Predicting **T**urning **P**oints in **B**usiness **C**ycles

Raffaele Mugno

Research Project , Ministero dell'Università e della Ricerca Scientifica, February, 2004

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Introduction

The aim of this article is twofold: to compare alternative turning point indicators of the business cycle, and to analyse the merits and faults of the techniques commonly used for constructing them.

As we have experienced, despite the efforts of Central Banks and Governments, economies repeatedly show periods of expansion and contraction. This recurring pattern of recession and recovery is called Business cycle.

The transition points across cycles are called peaks and troughs. A peak is the transition from the end of an expansion to the start of a contraction. A trough occurs at the bottom of a recession just as the economy enters a recovery.

One determinant of the broad asset allocation decision of many investment houses is to forecast the business cycle direction. In fact, a reliable accurate forecast that differs from market consensus can have a major impact on investment strategies.

As the economy passes through different stages of the business cycle, the relative performance of different sectors, might be expected to vary. For example, at a trough, just before the economy begins to recover from a recession, one should expect that cyclical sectors, those with above-average sensitivity to the state of the economy, would tend to outperform other sectors[1].

Hence, if we would be able to determine when the economy is near to a peak or a trough, we could nicely choose an optimal investment strategy and the related asset/sector allocation. Unfortunately, it is often difficult to say whether the economy is hearing up or slowing down at any moment. Nonetheless, given the cyclical nature of

1 Examples of cyclical sectors are producers of durable goods, such as automobiles or washing machines, because purchases of these goods can be deferred during a recession, sales are particularly sensitive to macroeconomic conditions. Other cyclical sectors are producers of capital goods, such as goods used by other firms to produce their own products. When demand is slack, there is minor expanding and purchasing of capital goods.Non cyclical sectors, or defensive sectors, have little sensitivity to the business cycle, such as food producers and processor, pharmaceutical firms, and public utilities. These sectors should outperform other sectors when the economy enters a recession.

the business cycle, it is not surprising to say that to some extent the cycle can be predicted.

A number of public and private institutions have constructed different indicators to forecasting business cycles, such as single, composite, leading, coincident and lagging indicators:

- Single indicators provide information from a single economic variable;
- Composite indicators combine a variety of individual economic variables into a single indicator.
- Leading economic indicators are those economic series that tend to rise or fall in advance of the rest of economy.
- Coincident indicators are those series that move in tandem with the rest of the economy.
- Lagging indicators move after the broad economy.

These indicators are used for three different purposes:

- as a tool for identifying turning points in the business cycle;
- as a summary indicator of the general development in economic activity
- as a device for making short-term forecasts of economic growth.

Indeed, the most relevant predictors of turning points in economic activity are the Leading Economic Indicators (LEI). In 1938 Burns & Mitchell introduced the leading indicators (Burns & Mitchell 1946), and until December 1995, the LEIs were produced by the Bureau of Economic Analysis at the Department of Commerce. Since that date, they have been produced by The Conference Board, a private, non profit organisations.[2]

These leading indicators series are widely watched by business, government, and academia to gauge whether a recession is forthcoming. It is believed that leading indicators have an advantage over more complex econometric models: they can be

[2] The box 1-Appendix 1- lists the series that are currently part of the Economic Indicators. The current list of LEI has changed from that originally proposed by Burns and Mitchell. Over time, as new information about turning points has become available, series have been added or dropped out.

readily understood and interpreted. However, it is often neglected the fact that the leading indicators suffer from some of the very same problems as the more complex econometric models. The series representing the leading indicators were chosen on the basis of their ability to predict past recessions. Using the econometric lingo, they were chosen on the basis of their **in-sample performance**, that is, their ability to predict, with hind-sight, recessions that have already occurred.

Whether the leading indicators are able to predict future recessions, **out-of-sample performance**, is a different matter[3]. Indeed, one of the reasons the Leading Economic Indicators list is periodically revised is that each new recession shows that some of the series were not good predictors after all (Moore 1983 and Conference Board 1997). For example, the only two series that have survived the test of time from the original Mitchell and Burns list of indicators are average weekly hours (manufacturing) and the S&P 500 Index. All other series from their original list have been discarded[4].

These considerations bring us to the main question of this paper: how good is the state of the art in turning points forecasting? We, firstly, discuss the definition of turning points and how to select business cycle reference series, then we examine the potential information content of single and composite indicators. Next, we analyse the methods commonly used for constructing single and composite indicators, and the different approaches to turning point forecasting, and their relative advantages and disadvantages.

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3 In fairness to the Leading Economic Indicators, some literature shows that they have predictive power, not only in-sample but also out-of-sample (Moore 1983; Zarnowitz and Braun 1988).

4 Nowadays, The Conference Board's Consumer Confidence Index is among the most widely followed economic statistics in the business and financial communities. The index reflects the current level and anticipated level of business activity. Each month's report indicates consumers' assessment of the present employment situation, as well as future job prospects and income expectations. The survey includes buying intentions for cars, homes, and major appliances. Confidence is reported for the nation's nine major regions,long before any geographical economic statistics are avail-able. Consumer attitudes are also shown by age and house-hold income. The series reports the public's expectations of inflation, interest rates, and stock prices. Consumers' travel plans are reported bimonthly. Includes 83 data series.

Defining Turning Points

The transition points across cycles are called peaks and troughs. A peak is the transition from the end of an expansion to the start of a contraction. A trough occurs at the bottom of a recession just as the economy enters a recovery. In other words, the beginning and the end of a recession are turning points in real GDP: the beginning represents a peak while the end represents a trough.

In order to identify business cycles we refer to two widely quoted explanations: the Okun's rule and the Burns and Mitchell's definition.

On one hand, according to the Okun's rule, the beginning of a recession is defined as the first of two consecutive quarters of decline in real GDP. By analogy, the end of a recession is marked by the first of two consecutive quarters of real GDP growth (Harding and Pagan 1998).

On the other hand, members of the NBER Business Cycle Dating Committee are guided by the Burns and Mitchell's definition:

Business cycles are a type of fluctuation found in the aggregate economic activity of nations, that organise their work mainly in business enterprises: a cycle consists of expansions occurring at about the same time in many economic activities, followed by similarly general recessions, contractions, and revivals which merge into the expansion phase of the next cycle; this sequence of changes is recurrent but not periodic; in duration business cycles vary from more than one year to ten or twelve years; they are not divisible into shorter cycles of similar character with amplitudes approximating their own. (Burns and Mitchell 1946).

Burns and Mitchell's definition emphasises three important business cycle characteristics, known as the three Ds: duration, depth, and diffusion.

Duration: a recession has to be sufficiently long; depth: it has to involve a substantial decline in output; diffusion: it has to affect several sectors of the economy. Faithful to the generality and complexity of Burns and Mitchell's definition, the NBER committee eschews numerical rules like the two quarters of decline in real GDP. Nonetheless, the empirical evidence (NBER) shows that after 1970 the recession and expansion dates determined using the two quarters rule are a good approximation of the NBER recession and expansion dates. The only difference is that NBER-defined recessions tend to be longer than recession defined using the two quarters rule. The NBER considers months of stagnant or very moderate growth as belonging to recessions rather than to expansionary periods. However, for practical purposes, turning points defined using the popular two quarters rule and NBER-defined turning points are not too far apart.

Selecting business cycle reference series

Economic indicators refer to developments in the business cycle. Commonly, a reference business cycle is used to asses the properties of a particular indicator. Yet, the business cycle is a theoretical concept, with no commonly agreed upon empirical identification method. In other words, no general agreement exists with respect to which series should be chosen as representative of the business cycle. Then the first question to address is: what could be defined as the reference business cycle?

In principle, a range of series can be taken into account when identifying the business cycle, including variables such as: employment; income; trade; output.

However, within the framework of leading indicator analysis, the reference series are:

- the volume of industrial production, these data have the advantage of being available on a monthly rather than a quarterly basis. Industrial production, however, accounts for only a part of the total economy;
- real GDP, it is a more comprehensive variable and therefore ultimately more relevant for analysing economy-wide fluctuations.

As several empirical researches have shown (ECB-FED Bulletin), the choice between industrial production and GDP may not be decisive, as developments in the growth of GDP and industrial production appear highly synchronised over the last 20 years.

However, the relative sizes of peaks and troughs in GDP and those in industrial production have varied in the past, depending in particular on the nature of the shock at the origin of the cyclical developments.

In practice, especially in the context of composite indicators, actual year-on-year growth rates in the reference series rather than estimates of the business cycle derived from statistical or econometric methods are most often used making inferences about recent cyclical developments. Quarter-on-quarter growth rates normally signal cyclical changes in a more timely manner than year-on-year growth rates. However, the larger volatility of quarter-on-quarter growth rates makes them more difficult to track by composite indicators, which might explain the focus on year-on-year growth rates.

Moreover, The determination of the reference business cycle deals with time series of aggregate economic activity that may be decomposed into four components: trend, cycle, seasonal fluctuations, irregular term.

The cycle is found by elimination of the seasonal component, the trend, and the irregular term. As these different components are not directly observable, they will vary with the method of decomposition used. Often, it is found that the results of indicator analysis do not depend decisively on the method chosen to determine the cycle in the reference series.

Among the different possible decomposition methods, the band-pass filter, proposed by Baxter and King (1999), is one of the most used. The band-pass filter eliminates a very slow-moving trend component and very high-frequency (irregular and seasonal) components, i.e.: only fluctuations within a specific frequency band are retained and are considered as corresponding to the cyclical developments. Following the standard approach, the band is defined as follows: the minimum duration of the business cycle is imposed as 18 months, so as to eliminate irregular and seasonal components, while fluctuations longer than 96 months are attributed to long term trend changes.

The turning points in the cyclical pattern of the reference index are determined with the commonly applied method developed by Bry and Boschan (1971). This method was initially devised for monthly data and has been adapted for the quarterly series on GDP. It essentially smoothes the cyclical component of a series and discards spurious cycles on the basis of rules regarding the minimum duration of the cycle.

Table 2 –Appendix 1- shows the turning points for the Euro Area determined by Bry and Boschan algorithm.

There is, however, one major drawback to using de-trended series as reference series. Whatever the technical method chosen, the estimation of the cyclical component is less reliable towards the end of the sample period. Data both before and after a given date are needed to estimate the components at this particular date. This poses problems at the beginning and at the end of a series. One possible solution is to discard estimates of the business cycles at the beginning and at the end of the sample. However, analysts are usually interested in the most recent developments. The common way of dealing with this problem is to extend the original series backwards and forwards by way of estimation and forecasting. This, however, implies that the estimated cycle at the end of the series is subject to revisions as new information becomes available, which may differ from the forecast values, a major drawback for practical purposes. Hence, de-trending methods are best suited for analysis of historical cyclical developments.

For composite indicators, where the focus is on the most recent developments, actual growth rates are often used to remove the upward trend movement and extract cyclical variations. The implicit underlying assumption is that the trend component grows at a constant pace.

Predicting turning points: Composite vs. Single indicators

One approach widely used to produce forecasts of turning points is to use leading indicators. Some literature shows that single Leading Indicators have predictive power, not only in-sample but also out-of-sample (Moore 1983; Zarnowitz and Braun 1988).

However, such predictive signals coming from single leading indicators are hard to decipher, these series often give conflicting signals. For instance, few months ago, US consumer sentiment plummeted, but building permits for new houses were positive. Which indicators should one trust?

To avoid this problem, forecasters often rely on composite indicators that are constructed by combining a number of series into a single indicator. The aim of composite indicators is to predict and monitor changes in the economy. They consist of groups of indicators, which have been found to show a consistent timing relationship with peaks and turning points in the growth of overall economic activity[5].

Before analysing the merits and faults of the two approaches, we briefly discuss how to compile these leading indicators.

When constructing single indicators, public and private institutions generally select

5 One of the most used is the Leading Economic Indicators Index, which is a weighted average of all leading indicators.

series on the basis of criteria of both a statistical and an economic nature.

With regard to statistical criteria:

- in order to be confident about the relationship between a particular variable and the business cycle, sufficiently long time series are needed.
- time series should be subject to as small revisions as possible. Large revisions are detrimental to indicators, as early estimates cannot be relied upon.
- limited volatility is important, so as to avoid false signals from the latest readings.
- timeliness is essential in view of the provision of early information. Candidate indicators must lead the reference series, taking into account both econometric lead times and publication schedules. Some series are published well in advance of the reference series, and therefore gain in terms of timeliness.

As regards criteria of an economic nature, it should be noted that series of leading indicators are chosen mainly on empirical grounds, i.e. on the basis of their observed behaviour vis-a-vis the reference series, rather than on the basis of economic theory. However, usually it is required that the leading properties of variables are economically plausible, i.e. only those variables whose observed relationship with the business cycle is in line with economic theory are selected. Constituent series might have leading properties for several reasons:

- candidate series may report developments in factors which have caused or influenced upturns and downturns in the past. For instance, large and protracted movements in oil prices have tended, in the past, to have a significant impact on economic activity. In that sense, the indicator approach reflects some of the relationships between economic series, which are embedded in macro-economic models;
- some economic series, such as production orders, refer to the situation at an early stage of the production process of the relevant sector of activity;
- other variables may reflect expectations about developments in activity. For instance, stock prices are thought to reflect expectations about future profits and future economic activity.

All we have written mainly applies to single indicators, so let us see the particularities of composite indicators.

When constructing composite indicators, the selected constituent series are normalised and synchronised.

Normalisation adjusts for the fact that not all the basic indicators exhibit cyclical fluctuations of the same amplitude. It thus prevents the selected constituents with stronger fluctuations from unduly dominating the composite indicator.

Synchronisation then adjusts for the different leads of the constituents. This causes the indicators to coincide on average, making the cyclical pattern of the composite indicator clearer than it would be without synchronisation.

The lead of the composite indicator is restricted to the lead of the constituent series with the shortest lead. Different possibilities may be envisaged to measure the relative leads of the constituent series, and none is invariably superior to the others. Moreover, measured lead times may not be stable over time. Therefore, the choice made on how to synchronise the constituent series is to some extent arbitrary.

The determination of the weights attributed to constituent series in composite indicators does not appeal to economic theory. The weights can be defined either arbitrarily or on a statistical basis. Two frequently used statistical methods are illustrated here.

- One method named principal component analysis relies on the idea that the fluctuations of each series reflect two elements, namely fluctuations common to the group of variables, on the one hand, and variable-specific developments, on the other. The first part, the so-called first principal component can be deemed to represent developments in the business cycle. The smaller the variable-specific component, the higher the weight attributed to one constituent. In this method, weights are attributed on the basis of the behaviour of each individual variable vis-‡-vis the group of constituent series, independently of the chosen reference series.
- By contrast, a second method, regression analysis, exploits the behaviour of a single variable vis-‡- vis both the group of constituent series and the chosen reference series. With this method, an individual series is given a higher weight if its development more closely reflects those of the reference business cycle. In that sense, regression analysis may be seen as appealing to economic relationships between the reference business cycles and the constituent series, reflecting these to the extent that they are borne out by the data, while principal component analysis is

a purely statistical method.

Now we can see the arguments commonly put forward to defend the use of composite indicators in addition to the analysis of the individual constituents.

The composite indicators do not measure the absolute level of output or actual rates of growth but are concerned only with identifying the cyclical variations around the long-term trend. As mentioned above, single economic variables sometimes provide different signals as regards current or future growth developments. Different kinds of shocks may cause these divergent patterns as they affect the various sectors of the economy to differing degrees and at different moments in time. In other words, while individual economic indicators contain some information about movements in the business cycle, they may also show extra or missing cycles and produce many false signals. Consequently, using indicators independently to monitor changes in the business cycle is unreliable. Aggregating individual indicators into a composite indicator broadens the coverage of the possible causes and early indications of future or current fluctuations in the economy. A composite indicator is, therefore, more likely to capture fluctuations in the economy and will produce fewer false signals than each component used independently.

A second argument relates to the fact that, statistical effects, such as measurement errors, calendar effects or base effects, may account for the latest readings of various series pointing towards different developments, thereby making an overall assessment more difficult. To the extent that these variations and errors are independent, they would cancel one another out in a composite index, the pattern of which would thus be less erratic and easier to read.

That said, Composite indicators might appear a convenient tool at first sight. However, it should be borne in mind that composite indicators, once constructed, aggregate information in a predefined manner. In particular, this impairs their usefulness in practice and may be misleading, as specific developments of different economic variables at different moments in time drive overall economic developments. Therefore, composite indicators cannot replace a thorough examination of underlying developments and the analysis of individual indicators remains essential for a reliable assessment of the current and near-future developments. In other words, being summary indicators, composite indicators conceal the specific pattern of individual variables, which must be analysed in order to obtain a more complete insight into the driving factors behind current and short-term changes in economic activity, and thereby into likely developments in a more medium-term perspective. Finally, in contrast to macro-econometric models, composite indicators do not appeal strongly to theoretical relationships and are therefore not suitable for scenario analysis and the assessment of medium to long-term prospects;

Let us recall some data. By the very nature of leading indicators, turning points in the LEI-index should anticipate turning points in economic activity. Still, turning points in the index are not always easy to recognise. From the NBER data (1970-1996) we know that the 1973 recession is the only case in which a peak in the LEI-index clearly leads to a peak in economic activity. It is much harder to recognise turning points in the index prior to the 1981 or 1990 recessions.

A rule often used to identify turning points in the index is the so-called three-consecutive-declines rule: three consecutive declines in the LEI-Index signal a turning point, suggesting that a downturn in economic activity may be imminent. The empirical evidence (NBER) shows that the three-consecutive-declines rule was helpful in predicting the 1973 recession, gave mixed signals prior to the 1980 recession, and was not helpful at all prior to the 1981 and 1990 recessions. In addition, the rule gave false signals in 1987 and 1995.

Other rules may perform better than the three-consecutive declines rule. Diebold and Rudebusch (1989) use a more sophisticated approach to capture turning points in the index (Neftci 1982). This approach uses a regime-switching model to compute at each point in time the probability of a turning point in the index. Since in each period the probability is updated using the most recent index data release, this method is called the sequential-probability-of-turning-point approach. Diebold and Rudebusch find that this approach performs reasonably well, and certainly better than the three-consecutive-declines rule, in predicting post-war US recessions.

In summary, the evidence suggests that leading indicators may be useful in predicting recessions. Like a Delphic oracle, leading indicators give valuable signs. However, interpreting those signs is less clear-cut than it would appear from reading the press. Additional tools may be needed to refine the accuracy of turning point prediction.

Predicting Turning points: Econometric model

An alternative approach to produce forecasts of turning points in economic activity is to use econometric models. This approach, widely used, embraces two different methods of tackling this matter. On one hand, statistical models are built to foresee future values of economic variables, such as real GDP. On the other hand, models are built to directly predicting the event of interest, in this case, turning points. For the first category of models, predicting turning points is a by-product of day-to-day forecasting. For the second category, it is the very goal of the model.

Econometric models differ substantially from one another in terms of their econometric methodology, the variables that are being forecast, and the importance of judgmental factors.

We refer to three leading building traditions of econometric models. Firstly, the structural models in the Cowles Foundation tradition (see Fair 1994 on this point). Secondly, the vector autoregression (VAR) models, often Baye-sian VARs, in the Litterman 1980 tradition, or Markov-switching VARs in the Hamilton 1899 tradition. Finally, the dynamic factor models, pioneered by Sargent and Sims (1977). In particular, Stock and Watson (1989) use a dynamic factor model to create indices of coincident and leading indicators.

The Cowels tradition modelling usually employs a large number of equations, with each block of equations representing a specific aspect of economic behaviour (consumer behaviour, firm behaviour, and so forth). Commercial forecasting models, like the Penn-MIT model, the Fair model, and the Macro-Advisors model, belong to this category.

Within VARs, the Markov-switching models are very popular. Basically, these models assume that there are two or more states or regimes which might characterise the variable we are interested in modelling. For example, GDP growth might be in a normal state or in a recession state, interest rates might be at low, moderate or high levels. The state of the variable at any time is not deterministic, but depends on its previous state and on the probability that the variable will switch states in the current time period. These transition probabilities in turn may be fixed, or may depend on other variables.

For example, the probability of GDP growth switching out of recession into the normal state might depend on the length of time the economy has already been in recession -the hypothesis of duration dependence-.

On a more general level, the most relevant difference between VAR and structural econometric models is due to their identifying assumptions. In structural econometric models an identification problem can arise in estimating simultaneous equations when it is impossible to distinguish from the data which equation is being estimated. To eliminate this problem, structural models often impose the restriction that variables factored into one block of equations—say, the household block—not be used in other blocks, either contemporaneously or with lags. The proponents of VARs claim that these restrictions have little or no ground in modern general equilibrium theory and prefer models with fewer variables but also fewer restrictions, (Sims 1980).

All these various models embody, implicitly or explicitly, a so-called extrinsic view of business cycles. According to this view, the underlying structure of the economy does not change from a recession to an expansion. The underlying structure is stable and can be described, or at least approximated, by a linear probabilistic model. From the extrinsic point of view, the main difference between recessions and expansions lies in the sign (negative or positive), and possibly in the size and duration, of the shocks that hit the economy (Stock and Watson 1989 and Diebold and Rudebusch 1996 for a discussion of this point).
In contrast, traditional business cycle research tends to view recessions and expansions as being intrinsically distinct; according to this intrinsic view, turning points represent shifts in the economic behavior of agents and are not simply the result of a large negative shock in economic activity.
Note that, regime-switching models somewhat bridge the extrinsic and intrinsic views. These models recognise that the parameters describing the economy may change from a recession to an expansion; at the same time, the models assume a linear probabilistic structure within regimes (Hamilton 1989). Bayesian turning point models also bridge the two views as they assume linearity with time-varying parameters (Zellner and Hong 1988).

In terms of forecasting, one implication of the intrinsic view is that day-to-day forecasting and predicting turning points may be different businesses altogether.

While there is no systematic record of the ability to predict turning points for all existing structural and VAR models, the common wisdom is that most of these models share a dismal record in predicting recessions. Chin, Geweke, and Miller (2000), also proponents of this approach, state that an unwritten rule of forecasting is that accuracy is enhanced by forecasting directly what is of interest, in this case turning points.

Perhaps in response to this poor performance, a different approach to turning point forecasting, pioneered by Estrella and Hardouvelis (1991) and then followed by Estrella and Mishkin (1998) and Chin, Geweke, and Miller (2000), was developed.

On a general level, this approach recognises that the set of variables that helps predict routine ups and downs in output may not necessarily be of much use in predicting recessions. Likewise, statistical models that are used in forecasting future values of economic time series may not be too useful in predicting a specific event, like a recession. Instead of using a linear regression model, the above-mentioned authors directly model the probability of a recession using a probit model. In a probit model the variables included and their respective coefficients are chosen not on the basis of their ability to track past movements in real GDP, but on the basis of their ability to indicate the likelihood of past recessions.

In particular, Chin, Geweke, and Miller (2000) proposed a 'new' probit to predicting turning points that appears able to rectify the shortcomings of time-series models.

Intuitively, the standard time-series models have three limitations: do not directly predict turning points-they predict sequences of variable values over the future; rarely allow for asymmetric movements in down/up swings; do not address the apparent non stationary variations in values at turning points.

They exploited two critical characteristics of the data at turning points[6]. One important characteristic is that the Downward/Upward swings are asymmetric[7]. Downward swings

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6 Chin, Geweke, and Miller (2000) focus on unemployment rate turning points, yet their method can be applied to all economic variables that move with the business cycle. They showed that the model even applies to predicting turning points in consumer price inflation

7 Asymmetry of cycles has been noted by many economists. See, for example, De Long and Summers (1986), Hamilton (1989), Neftci (1984), Rothman (1998), and Sichel (1993).

tend to be relatively long and gradual, while upward swings tend to be relatively short and steep[8]. The other important characteristic is that values at turning points appear non stationary in the sense that both the values at highs and the values at lows tend to vary considerably over time[9].

This model, closely related to Hamilton's, focuses on turning points in the unemployment rate because the authors wanted their method to be useful in real time. That requires that the variable of interest is reported with little delay and is not subject to much revision and that the turning points in the variable can be formally defined ruling out recessions defined by both GDP and NBER.

This model, in predicting probabilities associated with movements in observed economic variables, differs from other existing methods, whether leading-indicator or probit, that do not deal with the asymmetries and non stationarities of the values, and in contrast to Estrella-Mishkin, it uses financial and non financial variables in its probit specifications.

In conclusion, the main strength of the probit class models is that they are geared specifically toward predicting turning points. However, the very strength of the class is also its main weakness. The probit models focus on recessions, and recessions are rare events. Econometric models aimed at tracking real GDP have numerous observations at their disposal. Models aimed at pinning down recessions have only a handful.

Probit models suffer an additional disadvantage relative to econometric models when it comes to policy analysis. As emphasised in the press and in the policy debate, policymakers' actions may affect the likelihood of a recession. Policymakers need to assess how their actions change the probability that the economy may encounter a recession a few quarters down the road. Unfortunately, these issues cannot be addressed quantitatively in the context of probit models, which do not distinguish between policymakers' actions and shocks coming from elsewhere in the economy. Identified econometric models like the VAR, however, allow for such a distinction.

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[8] In the case of UR, on average, downward swings last roughly 51 months, and upward swings last roughly 23 months.

[9] Nonstationarity of turning points is evident in the analysis of Staiger-Stock-Watson(1997) and Pesaran-Potter(1997). In the case of UR, the highs have varied from roughly 6 percent to 11 percent, whereas the lows have 4 varied from roughly 4 to 6 percent.

Conclusions

There appear to be two direct approaches to predicting turning points. One uses leading Indicators and the other uses probit models. The first one is about to construct a regression model for the variable of interest. The model includes, as explanatory variables, leading indicators that are hypothesised to be effective in anticipating turning points. The explanatory variables are lagged, relative to the dependent variable, by an amount of time equal to the forecasting horizon. Models differ in both turning and explanatory variables. For instance, two of the best-known models, which predict recessions as defined by the NBER, are the index of leading indicators maintained by the Conference Board and the experimental leading indicator index of Stock and Watson (1989). In contrast, the Center for International Business Cycle Research (CIBCR) uses separate leading-indicator regression models to predict turning points in several observable economic variables. All of these models have in common that they forecast values for the variable of interest And then calculate turning-point probabilities from the distributions of forecasts.

The second direct approach is to construct a probit model, or some other dichotomous-variable model. The only published works of this kind are the models of Estrella And Mishkin (1998) and Chin, Geweke, and Miller (2000). As Estrella-Mishkin argue, a probit model is the natural one to use for the prediction of turning points.

While, Estrella-Mishkin consider only financial variables for their probit model specifications, Chin, Geweke, and Miller include financial and non-financial variables.

These works strongly suggests that special-purpose models can improve upon standard economic models for the purpose of predicting turning points. The special-purpose models have the properties that they directly predict the object of interest and account for asymmetries in swings and for non stationarities in turning-point values.

However, as the authors reckon, their works leave unanswered two important questions that warrant further research. The first question is, Can direct prediction of turning points be shown in practice to improve standard economic forecasts? Chin, Geweke, and Miller suggest that it may be fruitful to estimate two-regime Standard economic models, one for up swings and one for down swings. That two-regime standard model would then be combined with a turning-point model that indicates the probability of being in one regime versus the other, period by period. Until this is done, it is only conjecture to suggest that turning-point prediction can improve standard economic forecasts.

The second question is, Are the processes for turning points of different important variables related? Chin, Geweke, and Miller suggest that there are regularities in relationships among variables at intermediate (i.e., business cycle) frequencies. It would be worth while to explore, for instance, whether inflation and unemployment turning points are related. In particular, one could inquire whether turning points in unemployment and inflation should be modeled as a joint process. That is far different from analyzing correlations at high frequencies between the two variables, as is commonly done in the literature.

Until this is done, policy makers' expressed concern that a continued down swing in unemployment will lead to an up swing in inflation can not be summarily dismissed. That is because their concern is about intermediate-frequency trajectories and not about high-frequency correlations.

Appendix 1

BOX 1

Leading indicators

i. Average weekly hours of production workers (manufacturing)
ii. Average weekly initial claims for unemployment insurance
iii. Manufacturers' new orders (consumers goods and materials industries)
iv. Vendor performance-slower deliveries diffusion index
v. Contracts and orders for plant and equipment
vi. New private housing units authorised by local building permits
vii. Interest rates spread, 10 year treasury minus federal fund rate
viii. Stock price, 500 common stocks
ix. Money supply M2
x. Index of consumer expectations

Coincident indicators

i. Employees on non-agricultural payrolls
ii. Personal income less transfer payments
iii. Industrial production
iv. Manufacturing and trade sales

Lagging indicators

i. Average duration of unemployment
ii. Ratio of trade inventories to sales
iii. Change in index of labour cost per unit of output
iv. Average prime rate charged by banks
v. Commercial and Industrial loans outstanding
vi. Ratio of consumer instalment credit outstanding to personal income
vii. Change in consumer price index for services

Source: The Conference Board

The box 2 below show the EU turning points determined by Bry and Boschan algorithm:

	Industrial production	**GDP**
Trough:	December 1982	1982 Q4
Peak:	-	1984 Q1
Trough:	-	1984 Q4
Peak:	August 1985	1985 Q4
Trough:	October 1987	1987 Q2
Peak:	August 1990	1990 Q3
Trough:	-	1991 Q2
Peak:	-	1992 Q1
Trough:	June 1993	1993 Q3
Peak:	April 1995	1995 Q1
Trough:	November 1996	1997 Q1
Peak:	February 1998	1998 Q1
Trough:	November 1999	1999 Q1
Peak:	August 2000	2000 Q2

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