Business Cycle Indexes:
Does a Heap of Data Help?

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Abstract

Business cycle indexes are used to get a timely and frequent description of the state of the economy and its likely development in the near future. This paper discusses two methods for constructing business cycle indexes, the traditional NBER method and a recently developed dynamic factor model, and compares these methods for the euro area. The results suggest that a reliable indicator can be constructed from a limited number of series that are selected using economic logic.

Keywords: business cycles indexes, coincident and leading indicators, NBER method, generalized dynamic factor model
JEL-code: C23, E32

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1 Introduction

Business cycle indexes (BCIs) convert complex economic dynamics into one-dimensional figures that are easily tractable and are used to get a timely and frequent description of the state of the economy and to forecast economic activity in the near future. The methodology for constructing BCIs was originally developed at the National Bureau of Economic Research (NBER) in the U.S. in the 1930s and described in the seminal book of Burns and Mitchell (1946). It has since then been widely used (see e.g. Zarnowitz, 1992). In recent years these indexes are maintained and regularly published by The Conference Board (TCB) who have also developed similar indexes for other countries.

A more recent development in the construction of BCIs is the use of *dynamic factor models*. Earlier applications of dynamic factor models are Sargent and Sims (1977) and Geweke (1977). Recent examples are Stock and Watson (1989, 2002), Camba-Mendez, Kapetanios, Smith and Weale (2001), and the *Generalized Dynamic Factor Model* of Forni, Halli, Lippi and Reichlin (2000) and Forni and Lippi (2001).

This paper compares business cycle indexes constructed using the traditional NBER method and the Generalized Dynamic Factor Model (GDFM). Our main goal is to try and determine how selecting a number of variables from a larger data universe affects the ability of the resulting BCI to capture relevant business cycle information. In a recent paper Boivin and Ng (2003) also address this issue and, using simulations, they come to the conclusion that it is possible to select a relatively moderate number of indicators without losing much relevant information.[1] Our paper is largely complementary as we analyze this question in an applied setting and adopt economic logic rather than statistical algorithms to reduce the data set.

After a general introduction to business cycle measurement, we describe the methods under consideration in Section 2. Section 3 presents three BCIs for the euro area. The first index is *EuroTCB*, an index in the NBER tradition based on coincident indexes of The Conference Board for three euro area countries. The second is *EuroCOIN* of Altissimo et al. (2001), an index constructed using the GDFM and the third is our own index *EuroIJR* in which the GDFM is applied to the (limited) set of components of the TCB coincident and the leading indexes for the three euro area countries. Section 4 compares the three business cycle indexes in terms of correlations and chronologies of cyclical peaks and troughs. We find that the three business cycle indexes are very similar in terms of correlations and the dates

[1] Bai and Ng (2002) also find that the number of series need not be very large to get precise factor estimates.

of peaks and troughs are also comparable. The leads and lags around the turning points of euro area GDP are generally modest and none of the three indexes clearly outperforms the other two. Section 5 concludes.

2 Methodology

Business cycles are more or less regular patterns in fluctuations in economic activity, or in the well-known definition of Burns and Mitchel (1946, p3):

> 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.

In other words, expansions and contractions in economic activity are observed in time series of many variables across different sectors of most (market) economies at roughly the same time. This suggests that it is possible to select a limited number of business cycle indicators to capture relevant facts about the business cycle. This is the NBER approach as originally proposed by Burns and Mitchell (1946). Alternatively, a formal statistical model can be formulated to try to directly identify possible underlying 'shocks' that might drive the business cycle.[2] Factor models like the GDFM are part of this latter group.

Burns and Mitchel (1946) define the business cycle in terms of fluctuations in economic activity. However, the choice of a measure of 'economic activity' is not entirely straightforward. The usual choice is GDP, but since GDP is only available at a quarterly frequency extra variables are necessary to establish a monthly chronology. Therefore, the NBER Business Cycle Dating Committee adopts a more general approach in the U.S. by also looking at other (monthly) economic variables.

According to the definition, *contractions* of economic activity are an essential ingredient of business cycles. However, some economic theories predict movements around a permanent component or a 'trend' and many statistical methods require stationary variables. This has

[2]The term 'shock' should not be taken to mean that business cycles are set in motion through economic events such as for example stock market crashes or technology shocks. The shocks in the statistical model are simply the observation that for whatever reason a variable diverges from its long term mean.

given rise to the analysis of fluctuations around a trend, a class of cycles usually referred to as *deviation cycles* or *growth cycles* to distinguish them from the *classical cycle*, which looks at absolute contractions in economic activity. While policy makers are primarily interested in classical cycles, academics tend to focus on deviation cycles (Harding and Pagan, 2000). In this paper we will apply both cycle concepts, as will become clear below.

Given a reference series of economic activity, turning points of business cycles can be determined in levels or deviations from trend. The standard method is to use the algorithm of Bry and Boschan (1971). This algorithm calculates moving averages of different lengths to narrow down the region where the turning points are likely to be located and then pinpoints the exact month where the peak or trough occurred using the original series. The only restrictions are that a full business cycle (peak to peak or trough to trough) should last at least fifteen months, each business cycle phase (peak to trough, trough to peak) should last at least five months and peaks and troughs should alternate.

The NBER method

As mentioned above, the NBER defines U.S. economic activity explicitly in terms of monthly variables, namely employment, personal income, industrial production and manufacturing and trade sales, together making up the composite coincident index. The choice of these variables (in some form) can be traced back to the work of Burns and Mitchel (1946) who studied the cyclical behaviour of a large number of economic variables. Since then, the four components of the coincident index have stood up as a good representation of the reference business cycle. In the selection and evaluation of these variables, the classical cycle concept is used.

Potentially relevant economic variables are evaluated based on how closely they track the cyclical behaviour of the reference series. This can be done by looking at the correlations with the reference series at various leads and lags and to what extent these variables exhibit peaks and troughs at around the same time as the reference series. Consistently leading and lagging variables are then combined into leading and lagging composite indexes. The change in a composite index is calculated as the unweighted average of changes in the components, after normalisation; the level of the index is computed by cumulating the changes from a specified base year.

The indexes depends for a large part on the judgment of the researcher. One has to construct a 'good' reference series based on a measure of 'economic activity', find a way to determine its peaks and troughs and then evaluate whether other variables have a 'close' relationship to the reference series. The degree of subjectiveness of the NBER method has been a motivation to develop more statistically oriented methods. Such statistical methods of course also involve quite a number of (subjective) choices, but generally speaking they do impose more theoretical structure on the problem of measuring business cycles (for better or worse).

The Generalized Dynamic Factor Model

The basic idea of factor models is that a dataset consisting of a large number of stationary time series can be decomposed into a common component and an idiosyncratic component, where the common component is driven by only a few (q) common shocks. The Generalized Dynamic Factor Model can be written as

$$x_{it} = b_{i1}(L)u_{1t} + b_{i2}(L)u_{2t} + \ldots + b_{iq}(L)u_{qt} + \xi_{it} \equiv \chi_{it} + \xi_{it}, \tag{1}$$

where x_{it} is the t-th observation on the i-th time series and L is the lag operator. The dynamic factor loading $b_{ij}(L)$ describes the impact of the j-th common shock u_j on the i-th series. The common shocks and the factor loadings together make up the *common component* χ. After the influence of common shocks has been removed, only the idiosyncratic component ξ remains. Equation (1) makes clear that the model is explicitly dynamic since a common shock can affect a variable with leads or lags. The model is 'generalized' in the sense that contrary to the earlier dynamic factor models such as those of Sargent and Sims (1977) or Geweke (1977), the idiosyncratic components need not be uncorrelated. The factor model is basically a method of rank-reduction, where the information in the large matrix of observations is summarised in the matrix of common components of smaller rank.[3]

As Forni et al. (2000) show, the common component in this model is only uniquely identified in a dataset with an infinite number of observations and time series, but they present an estimator that is reasonably precise for datasets of more modest dimensions. The main identifying assumption is that there is a limited number of common shocks that explain an increasing percentage of the variance of the dataset as the number of time series in the dataset grows, while the importance of the idiosyncratic shocks remains bounded. The common components of Equation (1) can then be estimated by employing principal component analysis in

[3]A full discussion of this method is beyond the scope of this paper. For more details, see e.g. Inklaar and Romp (2003)

the frequency domain. The common component of a series is then the part that is driven by shocks that are common to all series while the remainder is idiosyncratic noise. Abstracting from mathematical complications, the common component of a series will be a sum of linear combinations of all the variables, where the weights on each of the variables is chosen so as to maximize the variance explained by the common component. The common component of GDP is then a logical candidate for a business cycle index. Since GDP (in logs) is rendered stationary by first differencing, the resulting index matches a deviation cycle. However, a trend can be restored by cumulating the differences into an index. One problem in applying this method is that the selection of the number of common shocks is not straightforward.[4] In this paper we will use one of the criteria suggested by Forni et al. (2000), namely that each common shock should explain at least a pre-specified percentage of total variance.

3 Euro area business cycle indexes

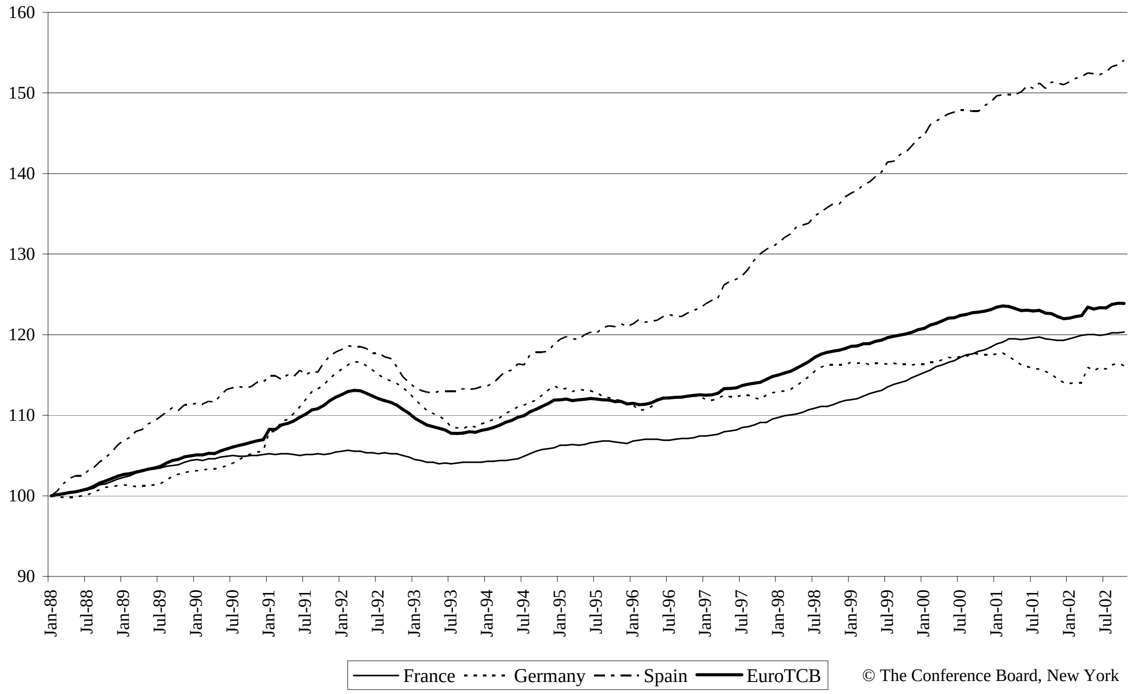
In this paper we compare three business cycle indexes for the euro area: *EuroTCB*, a coincident index constructed along the lines of the NBER methodology, *EuroCOIN*, in which the Generalized Dynamic Factor Model is applied to a large set of data, and the hybrid *EuroIJR*, in which the GDFM is used on the limited set of variables used in the construction of coincident and leading indexes for European countries by TCB.

EuroTCB

The Conference Board (TCB) publishes business cycle indexes for a number of euro area countries on a monthly basis. At present coincident and leading indexes are constructed for France, Germany and Spain. The components of the coincident indexes have been selected based on the components of the U.S. coincident index as well as their ability to match the business cycle turning points of GDP. The leading indexes have been constructed so that they lead the coincident index at business cycle turning points. Appendix A lists the components of the leading and the composite indexes for the three countries. The components of the leading and coincident indexes differ across countries, but they generally contain the same type of time series. The coincident indexes include measures of sales, income, production and employment. The leading indexes usually contain financial variables such as bond yields and share prices, natural leading series like orders for new goods and building permits, and

[4] See also Bai (2003).

Figure 1: The Conference Board indexes for France, Germany and Spain and the euro area index (EuroTCB), 1988-2002 (January 1988=100)



finally surveys of consumer or business confidence. All these series have been selected to match classical cycle turning points in each of the individual countries. It is therefore not clear whether they will provide a good representation of the euro area cycle, but given that these three countries account for about 60 percent of euro area GDP the representativity is probably reasonably good. Besides, these variables have not been selected to match the deviation cycle so good performance in that respect is also not guaranteed.

We construct the EuroTCB index as a weighted average of the coincident indexes of the three euro area countries. As weights we use the share of each country's GDP in 2001 from the GGDC Total Economy Database (2002), which is denominated in U.S. dollars converted at Purchasing Power Parity. Figure 1 shows the coincident indexes for France, Germany and Spain as well as the EuroTCB index for the period 1988-2002.[5] As the figure suggests, the indexes for France and Germany have the largest weight, namely 34 percent and 47 percent respectively.

[5] These indexes are available for a longer period of time, but due to the data availability of EuroCOIN, we focus on this period for comparability.

EuroCOIN

The EuroCOIN index is published monthly by the Centre for Economic Policy Research (CEPR) (`www.cepr.org`). Altissimo et al. (2001) describe the index in detail; we will cover the highlights here. The authors construct an index from a database with monthly observations for 951 series for France, Germany, Spain, and Italy, the Netherlands, Belgium and a number of euro area wide variables. From these 951 they select 246 series to obtain a feasible, real-time index. The series cover a wide range of subjects such as industrial production, prices, interest spreads and surveys. The generalized dynamic factor model is applied to this database, after any necessary first differencing to render the series stationary. The authors include all common shocks that capture 10 percent or more or total variance, which leads to the choice of four factors. The first four dynamic principal components together explain 55 percent of all variance in the data. Altissimo et al. (2001) then use the cyclical part of the common component of euro area GDP as their business cycle index. Due to the stationarity requirement of factor models, GDP is included in growth rates. EuroCOIN is the common component of GDP growth and hence models the deviation cycle of the euro area.

EuroIJR

Our third euro area business cycle index applies the generalized dynamic factor model to the components of the coincident and leading indexes for France, Germany and Spain of TCB. In the construction of this index, which we will refer to as EuroIJR, we combine features from both approaches. On the one hand, we use data that analysts consider to be informative of the cyclical development in euro area countries. The turning points of these series generally lead or coincide with GDP of the country in question. The fact that only a limited number of series enters into the index makes it easier to relate changes in the index to changes in the components and therefore to interpret changes in the index. On the other hand, we use the GDFM to combine these series into an index. This will allow us to conclude whether it is possible to select only a relatively small number of series to analyze classical or deviation cycles without loss of crucial information.

In total 37 variables enter into the coincident and leading indexes of France, Germany and Spain (see the overview in Appendix A). For each country, there are four coincident series. For France, the leading index contains ten indicators, while the corresponding indexes of Germany and Spain have eight and seven respectively. In addition to these variables, we include quarterly GDP growth for the euro area as a whole from the OECD Quarterly

National Accounts. Since we are constructing a monthly index, we apply the quarter-on-quarter growth rate of GDP to each month in the quarter.[6] As a result, when we date the business cycle (classical or deviation), the peak or trough will always be the final month of the relevant quarter. All series are analyzed as normalized exponential growth rates (first differences in logs), since stationarity is a prerequisite to the GDFM. Our data cover the period from February 1987 to October 2002.

As mentioned in the discussion of the GDFM, we apply one of the criteria of Forni et al. (2000) and include common shocks as long as they explain at least five percent of total variance. This leads us to select six common factors that together capture fifty percent of total variance in our dataset.[7] We then use the cyclical frequencies of the common component of euro area GDP as our business cycle index.[8] The EuroIJR index as well as the GDP growth rate is shown in Figure 2. The index is calculated as a two-sided weighted average of all 38 variables (including euro area GDP), where the weights are determined in the GDFM. Although the largest weight is put on developments in euro area GDP itself, all series make a non-negligible contribution to the resulting index. As is the case with EuroCOIN, the common component of GDP growth corresponds to the deviation cycle of the euro area.

4 Comparison

In this section we evaluate our three BCIs for the euro area in terms of the correlation with GDP growth and in terms of cyclical peaks and troughs. In this analysis we look at both peaks and troughs in the classical cycle and the deviation cycle. We define the euro area deviation cycle by the growth rate of euro area GDP and consequently all three BCIs are taken as growth rates, see Figure 3. We define the euro area classical cycle by the level of euro area GDP. Figure 4 shows euro area GDP and the three BCIs as indices with January 1995=100. In both figures the short term fluctuations show differences but overall the similarities between the indexes are striking. Especially the recession of 1993 clearly stands out in all three indexes.

[6] This procedure corresponds to linearly interpolating the *level* of GDP for each month. An alternative would be to interpolate the growth rates instead of the level. There is no strong case for either of these options, but at least for the procedure we choose, it is immediately clear that we do not know the month-to-month developments in GDP, since we assume the same growth rate for each month.

[7] The ten percent norm of Altissimo et al. (2001) leads them to select four factors. However, our index is qualitatively similar whether we select four or six common factors.

[8] We take the cyclical frequencies to be all fluctuations with a period of at least 15 months. The turning points for an index that includes fluctuations at all frequencies are very similar, though.

Figure 2: Growth rates of euro area GDP and EuroIJR(1988-2002)

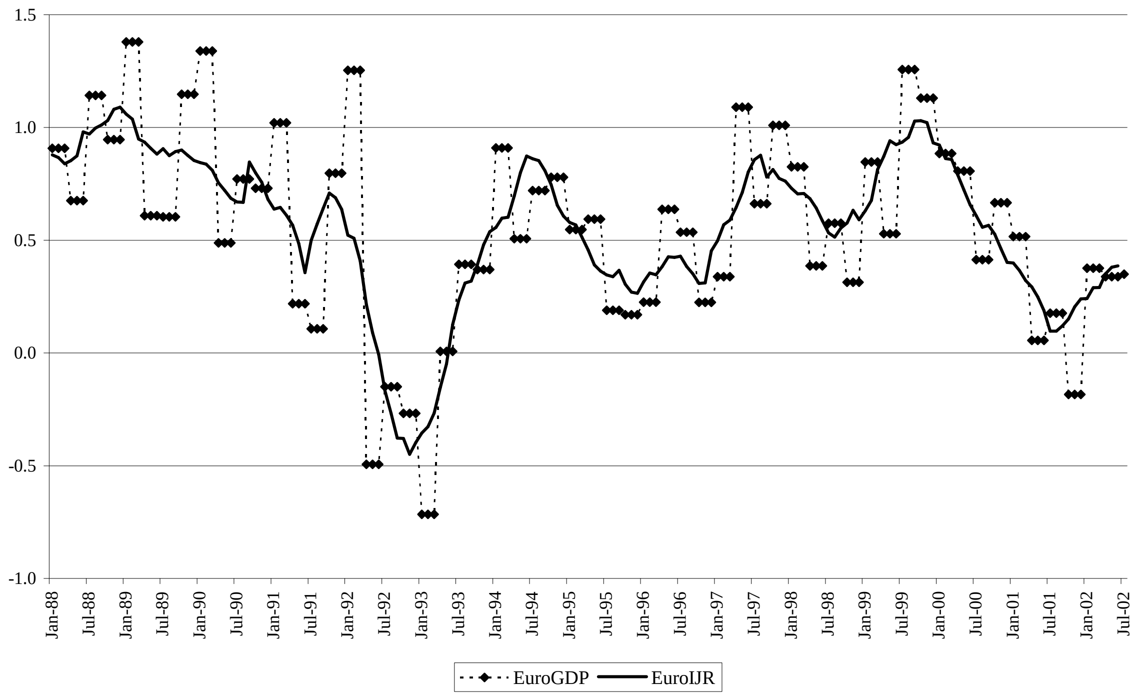


Table 1 shows the correlations between the three indexes in growth rates as well as the change in euro area GDP. These correlations confirm the conclusions from visual inspection by showing large and positive coefficients (all significant at the 1 percent level). In other words, the three indexes all capture a large amount of the variation in euro area GDP.

The notion that the three indexes capture largely the same phenomena receives further confirmation when looking at the turning points of the three indexes and comparing them to the turning points in GDP. To determine the turning points we use the algorithm of Bry and Boschan (1971).[9]

Table 2 shows the turning points of the indexes in levels (cf. Figure 4). These turning points correspond to the turning points of the classical cycle and signal absolute expansions and contractions in economic activity. Table 3 shows the turning points for the growth rates of the indexes (Figure 3). These turning points signal slowdowns and accelerations in economic growth and correspond to the deviation cycle. A turning point of the deviation cycle will generally lead a turning point of the classical cycle since a slowdown in growth usually occurs before growth turns negative. Furthermore, a series generally has more deviation cycle turning

[9]We use the Bry-Boschan algorithm of Mark Watson, converted from Gauss to Matlab.

Figure 3: Euro area business cycle indexes and euro area GDP: growth rates (1988-2002)

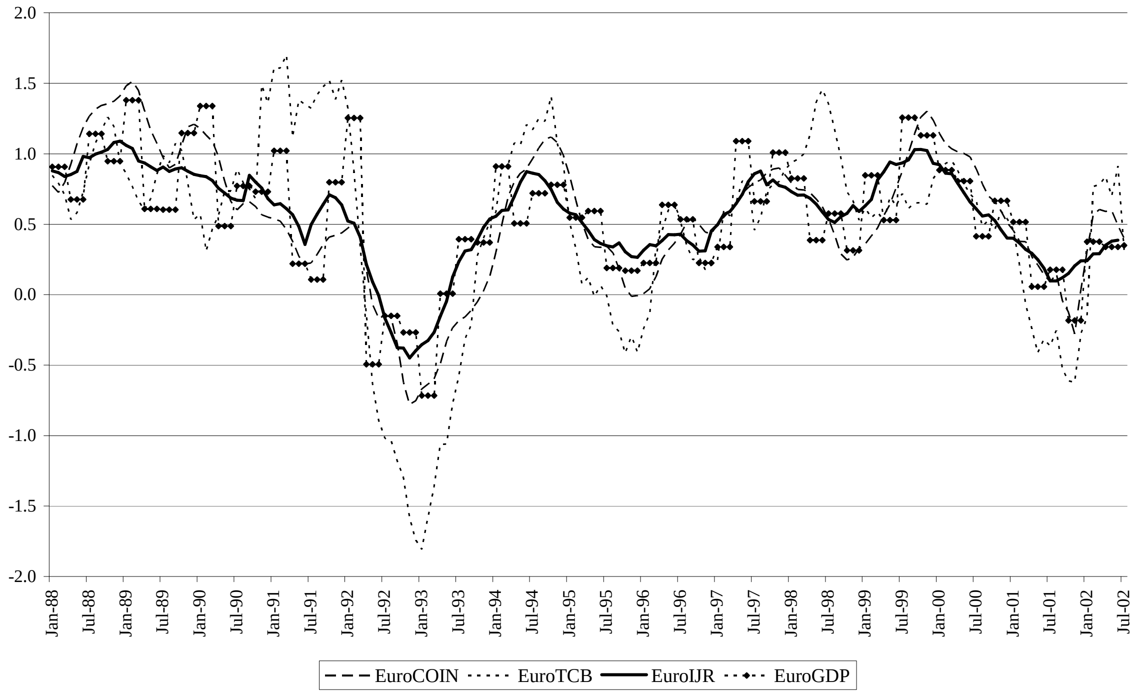


Table 1: Correlation coefficients between euro area GDP growth and Euro area business cycle indexes (growth rates)

	Euro GDP	EuroCOIN	EuroTCB	EuroIJR
Euro GDP				
EuroCOIN	0.80			
EuroTCB	0.68	0.72		
EuroIJR	0.80	0.90	0.78	

Figure 4: Euro area business cycle indexes and euro area GDP: levels, January 1995=100 (1988-2002)

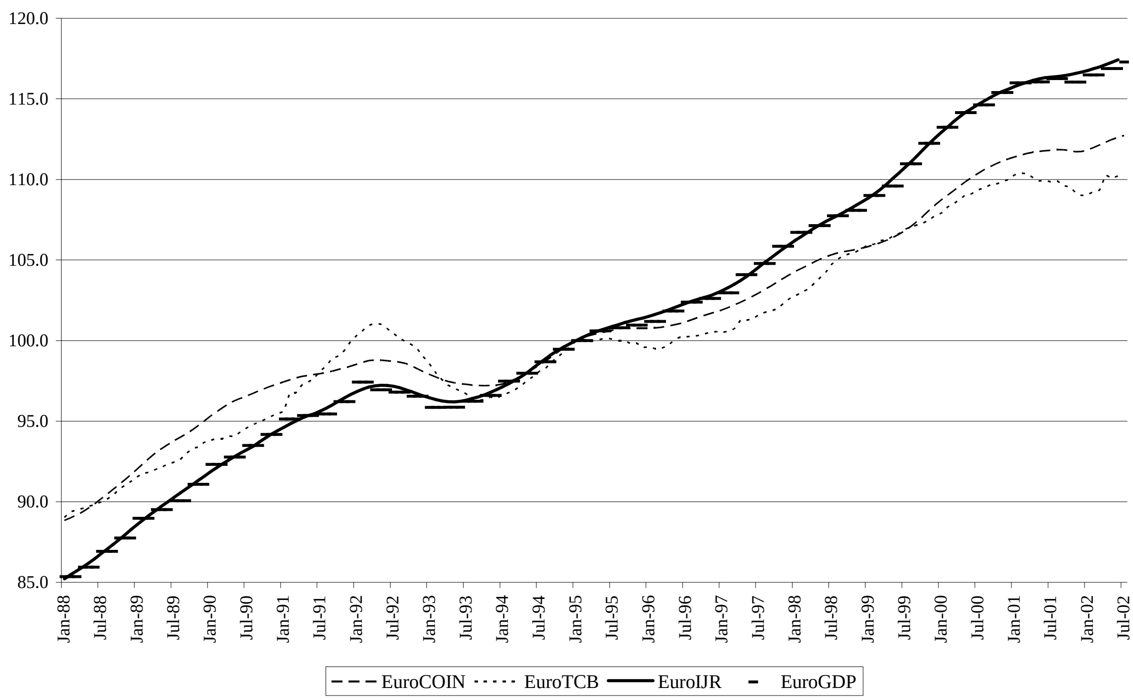


Table 2: Business cycle turning points of euro area GDP and business cycle indexes (levels) and leads/lags relative to euro area GDP

	Peaks and troughs				*Leads/Lags with respect to GDP*		
	EuroGDP	EuroCOIN	EuroTCB	EuroIJR	EuroCOIN	EuroTCB	EuroIJR
Peaks	1992-3	1992-4	1992-3	1992-5	1	0	2
			1995-6			E	
			2001-2			E	
Troughs	1993-4	1993-10	1993-8	1993-5	6	4	1
			1996-2			E	
			2001-12			E	

Notes: '-': lead of x months; '+': lag of x months; 'E': extra peak/trough

points than classical cycle turning points as absolute declines in economic activity are rarer than slowdowns in growth. This is confirmed by comparing the turning points of GDP in Table 2 and Table 3. In the period 1988-2002, GDP showed only one classical cycle, but four deviation cycles.

Tables 2 and 3 show that none of the three indexes perfectly matches the peaks and troughs of the cycles of GDP. However, the similarity between the turning points of the indexes and of GDP is large. Table 2 indicates that the euro area had one classical cycle between March 1992 and April 1994. Our EuroIJR index had its peak two months later and its trough one month later than GDP. The EuroCOIN index lagged one month at the peak and lagged half a year at the trough. The EuroTCB lagged at the trough in 1993 and the index also signaled two additional cycles, in 1995 and 2001. This is also clear from Figure 4 where the EuroTCB index showed negative growth during these months. The other indexes as well as GDP also showed negative growth in 2001, but for a much shorter period. The Bry-Boschan algorithm smoothed these dips and thus did not produce recession signals. So, the EuroTCB index overestimates the number of downturns over this period. This was most serious in 1995-1996 where it is the only index with negative growth.

Table 3 shows the turning points of the euro area deviation cycle and the turning points for (the growth rates) of each of the BCIs. The main problem in correctly identifying the turning points of the deviation cycle of euro area GDP is that the BCIs miss cycles. This problem is most noticeable with the EuroCOIN index which shows a peak at the start of 1989 and a trough only at the end of 1992. EuroTCB and EuroIJR show another trough

Table 3: Business cycle turning points of euro area GDP and business cycle indexes (growth rates) and leads/lags relative to euro area GDP growth

	Peaks and troughs				*Leads/Lags with respect to GDP*		
	EuroGDP	EuroCOIN	EuroTCB	EuroIJR	EuroCOIN	EuroTCB	EuroIJR
Peaks	1990-3	1989-2	1988-10	1988-12	-13	-17	-15
	1992-3		1991-3		M	-12	M
	1994-12	1994-10	1994-10	1994-8	-2	-2	-4
	1997-12	1997-11	1998-6	1997-11	-1	6	-1
	1999-9	1999-11	2000-3	1999-10	2	6	1
Troughs	1989-9		1990-2	1988-3	M	5	-18
	1991-9				M	M	M
	1993-3	1992-11	1993-1	1992-12	-4	-2	-3
	1995-12	1995-11	1995-10	1995-11	-1	-2	-1
	1998-12	1998-10	1999-4	1998-9	-2	4	-3
	2001-12	2001-11	2001-11	2001-10	-1	-1	-2
Average lead/lag					-2.8	-1.0	-5.1
Standard deviation					4.5	7.4	6.7

Notes: '-': lead of x months; '+': lag of x months; 'M': missing peak/trough and peak in 1990 and 1991. Another problem is that the Bry-Boschan algorithm identifies March 1990 as a peak for euro area GDP at the beginning of the sample instead of at the start of 1989 when all three indexes have their peak. The identification problems become noticeably smaller from 1993 onwards, although there are still some considerable leads and lags around peaks and troughs. Although the average lead for EuroIJR is higher than for the other two indexes, all three indexes have an average lead that is smaller than one quarter when the misidentified peak in the early 1990s is excluded. Given that GDP is only available at the quarterly frequency, that is the best possible achievement. In other words, none of the indexes clearly outperforms the other two in terms of leads and lags and the three BCIs are able to track both the classical and the deviation cycle of the euro area.

5 Conclusion

A timely and up-to-date picture of economic circumstances is invaluable for decision makers in both government and business. Since GDP is only released once a quarter and with a considerable lag, earlier and more frequent indexes of the state of economic activity are useful, especially in turbulent economic times.

In this paper we discuss two different methods for constructing business cycle indexes. One the one hand we consider the NBER method in which variables are selected based on a researcher's judgment of how closely the cyclical behaviour of a variable matches that of an index of economic activity such as GDP. On the other hand we look at the generalized dynamic factor model of Forni et al. (2000) that uses statistical criteria to give a variable a larger or smaller weight.

An advantage of the generalized dynamic factor model is that business cycle indexes can be constructed with a relatively smaller number of (judgmental) choices about the components and their weight in the index, since many of those choices are part of the statistical model. One advantage of the NBER method is that the business cycle index is generally constructed from only a limited number of variables. As a result, changes in the index can easily be traced back to the component or components that drive this change. This allows analysts and users to evaluate which part of the economy has caused a recession, say a slowdown in the manufacturing sector or a drop in employment, and which part was less of a factor, such as a drop in sales or income. If the number of components of the index grows too large, this insight is lost.

Using both the NBER method and the generalized dynamic factor model, we construct three business cycle indexes. Our first index is a GDP-weighted average of the business cycle coincident indexes for France, Germany and Spain from The Conference Board constructed according to the NBER method. The second is the euro area index of Altissimo et al. (2001) constructed by applying the generalized dynamic factor model to a dataset with nearly 1000 economic variables. The third index is a hybrid one that uses the 37 components of the Conference Board's coincident and leading indexes for France, Germany and Spain plus euro area GDP and applies the generalized dynamic factor model to weigh and combine these into a business cycle index.

One of the most important uses of a business cycle index is to signal peaks and troughs of classical and deviation cycles. We compare our indexes using that criterion. Although none of the three indexes perfectly matches the turning points of euro area GDP, all three are reasonably close. The correlations between the indexes and GDP are also quite high. These results suggest that it is quite feasible to construct a business cycle index using only a limited number of economic variables as long as these variables are selected using economic logic. In other words, after a careful selection of the variables a heap of data is not necessary to construct an insightful business cycle index.

A Components of The Conference Board's Coincident and Leading Indexes for France, Germany and Spain

France	LEAD	Bond Yield 10 year
France	LEAD	Yield Spread - 10 year minus Day-Day Loan
France	LEAD	Stock Price SBF 250 Index
France	LEAD	Personal Consumption of Manufactured Goods
France	LEAD	Building Permits - Residential
France	LEAD	New Unemployment Claims
France	LEAD	Industrial New Orders
France	LEAD	Consumer Confidence Index
France	LEAD	Change in Stocks
France	LEAD	Ratio Deflator of Manufacturing Value Added to Unit Labor Cost
France	COIN	Retail sales
France	COIN	Industrial Production
France	COIN	Real Imports
France	COIN	Paid Employment
Germany	LEAD	New Orders - Investment Goods
Germany	LEAD	Yield Spread - 10 year minus 3 month
Germany	LEAD	New Orders - Consumer Confidence Index
Germany	LEAD	Change in Inventories
Germany	LEAD	New Orders - Residential Construction
Germany	LEAD	Stock Prices
Germany	LEAD	Gross Enterprise and Property Income
Germany	LEAD	Growth Rate for Consumer Price Index for Services
Germany	COIN	Industrial Production
Germany	COIN	Employment - Number of People Employed
Germany	COIN	Manufacturing Sales
Germany	COIN	Retail sales
Spain	LEAD	Construction Component of Industrial Production (3 month moving average)
Spain	LEAD	Capital Equipment Component of Industrial Production(3 month m.a. s.a.)
Spain	LEAD	Spanish Contribution to euro M2(s.a.)
Spain	LEAD	Spanish Equity Price Index
Spain	LEAD	Long-term Government Bond Yield (Inverted)
Spain	LEAD	Order Books Survey (3 month moving average s.a.)
Spain	LEAD	Job Placings (3 month moving average s.a.)
Spain	COIN	Final Household Consumption (Q)
Spain	COIN	Industrial Production Excluding Construction (3 month moving average)
Spain	COIN	Real Imports (3 month moving average)
Spain	COIN	Retail Sales Survey (s.a.)

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