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FvS Business Cycle Indicator for Germany

Technical Note

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Abstract

The FvS Business Cycle Indicator (FvS-BCI) tracks the actual economic activity in Germany on a monthly basis, based on a set of hard real economic data. Based on the FvS-BCI, we perform the business cycle dating for Germany. This note describes the methodology staying behind the FvS-BCI and the dating procedure.

Zusammenfassung

Der FvS Konjunkturindikator (FvS-KI) bildet die tatsächliche wirtschaftliche Aktivität in Deutschland auf monatlicher Basis ab, basierend auf einer Reihe von harten realwirtschaftlichen Daten. Auf Basis des FvS-KI führen wir die Konjunkturdatierung für Deutschland durch. Im Folgenden beschreiben wir die Methodik, die hinter dem FvS-KI steht, und das Datierungsverfahren.

Methodology

We construct the FvS Business Cycle Indicator (FvS-BCI) for Germany with the final aim to perform the business cycle dating for Germany. Such a business cycle dating procedure is well-established in the United States, where the National Bureau of Economic Research (NBER) documents and officially announces the turning points in the business cycle of the US economy. A similar procedure has been missing so far for Germany.[1]

The NBER's Business Cycle Committee decides on the turning points (trough and peak) in the US business cycle several quarters after the passing of the turning points. The committee waits until a sufficient amount of data is available to avoid the need for major ex-post revisions. The idea is to infer from these data on real GDP (and real Gross Domestic Income, GDI), which the Committee regards as the best single measure of aggregate economic activity.

Following the NBER's approach, we analyze a wide range of economic indicators to better capture the overall development of the German economy. However, we depart from their approach in two important respects. First, we avoid looking at quarterly GDP or GDI data, and instead look at a broader list of monthly indicators, also with data covering only a part of the economy. Second, based on these monthly indicators, we use principal component analysis (PCA) to derive a single and reliable Business Cycle Indicator for Germany to capture swings of the business cycle. These methodological innovations with respect to the NBER's approach are important as they allow us to avoid the issue of repeated data revisions, which is typical for GDP figures. Indeed, as new available surveys come in and methodological improvements are integrated, GDP series need to be revised. This causes sometimes substantial delays in announcing the turning points of the business cycle. Accordingly, using other economic indicators than GDP should reduce the problems caused by the delay.[2] Moreover, by applying PCA and deriving the single BCI, we base our judgement concerning the turning points on a more transparent and comprehensive procedure.

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1 For a thorough economic analysis of our Business Cycle Indicator, see Gehringer, A. and Mayer, T. (2021). Measuring the business cycle chronology with a novel Business Cycle Indicator for Germany. Journal of Business Cycle Research, forthcoming.
2 Anas, J., Billio, M., Ferrara, L., and Lo Luca, M. (2007). A turning point chronology for Euro-zone. University of Venice Working Paper No. 33.

Analytically, if there are *n* explanatory, closely related variables in the regression model, PCA transforms them into *n* uncorrelated new variables (principal components), of the form:

$$
\begin{gathered}
p_1 = \alpha_{11}x_1 + \alpha_{12}x_2 + \cdots + \alpha_{1n}x_n \\
p_2 = \alpha_{21}x_1 + \alpha_{22}x_2 + \cdots + \alpha_{2n}x_n \\
\dots \\
p_n = \alpha_{n1}x_1 + \alpha_{n2}x_2 + \cdots + \alpha_{nn}x_n
\end{gathered}
$$

where x_j, and p_i (with $i, j = 1, \dots, n$) are the original explanatory variables and the newly estimated principal components, respectively, and α_{ij} are estimation coefficients (so called factor loadings) on the *j*th explanatory variable in the *i*th principal component. It is required that the sum of the squares of the coefficients for each component is one:

$$\sum_{j=1}^{n} \alpha_{ij}^2 = 1 \quad \forall \quad i = 1, \dots, n.$$

The principal components are derived in descending order of importance. Moreover, in the case of collinearity of the original variables, the first components will account for much of the variation, whereas the last few principal components will account for little variation and can be discarded. The stronger the correlation between the original variables, the higher is the explanatory power of the first principal components.

To validate PCA, the so-called Kaiser-Mexer-Olkin's (KMO) measure of sampling adequacy can be calculated. KMO takes values between 0 and 1, with relatively high values suggesting that variables have sufficient in common to warrant a PCA. Small KMO values suggest that the sample is insufficiently adequate to apply a PCA.

A potential issue within the framework of the PCA may occur when the underlying time series are affected by exogenous trends and have complex structures, resulting in non-stationary series.[3] The presence of non-stationarity, which may reflect a persistent trend in the series, could increase the value of the variance that is maximized for every principal component, but at the same time deliver poor information by the component. Specifically,

[3] See Schmitt, T.A., Chetalova, D., Schäfer, R., and Guhr, T. (2013). Non-stationarity in financial time series: generic features and tail behavior. *Europhysics Letters* 103(5): 58003 and Zhao, X., and Shang, S. (2016). Principal component analysis for non-stationary time series based on detrended cross-correlation analysis. *Nonlinear Dynamics* 84: 1033-1044.

under non-stationarity, the PCA could result in a few components assigning similar factor loadings to all variables.[4]

We therefore analyse the time-series properties of our data first. If they are non-stationary, we perform the PCA analysis on first-differenced data and recalculate our Business Cycle Indicator, which we then compare with its baseline estimate. Given that a trend is the most important driver of non-stationarity, this exercise should easily reveal how much of a problem the PCA with non-stationary data is in our framework.

In our PCA exercise, we use 20 economic indicators for which we can rely on monthly observations and which together cover the entire breadth of activity in the economy (**Table 1**).

[4] See Lansangan, J.R.G., and Barrios, E.B. (2009). Principal component analysis of nonstationary time series data. *Statistics and Computing*, 19: 173–187.

Table 1: Monthly data used in the principal component analysis

Indicator	*Description of raw series and starting date*
Sales overall, of which:	
Manufacturing	Constant prices, Index, 2015=100, since Jan. 1991
Intermediate goods	Constant prices, Index, 2015=100, since Jan. 1991
Capital goods	Constant prices, Index, 2015=100, since Jan. 1991
Cars & car parts	EUR, since Jan. 1991
Sales domestic, of which:	
Manufacturing	Constant prices, Index, 2015=100, since Jan. 1991
Intermediate goods	Constant prices, Index, 2015=100, since Jan. 1991
Capital goods	Constant prices, Index, 2015=100, since Jan. 1991
Cars & car parts	EUR, since Jan. 1991
Retail trade	Constant prices, Index, 2015=100, since Jan. 1991
Wholesale trade	Constant prices, Index, 2015=100, since Jan. 1994
Employment	No. of persons, domestic concept, since Jan. 1991
Industrial production, of which:	
Intermediate goods	Constant prices, Index, 2015=100, since Jan. 1991
Capital goods	Constant prices, Index, 2015=100, since Jan. 1991
Consumer goods	Constant prices, Index, 2015=100, since Jan. 1991
Electricity, gas, steam & air-cond.	Constant prices, Index, 2015=100, since Jan. 1991
Vehicle registration, trucks	No., since Jan. 1991
Vehicle turnover	Constant prices, Index, 2015=100, since Jan. 1994
International trade, of which:	
Import value	EUR, since Jan. 1991
Export value	EUR, since Jan. 1991
Service trade, turnover	Constant prices, Index 2015=100, since Jan. 1994

Given that we use our BCI for the inspection of the past business cycle performance, we focus on hard economic data only, which deem to reflect the actual economic situation of the real economy. Accordingly, our data set does not include financial series, like the stock market index, interest rates or exchange rates, which undeniably might send important cyclical signals, but by their nature are rather volatile around the cycle. This could contribute to an undesired noisiness of the incoming signals. We also do not consider survey information, like the purchasing manager index or different sentiment or confidence indicators, given that they often send premature or exaggerated signals on the cyclical state of the economy.

We use the largest possible set of hard-data indicators. All raw series are calendar and seasonally adjusted. We additionally use smoothed data, which are calculated as centered moving averages over one-year periods. Since PCA is scale sensitive, we index all time series to January 2019 = 100.

The longest data series are available back to 1991, but some series are available only starting in 2008 (international trade data). For this reason, the workable version of our monthly BCI, which we will update on a regular basis, is available from January 2008. However, to validate our model prior to 2008 we compare the performance of the FvS-BCI with quarterly real GDP data back to 1991.Our PCA estimates show that the first principal component is responsible for almost 74% of variation in our set of explanatory variables.

In **Table 2**, we report the factor loadings corresponding to each variable from the first principal component. Each of the remaining 18 principal components is negligible, since their individual contribution to the overall sample variation is under 1%. Hence, we construct our FvS-BCI based on the first principal component.

Since the squares of the estimated coefficients for a principal component add up to one, we use the coefficients of the first principal component to weigh the respective explanatory variables. Thus, the FvS-BCI is a weighted average of our monthly indicators.

As discussed above, our operational version of the Indicator, which we will continue to update on a monthly basis, is available since 2008. To determine a historical record of recessions of the German economy since 1991 on a monthly basis, we calculate a monthly series for the BCI for the period 1991-2007 based on estimates with the restricted set of data as explained in the previous section and splice this series with the series calculated with the full set of data as of 2008.

Based on this combined monthly series of the FvS-BCI, we inspect the Indicator to determine the monthly dates of the turning points in the business cycle starting in 1991. A recession from peak to trough is identified when the BCI shows a sustained decline followed by a sustained recovery.

In our dating exercise, we implement raw FvS-BCI series, rather than the smoothed one. In doing so, we aim at avoiding the lag in inspecting economic activity, which typically exists when using the smoothed series.[5]

[5] See Zhao, Y. (2020). Predicting U.S. business cycle turning points using real-time diffusion indexes based on a large data set. *Journal of Business Cycle Research* 16: 77-97.

Table 2: Factor loading of the first principal component

Indicator	Factor loading
Sales overall, of which:	
Manufacturing	0.2666
Intermediate goods	0.2487
Capital goods	0.2661
Cars & car parts	0.2570
Sales domestic, of which:	
Manufacturing	0.2117
Intermediate goods	0.1989
Capital goods	0.2455
Cars & car parts	0.2439
Retail trade	0.1644
Wholesale trade	0.1982
Employment	0.1907
Industrial production, of which:	
Intermediate goods	0.2513
Capital goods	0.2558
Consumer goods	0.2390
Electricity, gas, steam & air-cond.	0.0552
Vehicle registration, trucks	0.2421
Vehicle turnover	0.2049
International trade, of which:	
Import volume	0.2404
Export volume	0.2525
Service trade, turnover	0.1114

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