0.2500	6.2695
2	8	0.1250	0.3918
3	12	0.0833	0.0774
4	16	0.0625	0.02449
5	20	0.0500	0.01003
6	24	0.0417	0.004838
7	28	0.0357	0.002611
8	32	0.0313	0.001531
9	36	0.0278	0.000956
10	40	0.0250	0.0006270
15	60	0.0167	0.0001238
20	80	0.0125	0.00003918

so that the NVR that will extract a given band of low frequencies can be computed from both expressions.⁵ Actually, Tables 1a and 1b show the implied cycles per sample and the cycles (in quarters and years) for different values of the NVR. Suppose, for instance, that we are interested in including in the trend (of a quarterly series) cycles up to 10 years. Then, Table 1b specifies that the corresponding $\text{NVR} = 0.000627$. If, on the contrary, we want to know the cycles in the trends for certain NVR values, we should go to Table 1a to find out that, for instance, an NVR of 0.01 will leave on the trend cycles higher than 5 years.

With this in mind, it is then straightforward to verify the existence of well-defined cyclical structures, allowing for the possibility of a pseudo-cycle within the trend. In a sense, different NVR values produce estimates similar to those of cyclical trend models, which reveal long-term oscillatory behavior in the trend.⁶ Although large differences in the chosen NVR may, apparently, track the long-term behavior of any time series equally well, when we look at their associated trend-derivative plots, the picture changes dramatically. In some cases, estimated trends actually contain some higher-frequency components related to the shorter-period annual cycle; components which are amplified by the derivative operation inherent in the trend-derivative estimation and show up very well on the derivative plot (see García-Ferrer 1992; Queralt 1994). Confirmation of this evidence for the U.S. quarterly GNP data is accomplished in the following section, where we show the properties of the trend derivative as a business-cycle indicator.

⁵Note, however, that using Equation 9 has some advantages. It not only provides an exact relationship, but also allows us to compute the bandwidth for any value of α , not necessarily the F_{50} . Nevertheless, in the case of the quarterly data used in this paper, numerical differences between the exact and the approximate expressions are negligible.

⁶Antecedents of embedding the trend and the cycle within a single component are among others, Harvey (1985), and García-Ferrer and Sebastian (1995).

3 Analysis and Anticipation of the U.S. Business Cycles

Traditional macroeconometric practice has considered business cycles as stationary stochastic processes. However, since economic time series exhibit nonstationarity, as argued by Nelson and Plosser (1982), much of the recent empirical literature has concentrated first on removing the smooth trend from the data, and then on computing summary statistics on the transformed data. Therefore, the most common use of a trend line is to smooth out a data series. The question is, How smooth should *smooth* be? This point is not trivial: the greater the smoothness of the trend, the greater the emphasis put on the cycle, and vice versa.

This last issue is particularly important, given the surprisingly scant discussion in the literature on how assumptions about the nature of the trend component affects business-cycle characteristics. More recently, however, some authors (see, e.g., Singleton 1988; Canova 1991; Harvey and Jaeger 1993; King and Rebelo 1993; Cogley and Nason 1995; among others) have warned us about the possible distortions induced by the use of arbitrary prefiltering procedures, as well as the lack of robustness of certain cycle regularities. Overall, two lessons seem to be emerging from these findings. First, a consensus is developing that the choice of a signal-extraction method depends on the purpose of the research as much as its statistical properties (Wickens 1995); and second, that any useful detrending technique requires the researcher to make initial judgments on either the length of the cycle or the required degree of smoothness of the trend (Canova 1994). Consequently, the first objective of our proposal is to analyze its ability to broadly replicate the features of U.S. business cycles as well as reproduce the NBER turning points from a historical perspective. Later on, we go one step further and provide evidence of its forecasting ability in anticipating peaks and troughs.

We conduct this exercise on seasonally adjusted quarterly U.S. real GNP data for the period 1947(1)–1992(4) (in billions of 1987 dollars). The U.S. series data are taken from NBER sources, and are reproduced by Niemira and Klein (1994, pp. 456–458). Time plots for the log of the data and its quarterly growth rates appear in Figure 2. Shaded areas indicate recessions according to the NBER chronology presented in Table 2.⁷ Although, historically, the phases of the business-cycle reference dates have been determined judgmentally by the NBER, the standard set of dates provides economists with a common point of reference for analyzing economic activity. On the other hand, a widely used alternative to the NBER cycle-dating rules is to define a turning point as the first of at least two successive increases (declines) in the growth rate of the GNP. Although, unfortunately, this shortcut for determining the reference business cycles is not totally accurate (in fact, the 1980 U.S. recession only had one quarter when real activity contracted), this rule of thumb (which is only a part of a sequence of rules posited by Shiskin in 1974; see, e.g., Niemira and Klein [1994]) may be an interesting alternative when analyzing international data where the NBER reference cycles are missing. Finally, another NBER definition of the business cycle is termed the deviation cycle or, more commonly, the *growth cycle*. According to Niemira and Klein (1994, p. 7), “... a growth cycle is a pronounced deviation around the trend rate of change. Thus this definition portrays periods of accelerating and decelerating rates of growth in the economy, a type of fluctuation that also has a longstanding history.”⁸

The NBER U.S. post–World War II business-cycle chronology depicted in Table 2 shows the presence of nine business cycles with different durations and different expansion/contraction ratios. The average duration of the cycle is 5.0 years ($\hat{\sigma} = 2.6$), and the maximum and minimum durations are, respectively, 9.7 (1961–1969) and 1.5 (1980–1981) years. According to this empirical evidence, it seems appropriate to analyze the historical chronology of the business cycle in a Schumpeterian framework as a sum of short-, medium-, and long-term cycles (van Duijn 1983), by defining trends of different degrees of smoothness using historical observations on the lengths of different business cycles. Consequently, under this view, cycle and growth theory are inseparable, because the economy evolves by means of cyclical growth in which each cycle has both unique and common features.

⁷Precise definitions of the “contraction” and “expansion” terms used by the NBER have been too vague since Burns and Mitchell gave the official definitions of these concepts in 1946. The more recent (1992) official definition, “... [a] recession is a recurring period of decline in total, output, income, employment, and trade, usually lasting from six months to a year, and marked by widespread contracting in many sectors of the economy...” is only slightly more specific.

⁸Niemira and Klein (1994) provide the dates (p. 7) of the growth cycles for the postwar U.S. data, and some important reasons to monitor the stage of those growth cycles (p. 10).

Figure 2a
U.S. quarterly GNP (logs) 1947(1)–1992(4)

Figure 2b
Quarterly growth rates of U.S. GNP 1947(1)–1992(4)

Table 2
U.S. business-cycle durations and relationships between expansions and contractions: 1945(1)–1992(4)^a

Cycle		Duration of Contraction (Months)	Cycle		Duration of Expansion (Months)	Ratio: Expansion/ Contraction	Duration of Cycle (Months [Years])
Peak	Trough		Trough	Peak			
1945(1)	1945(4)	8	1945(4)	1948(4)	37	4.6	45 [3.8]
1948(4)	1949(4)	11	1949(4)	1953(3)	45	4.1	56 [4.7]
1953(3)	1954(2)	10	1954(2)	1957(3)	39	3.9	49 [4.1]
1957(3)	1958(2)	8	1958(2)	1960(2)	24	3.0	32 [2.7]
1960(2)	1961(1)	10	1961(1)	1969(4)	106	10.6	116 [9.7]
1969(4)	1970(4)	11	1970(4)	1973(4)	36	3.3	47 [3.9]
1973(4)	1975(1)	16	1975(1)	1980(1)	58	3.6	74 [6.2]
1980(1)	1980(3)	6	1980(3)	1981(3)	12	2.0	18 [1.5]
1981(3)	1982(4)	16	1982(4)	1990(3)	92	5.8	108 [9.0]
1990(3)	1991(1)	8	1991(1)				
Average		10.4			49.9	4.8	60.6 [5.0]

^a Source: NBER.

Figure 3
Quarterly growth rates of U.S. GNP and medium-term trend derivative

3.1 The trend derivative as a business-cycle indicator

One of the advantages of the IRW trend model exposed in the previous section is that it allows us to incorporate in the trend those cycles consistent with the historical records. Within the range of hypothetical NVR values, it only seems logical to use those that incorporate in the trend the cycles with similar lengths as the ones shown in the historical chronology of the business cycle. Accordingly, we define our *long-run trend* as the one including cycles greater than 9 years; the *medium-run trend* includes fluctuations above 5 years; and the *short-run trend* incorporates those cycles around the 3-year period. The heuristic approach of defining three trends for the U.S. case is entirely based on the business-cycle chronology depicted in Table 2. Out of the nine cycles observed, two have a duration above 9 years; another two have a duration below 3 years, and five have a duration of 4–6 years. Therefore, all historical cycles are approximately incorporated into some of the three trends.⁹ For quarterly series, the corresponding NVRs as well as the cycles in quarters and years are listed in the following table:

Trend	NVR	Cycles	Quarters	Years
Short	0.1	0.0888	11.26	2.81
Medium	0.01	0.0500	20.00	5.00
Long	0.001	0.0281	35.59	8.90

Given the optimal properties of the IRW algorithm (Queralt 1994), another interesting feature of our model is that it allows for the joint estimation of the trend and the trend slope (derivative) directly from our state-space model by applying the prediction and correction equations of the Kalman filter (Young 1984). The estimated derivative can be considered as a linear approximation to the growth rate of the trend if the log transformation has been applied to the original series. Also, as Figure 3 shows, the derivative can be seen as a smooth approximation to the growth rate of the original variables, and consequently the definition of the cycle can be closely linked to the changes in the trend and hence to the derivative.

At this point, it may be worth it to compare our approach with the filter adopted by Hodrick and Prescott (1980), hereafter denoted “the HP Filter,” given its wide use in characterizing business-cycle facts for different sampling-interval data sets and a large number of countries. The HP filter may be rationalized as the optimal estimator of the trend component in the model of Equation 5. However, the working assumption in the HP case is to identify the cycle as the stationary “residual” of the IRW trend. Therefore, using Equation 7, the

⁹A quantitative rule of thumb that works well for all countries showing asymmetric business-cycle behavior is to determine the number of trends such as the maximum, minimum, and average durations are approximately represented in some of the chosen trends.

optimal estimate of the HP cycle is given by:

$$\hat{\varepsilon}_{t/N} = \frac{(1-L)^2(1-L^{-1})^2}{\text{NVR} + (1-L)^2(1-L^{-1})^2} Y_t. \quad (10)$$

On the other hand, given the definition of the trend derivative, i.e., $D_t = (1-L)T_t$, $\hat{\varepsilon}_{t/N}$ is related to $\hat{D}_t$ by the following:

$$\hat{\varepsilon}_{t/N} = \frac{1}{\text{NVR}}(1-L)(1-L^{-1})^2 \hat{D}_t. \quad (11)$$

Expressions 10 and 11 allow us to reproduce the HP results by careful choice of the NVR. As a matter of fact, Jakeman and Young (1984) demonstrated the equivalence of the two methods and the existence of a one-to-one correspondence between the NVR value and the choice of the single parameter (usually denoted by λ) in the HP methodology.¹⁰

Lately, the HP methodology has been criticized on two grounds: (1) possible distortions can be induced in terms of producing spurious cycles, even in random-walk processes (the Yule-Slutsky effect), and (2) the method is tailor-made for extracting the business-cycle component from the U.S. GNP (see Harvey and Jaeger 1993; King and Rebelo 1993; Cogley and Nason 1995; among others). Now let's think about this for a moment within our own framework. Hodrick and Prescott did not estimate λ ; instead, they imposed it, based on highly debatable assumptions (Nelson and Plosser 1982). However, for the U.S. GNP case, and if someone is willing to identify the cycle as the stationary detrended series, anybody using the HP filter (with $\lambda = 1,600$) is on safe ground. Given the business-cycle chronology of Table 2, none of the historical cycles are likely to be left out of the trend. Another matter is that the uniformly standardized value of λ that is used in many applications of the HP filter to different economic aggregates possessing different degrees of smoothness may distort features of certain cycle regularities.

The previous contention leads us again to the key issues of smoothness and the ability of alternative detrending methods to broadly replicate business-cycle turning points showing asymmetric lengths. In this regard, Canova (1991) illustrated how previous "criticism" applies not only to the HP procedure, but is also shared by a large number of both univariate and multivariate detrending alternatives. Using similar quarterly U.S. GNP data, he found that just three out of nine procedures (HP among the three) were the only methods that captured all NBER turning points (plus some additional false alarms), although in some cases the lag in recognizing a turning point could be as large as four quarters.

Using the trend derivative as a device for anticipating peaks and troughs in the business cycle also allows us to use alternative definitions of expansions and recessions within our framework. Following García-Ferrer et al. (1994), we define *the anticipation of a recession* to be that particular point where the (estimated) derivative reaches its maximum numerical value, and *the anticipation of a (potential) recovery* to be the derivative's minimum. Needless to say, the practical usefulness of these definitions are, again, strongly linked to the chosen NVR. If in the case of quarterly data we select a very small NVR value (like the 0.000625 value of the HP filter), the corresponding derivative will be too smooth (with long swings) and will probably miss intermediate shorter cycles. If on the contrary, we select a larger NVR, say 0.1, there are chances of identifying too many small cycles that actually did not occur.

In Figure 4, plots of the three derivatives for the U.S. GNP corresponding to the previously defined NVR values together with HP cycle ($\lambda = 1,600$) are presented. As before, shaded areas indicate NBER recessions. In all cases an asterisk (*) in the graphics indicates a failure in terms of either missing some cycles or identifying others that actually did not occur. Empirical results in terms of the derivatives confirm previous expectations. While the short-term derivative wrongly anticipates too many cycles and the long-term one misses those of moderate length, in the medium-term case there is mixed evidence of failures, depending on the length of the cycle. The HP cycle does not fare better, and identifies three spurious recession cycles that are not present in the data: 1962(3)–1963(4), 1964(4)–1965(1), and 1986(2)–1987(3). Also, in most of the remaining cases where recessions are correctly identified, the HP cycle always lags observed recessions, and remains in a recessionary path long after the economy has already recovered. These results confirm the need of making initial judgments on the length of the cycle and the use of a "mixture" of cycles if we want to accurately reproduce turning points caused by big differences in the average life of the business cycles.

¹⁰The widely used value of $\lambda = 1,600$ is equivalent to an $\text{NVR} = 0.000625$.

Figure 4a
Long-term trend derivative ($NVR = 0.001$) and NBER recessions

Figure 4b
Medium-term trend derivative ($NVR = 0.01$) and NBER recessions

Figure 4c
Short-term trend derivative ($NVR = 0.1$) and NBER recessions

Figure 4d
HP cycle and NBER recessions

3.2 Historical performance on the chronology of the business cycle

Given the characteristics of our trend derivatives as outlined in the previous sections, the empirical application of our methodology should comply (ideally) with the following requirements:

- from a historical point of view, it can capture the peaks and troughs of the business cycle,
- it can anticipate cyclical movements of recession and recovery of the economy, and
- information about this anticipation behavior can be used to improve forecasting performance.

In this section, we will discuss the first two requirements, leaving the *ex ante* forecasting exercise for later discussion.

Using the whole sample of 1947(1)–1992(4), we have estimated the short-, medium-, and long-term trends, as well as their derivatives for NVR values equal to 0.1, 0.01, and 0.001, respectively, for the U.S. GNP. Plots of the three derivatives together are shown in Figure 5a, and several characteristics of these plots are worth mentioning. First, the three derivatives are smooth, without signs of irregularities, due to the leakage of higher frequencies. As expected, the lower the NVR value, the smoother the derivative plot. Second, points where the three derivatives cross (A, B, C, D, G, and I) indicate the *inflection points* of the derivatives, where the three trends are growing (decreasing) at the same rate.¹¹ Third, there are well-defined peaks and troughs, so that the four stages (recession, contraction, recovery, and expansion) of the NBER business-cycle methodology can be identified. The interpretation of each point is the following:

A—The three derivatives cross in their inflection points, and they are decreasing. It anticipates the 1953 crisis.

B—Again, the 1957 crisis is anticipated when the three derivatives cross and all of them are falling.

C*—In this point the three derivatives cross, but not all of them are decreasing (the long-term derivative is growing). The short- and medium-term derivatives pick up the sign of the crisis. Then, the recession is only anticipated by the short- and medium-term derivatives, maybe because we were facing just one negative quarterly growth rate of the GNP. Had we used the alternative cycle-dating rules, this short period (1960(2)–1961(1)) would not be considered a recession.¹²

D and E—At point D, the three derivatives are falling. This situation anticipates the next recession. However, before the U.S. economy enters a recession, a short-term growth cycle takes place. At point E the anticipation of the 1969 crisis is confirmed.

¹¹According to Schumpeter (1939), these crossings represent equilibrium or near-equilibrium points.

¹²Revisions in the series may have altered the sign of GNP growth one quarter, leaving just one negative growth rate.

Figure 5a

Short-, medium-, and long-term trend derivative of the U.S. GNP. 1947.1–1992.4

Figure 5b

Short-, medium-, and long-term trend derivative of the U.S. GNP. 1987.1–1997.4

F—The three derivatives cross in their inflection points, and they are decreasing. The 1973 crisis is anticipated at this point.

G—There is again a crossing of the three derivatives in the inflection points. In this case, the crossing anticipates the 1980 crisis.

H*—The 1981 crisis is not anticipated by the medium- and long-term-derivatives, because there are only four quarters between this crisis and the previous one. The short-term derivative, while it is falling, crosses the medium-term derivative at point H*. This is the unique sign of the recession. As happened at point C*, there is only one negative quarterly growth rate of the GNP during this period.

I—Point I anticipates the 1990 crisis; the three derivatives cross at their inflection points while they are falling.

On the other hand, Figure 5a shows how the local minima of the three derivatives anticipate the recoveries. These minima dates are the same for the three derivatives. When the crisis periods are anticipated due to the crossings of two derivatives, the recoveries are anticipated by the minima of these derivatives (points $C_{\min}$ and $H_{\min}$).

Table 3
U.S. business growth cycles in the post–World War II period^b

Growth Cycle		Duration of Contraction (Months)	Growth Cycle		Duration of Expansion (Months)	Duration of Cycle (Months [Years])
High	Low		High	Low		
1948(3)	1949(4)	15	1949(4)	1951(1)	5	20[1.7]
1951(1)	1952(3)	16	1952(3)	1953(1)	8	24[2.0]
1953(1)	1954(3)	17	1954(3)	1957(1)	30	47[3.9]
1957(1)	1958(2)	14	1958(2)	1960(1)	22	36[3.0]
1960(1)	1961(1)	12	1961(1)	1962(2)	15	27[2.3]
1962(2)	1964(3)	29	1964(3)	1966(2)	20	49[4.1]
1966(2)	1967(4)	16	1967(4)	1969(1)	17	33[2.8]
1969(1)	1970(4)	20	1970(4)	1973(1)	28	48[4.0]
1973(1)	1975(1)	24	1975(1)	1978(4)	45	69[5.8]
1978(4)	1982(4)	48	1982(4)	1984(3)	19	67[4.5]
1984(3)	1987(1)	30	1987(1)	1989(1)	24	54[4.5]
Average		21.9			21.2	43.1[3.6]

^b Source: Reprinted from Niemira and Klein (1994, p. 7).

From the analysis of the U.S. NBER business cycles, we suggest the following strategy to use the derivatives to anticipate the stages of the business cycle:

1. To anticipate a recession, two conditions seem to apply: the three derivatives cross in the inflection points, and they are decreasing.
2. The local minimum of the three derivatives at the same time anticipates recoveries.

The sample period used so far was used to reproduce the NBER chronology up to the last cycle observed. However, it would be interesting to check whether our procedure announces “false” recession calls when we expand the sample period using the last available data. To do so, we have expanded our GNP data set until 1997(2). Results are shown in Figure 5b. While the short- and medium-term derivatives cross at point J when they are decreasing, the long-term derivative is still growing, and therefore there is no indication of an upcoming recession during this expanded period.

3.3 Anticipating U.S. growth cycles in the post–World War II period

Another interesting test of our model is related to its ability to reproduce and anticipate the growth cycles of the U.S. economy. Although this concept does not have the same universal recognition as that of the business cycle, a growth cycle shares many of its characteristics and, consequently, extensive research at the NBER has been done to examine fluctuations in business activity. Among other things, Niemira and Klein (1994) point out several reasons to monitor the growth cycles: (1) they are closely tied to inflation cycles, (2) growth-cycle peaks lead their associated business-cycle peaks, (3) growth cycles are more symmetric in length and amplitude than business cycles, and (4) the U.S. Department of Commerce composite index of leading indicators has a better track record for forecasting growth cycles than business cycles.

In Table 3, a chronology of U.S. post–World War II growth cycles is presented. The average duration is 21.9 ($\hat{\sigma} = 10.0$) months for contractions and 21.2 months ($\hat{\sigma} = 10.4$) for expansions, confirming a greater symmetry than the one observed in the business cycles for the same period. Also, the average duration of the cycle is 3.6 years ($\hat{\sigma} = 1.3$), and the maximum and the minimum durations are respectively, 5.8 years (1973–1978) and 1.7 years (1948–1950). Given this average duration, it seems that a good candidate to capture its cyclical behavior is the short-run trend derivative we used in the previous section. In Figure 6, we plot this derivative for the whole sample period (the last high expansion value according to Niemira and Klein [1994, p. 7] corresponds to February 1989). Shaded areas in this case indicate the contraction periods. As Figure 6 shows, growth cycles are reproduced and anticipated by the local maxima and minima of our short-run trend derivative. Of the 22 turning points in the sample, the model successfully anticipates 19 of them. There are, however, three cases where a failure is observed, and an asterisk is included in the graph. We are not able to anticipate the short expansion between 1952(3) and 1953(1) that lasted 8 months. Given its short duration, our derivative does not react “fast” enough, and fails to consider it as a separate cycle. In the other two cases we have the opposite problem, and we wrongly anticipate two turning points that do not occur. In both cases, the contraction periods are considerably above the average. The second and fourth columns of Table 4 show

Figure 6
U.S. GNP short-term trend derivative and U.S. growth cycles

Table 4
Anticipation dates of U.S. growth cycles

High	Anticipation Contraction ^c	Low	Anticipation Expansion ^c
1948(3)	—	1949(4)	1948(4)[−4]
1951(1)	1950(2)[−3]	1952(3)	*
1953(1)	*	1954(3)	1953(3)[−4]
1957(1)	1955(1)[−8]	1958(2)	1957(3)[−3]
1960(1)	1958(4)[−5]	1961(1)	1960(2)[−3]
1962(2)	1961(3)[−3]	1964(3)	1964(2)[−1]
1966(2)	1965(2)[−4]	1967(4)	1966(4)[−4]
1969(1)	1968(1)[−4]	1970(4)	1969(4)[−4]
1973(1)	1972(2)[−3]	1975(1)	1974(2)[−3]
1978(4)	1978(1)[−2]	1982(4)	1981(4)[−4]
1984(3)	1983(3)[−4]	1987(1)	1986(1)[−4]
1989(1)	1987(3)[−6]	?	1990(3)

^cFigures in brackets represent the number of leading quarters.

*Failures.

the anticipation dates (with the number of lags in parenthesis) of the contraction- and expansion-growth cycles of our model.

3.4 Real-time forecasting of the U.S. business cycle

In the previous two sections, we analyzed how both business and growth cycles can be reproduced and anticipated (from a historical point of view) using the trend derivatives. Since it may be argued that the fact that the derivatives can anticipate business-cycle turns may be due to our algorithm being a two-sided filter, in this section we go one step further to verify if at a certain time t (using information up to that point) it is possible to predict business-cycle turning points using the information embedded in our subjective trend derivatives at time t .¹³ Considering $t = 1976(1)$, we proceed by estimating our model adding one observation at a time. For each new data point ($t, t + 1, t + 2, \dots$) we get three estimated derivatives. Each derivative includes a final numerical value that indicates the trend growth (at that point) of each of the short-, medium-, and long-term trends. Those points represent the estimated growth values of each trend using present and past information without any “contamination” of future information due to filtering/smoothing operations in our state-space model (a one-sided filter).

Under these conditions, it is possible to build three new series, called short-, medium-, and long-term inertias (henceforth STI, MTI, and LTI, respectively), which are defined as the links of all of the estimated

¹³Note that this is a truly ex-ante predictive experiment, since identification of the NVR values by looking at historical business-cycle durations are made using information up to 1976(1).

Figure 7

Short-, medium-, and long-term trend inertias of the U.S. GNP

growth rates using information at times t , $t + 1$, $t + 2$, ... etc. In our case, the first value of the STI will be the last short-run derivative value using information until 1976(1). The second will be the last derivative value corresponding to 1976(2), and so on; and the last STI value will be obtained when $t = 1992(4)$. This information set is called *inertia*, since its values are the ones used by the IRW model to forecast future trends outside the sample period. Therefore, the inertias can be interpreted as the expected future trend growth if the economy remains (*ceteris paribus*) stable.

If the economy is in a well-defined (positive or negative) growth path, which of the three derivatives will first detect the possibility of a turning point? The short-term trend will first detect these changes, the medium-term trend will follow, and the long-term trend will be last. Starting in 1976(1), Figure 7 plots the corresponding STI, MTI, and LTI until 1992(4). The following points are worth mentioning:

- A**—Before the beginning of the 1980 crisis, the STI is above the MTI, and this in turn is above the LTI. At point 1 the STI falls and crosses the MTI, and at point 2 the STI crosses the LTI while the MTI is already falling. Information about the possibility of a turning point is already in the inertias at point 3 (1979(2)), where the 1980 crisis is anticipated with a three-quarters lead.
- B**—Between 1984 and 1987, the NBER identifies a growth cycle for the U.S. economy. This cycle should not be confused with either a business cycle or the circumstances described in A. During this period, there are inertias that are still growing, and consequently, the previous rules do not apply.
- C**—At the end of 1988, there is again a contemporaneous crossing of the three inertias. For this particular period, the information about a possible turning point is so strong that the three inertias incorporate it without any lag. Again the important 1990(3) crisis is anticipated with a lead of six quarters.
- D and E**—At these points, we observe the opposite of A and C. The inertias grow and cross to turn into an expansion situation where the STI is above the MTI, which is, in turn, above the LTI. These points do not anticipate the recovery but only confirm it. As happened in Section 3.1, to be able to predict recoveries we have to pay attention to the inertia's local minima. In this case, the inertia's local minima are dated on 1980(3), 1982(3), and 1991(1), while the official NBER recovering dates are 1980(3), 1982(4), and 1991(1). Consequently, with the exception of the 1982 recovery, the other two recoveries are contemporaneous with our forecasts.¹⁴ Table 5 presents a summary of our historical and forecasting business-cycle chronology for the U.S. data.

The differences between recession- and recovery-anticipation time leads (within our empirical framework) are related to the different historical lengths shown by the two components of the U.S. business cycle. The much shorter recession periods do not fully allow the algorithm to incorporate the most recent information,

¹⁴If instead of selecting the NBER dating chronology, we would have chosen the other "first of at least two successive changes in the growth rate" rule, the three recoveries would have been anticipated by our inertia's local minima.

Table 5

NBER historical and forecasting chronologies for U.S. business cycles

NBER		Historical ^c		Forecasting ^c	
Peak	Trough	Peak	Trough	Peak	Trough
1948(4)	1949(4)		1948(4)[-4]		
1953(3)	1954(2)	1952(1)[-6]	1953(3)[-3]		
1957(3)	1958(2)	1956(2)[-5]	1957(3)[-3]		
1960(2)	1961(1)	1959(4)[-2]	1960(2)[-3]		
1969(4)	1970(4)	1968(4)[-4]	1969(4)[-4]		
1973(4)	1975(1)	1973(1)[-3]	1974(2)[-3]		
1980(1)	1980(3)	1979(1)[-4]	1980(1)[-2] ^d	1979(2)[-3]	1980(3)[0] ^d
1981(3)	1982(4)	1981(1)[-2] ^d	1981(4)[-4]	1981(3)[0] ^d	1982(3)[-1]
1990(3)	1991(1)	1989(1)[-6]	1990(3)[-2]	1989(1)[-6]	1991(1)[0]

^cThe figures in brackets represent the number of leading quarters.^dOnly anticipated by the short-term derivative.

and consequently, signals of recovery anticipation are much weaker than those of recession. In spite of its shortcomings and the reduced scope of the present forecasting exercise, our experience with the U.S. business-cycle analysis allows us to suggest the following strategy to use the inertias as potentially useful forecasting tools:

1. To anticipate a recession, we have to wait until the LTI is above the MTI and the STI; the three inertias should be decreasing.
2. With regard to recoveries, anticipation should be considered at the local minimum of the STI, since it is always the first to detect turning points.
3. The economy will be in an expansion path when the STI is above the MTI and this, in turn, is above the LTI one.

Somehow this strategy is similar to the rules followed by the so-called moving-average oscillator that is used when deciding investments in the stock market. According to those rules, sell and buy signals in the stock market are generated by two long- and short-term moving averages. A buy (sell) proposal is advised when the short-run moving average is above (below) the long-run moving average. Brock, Lakonishox, and Lebaron (1992) showed how this particular investment strategy outperforms the more complicated random walk, AR, or GARCH modeling alternatives.

4 Historical Analysis and Prediction of International Business Cycles

The main objective of this section is to try to confirm the strategy developed for the U.S. by analyzing the cyclical fluctuations of three European countries: Germany, France, and Spain. Again, attention is devoted to quarterly seasonally adjusted GNP data where both the number of observations as well as the time periods differ slightly among countries. The (West) German and French series are taken from the OECD data files, and the Spanish GNP series comes from the Instituto Nacional de Estadística (INE) data files. Since for these particular data sets the NBER does not provide a business-cycle chronology, we have adopted the alternative of defining a turning point as the first of at least two consecutive increments (decrements) in the GNP growth rate. The peaks and troughs identified for each country following this rule are shown in the first two columns of Table 6. In what follows, we treat each country on an individual basis. An alternative chronology for some European countries, based upon cyclical movements in the monthly index of the industrial production for the period 1961(1)–1994(2) is given by Artis, Kontolemis, and Osborn (1997).

When applying our technique across countries, decisions about sensible values of the NVR have to be based on their respective business-cycle durations. Although the historical periods considered in the cases of the three European countries are considerably narrower than in the U.S. case, and consequently the number of business cycles is also shorter, the duration asymmetry shown in the European cases (see Table 6) leads us to maintain the same NVR values as the ones used in the previous section. Only for the case of Germany (see Figure 8d) does the informational content of the short-term derivative seem to be redundant in anticipating recessions; still, it is useful for recoveries.

Table 6

Dates of historical and forecasting chronologies for international business cycles: France, Germany, and Spain

Business Cycle Dates		Historical ^c		Forecasting ^c	
Peak	Trough	Peak	Trough	Peak	Trough
France					
1974(4)	1975(2)	1974(1)[-3]	1974(3)[-3]		
1980(4)	1981(2)	1978(3)[-5]	1980(3)[-5]		
1990(4)	1991(2)	1990(1)[-3]	1990(4)[-2] ^d	1990(3)[-1]	1991(2)[0] ^d
1992(2)	1993(2)	1992(1)[-1] ^d	1992(4)[-2]	1992(1)[-1] ^d	1993(2)[0]
Germany					
1974(2)	1975(1)	1973(2)[-4]	1974(3)[-2]		
1981(4)	1983(1)	1979(4)[-8]	1982(1)[-4]	1980(2)[-6]	1982(2)[-3]
1992(2)	1993(2)	1991(3)[-3]	1992(3)[-3]	1991(4)[-2]	1993(2)[0]
Spain					
1975(1)	1975(3)	1974(1)[-4]	1975(1)[-2]		
1978(4)	1979(2)	1977(4)[-4]	1979(1)[-1] ^d	1977(4)[-4]	1979(2)[0] ^d
1980(3)	1981(2)	1980(2)[-1] ^d	1980(4)[-2]	1980(3)[0] ^d	1981(2)[0]
1992(3)	1993(3)	1990(3)[-8]	1992(4)[-3]	1990(3)[-8]	1993(2)[-1]

^cThe figures in brackets represent the number of leading quarters.

^dOnly anticipated by the short-term derivative.

Figure 8a

Germany's quarterly GNP

4.1 Germany

Our data entails 105 quarterly GNP observations from 1968(1)–1994(1). Plots of the original data as well as growth rates are shown in Figures 8a and 8b. Shaded areas in the time plots indicate recessions according to the adopted rule. To reproduce a historical confirmation of the German business cycle, we have computed the short-, medium-, and long-term derivatives for the whole sample. Time plots of the three derivatives (and the shadowed recession periods) are shown in Figure 8c:

1. points A, B, C, and E in the plot are the inflection points where the three derivatives cross;
2. points A, C, and E anticipate recessions;
3. the minima of the derivatives anticipate recoveries; and
4. in F we can detect a growth cycle. At that point some derivatives cross, but the long-run derivative is still growing.

To analyze the forecasting performance in the German case, we compute the three *inertias* from the first

Figure 8b
Quarterly growth rates of the German GNP

Figure 8c
Short-, medium-, and long-term trend derivative of the German GNP

Figure 8d
Short-, medium-, and long-term trend inertias of the German GNP

Figure 9a
France's quarterly GNP

quarter of 1976 until the end of the sample, adding one observation at a time (Figure 8d). Again, we can observe the following:

1. anticipation of the 1981 crisis can be identified by the inertias crossing in A (1980(2)) with a *six-quarters lead*;
2. the minimum of the STI in 1982(2) anticipates the following recovery;
3. in C, anticipation of the 1992 recession is detected with a *two-quarters lead*; and
4. in D, a growth cycle is identified.

A summary of the historical chronology and anticipation dates for the German business cycle is shown in columns 3–6 of Table 6.

4.2 France

In this case, our data comprises 96 quarterly observations between 1970(1)–1993(4). Plots of the original GNP variable and its growth rates are shown in Figures 9a and 9b. As usual, shaded areas indicate recession periods that are dated in the first two columns of Table 6. Figure 9b shows how in the French case there are several isolated quarters with negative growth rates between 1980 and 1990. Although none of them could be characterized as a properly defined business cycle (according to the NBER rule) they introduce important distortions in our turning-point-detection strategy.

The historical chronology using the three derivatives is presented in Figure 9c. The main conclusions are the following:

1. Points A, C, and E anticipate recessions. There, the two conditions hold: the three derivatives cross, and they are decreasing.
2. At point E, the 1990 crisis is anticipated. However, given the short period of time elapsed before the following 1992 recession, only the short- and medium-term derivatives will later anticipate this 1992 crisis.
3. All recoveries are anticipated at the derivatives' minima.
4. In the neighborhood of F, a growth cycle is detected due to the presence of several (not successive) quarters with negative growth rates.

Regarding business-cycle predictions, the inertias are computed from 1988(1) until the end of the sample. Plots of the three inertias are shown in Figure 9d. The 1990 recession is correctly forecasted by the three (1, 2, and 3) phases. However, the following recovery is not anticipated by the minimum of the STI. Such a minimum point is contemporaneous with the end of the crisis. The following turning-point forecast (the 1992 recession) is correctly anticipated just by the STI with a one-quarter lead. As in the previous case, the recovery is also contemporaneous with the minimum of the STI.

Figure 9b
Quarterly growth rates of the French GNP

Figure 9c
Short-, medium-, and long-term trend derivative of the French GNP

Figure 9d
Short-, medium-, and long-term trend inertias of the French GNP

Figure 10a
Spain's quarterly GNP

4.3 Spain

Our quarterly data set that includes 97 observations between 1970(1) and 1994(1) is plotted in Figure 10a, and its growth rates are in Figure 10b. The dating of the four cycles for the Spanish economy is shown in the first two columns of Table 6. Following the same strategy as in previous cases, the plots of the three derivatives (Figure 10c) indicate the following:

- the short-term derivative captures very well the cyclical fluctuations of the Spanish economy;
- recession periods are well anticipated in A, B, and C, where the derivatives cross and are decreasing;
- only the short-term derivative anticipates the 1980 crisis—the other two derivatives are still recovering from the previous crisis between 1978 and 1979;
- there is an anticipation of the growth cycle in D where the derivatives cross, but not all of them are decreasing;
- the minima of the short-term derivative anticipate recoveries, and
- at 1994(1), the Spanish economy was in a recovery stage after the short-term derivative reached its minimum.

To analyze the forecasting performance of the model, the inertias are computed from the first quarter of 1975 and plotted in Figure 10d. If we concentrate our interest on the last recession period, it can be easily observed how such a crisis is forecasted with an *eight-quarter lead*. As in some of the previous cases, the three stages (points 1, 2, and 3) are also well defined in this case. Again, the following recovery is only anticipated by the STI with a one-quarter lead. A whole summary of the business-cycle dating performance for the Spanish economy is shown in columns 3–6 of Table 6.

5 Conclusions

This paper has analyzed the chronology of the business cycle in a Schumpeterian framework, as a sum of short-, medium-, and long-term cycles. The lengths and shapes of those cycles are determined subjectively using historical information based on the characteristics of the sample-period data. Our univariate unobserved-components model thus defines a cyclical trend component that is used to reproduce and anticipate business and growth cycles for the U.S. After associating the trend with the low frequencies of the pseudo-spectrum in the frequency domain, manipulation of the spectral bandwidth allows us to define the different trends that contain specific properties. The paper shows how these properties can be exploited in anticipating business-cycle turning points, not only historically, but also in a true ex-ante forecasting exercise

Figure 10b
Quarterly growth rates of the Spanish GNP

Figure 10c
Short-, medium-, and long-term trend derivative of the Spanish GNP

Figure 10d
Short-, medium-, and long-term trend inertias of the Spanish GNP

using the concept of inertia. The same type of exercise is repeated later with similar results for recent French, German, and Spanish GNP data.

A few conclusions can be drawn from this exercise. First, crossings of the derivatives of the short-, medium-, and long-term trends anticipated the beginnings of recession periods under certain circumstances. The anticipation lead varied from cycle to cycle. Second, with regard to recoveries, the minimum of the short-run trend derivative always anticipated (or at least was contemporaneous with) the following recovery. This different leading behavior between recessions and recoveries was explained by the different historical lengths shown by the two components of the business cycle. Third, for the U.S. postwar growth cycles, our short-term trend derivative successfully anticipated 19 out of 22 turning points in the sample. In the three cases where a failure was observed, the length of the contractions (expansions) were considerably above (below) the average. Fourth, when the inertias were used to analyze the forecasting (out of the sample) performance of the model, similar results held for the U.S. as well as for the French, German, and Spanish cases.

Our attempt to define trends of different degrees of smoothness using historical observations on the length of different business cycles raises another issue related to any reader who might be interested in applying our procedure in practice to say, her own country's GNP or another economic series. What if there are not large differences in the average lives of the business cycles? Or, what if there were only two types of cycles: those with very short duration, and those with very long duration? Although it is not possible to give a valid "recipe" for all general circumstances, we have provided some hints on how to proceed when the situation differs from the empirical examples given in this paper. If there are not big differences in the lengths of the cycles, using only one trend (based on an initial judgment on the average length cycle) may be sufficient. Quarterly U.K. and Japan real GNP data results (Queralt 1994) provide evidence on how one long-term trend derivative (Japan) and one medium-term trend derivative (U.K.) can correctly reproduce turning points in those countries from a historical point of view. Real time ex-ante forecasts, however, can be poor if coming recessions differ considerably from their historical records. Also, readers interested in applying this procedure using samples with different periodicity (such as annual or monthly data) can easily obtain the corresponding NVR values and cycles of our Table 1 using Equations 8 and 9.

Before concluding, two caveats should be noted. First, the numbers used for the GNP series in this paper are of a final revised form, whereas, in real-time forecasting, only preliminary and partially revised data are available. If the output series were subject to only small revisions, the use of final revised GNP data would not be a critical flaw. But if the GNP is extensively revised from its preliminary estimate to its final value, evaluation of the real-time predictive performance would require the use of preliminary GNP data that would have been available at the historical date of each forecast (Diebold and Rudebusch 1991). Second, the inertias provide a good economic forecasting tool in anticipating recessions and recoveries for the business-cycle behavior after World War II. However, since we are using historical data, we know beforehand the exact dates of future recession/recovery events, and therefore we can confirm the lead/lag announcement of our procedure. In real-time forecasting exercises, we lack this "future" information, and when the announcement is made we cannot state precisely when the turning point will actually occur. As forecasting practitioners know, this problem is a well-known shortcoming of univariate models that requires the use of other (monthly) leading indicators to complement early warnings with confirmed evidence.

While the results obtained here are promising, more comparative-modeling exercises that include a larger data set must be performed before any general conclusion can be reached. In particular, given the restrictive assumptions of our IRW trend model to forecast trend reversals, important areas for future research include alternative (more flexible) trend specifications as well as modeling and forecasting the derivatives to obtain qualitative (anticipation messages) and quantitative (point forecasts) information.

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