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Indicator-based estimates of the output gap in the euro area

Sebastian Weiske
(Staff of the German Council of Economic Experts)

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German Council of Economic Experts†

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Abstract

The output gap is a key variable of business cycle analysis and policy. Obtaining reliable estimates for it, is very difficult, though. Most real-time estimates are frequently revised over time. The idea of this paper is to use various indicators, for example from business surveys, that (i) were highly correlated with the output gap in the past and (ii) that are ideally not subject to revisions. According to a real-time analysis, indicator-based estimates prove to be more reliable than estimates from international institutions. Currently, estimates point to positive output gaps in the euro area.

Keywords: Business Cycles, Output Gap, Real-time Estimation, Business Survey Data

JEL Codes: E32, E37, E6

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†Staff of the German Council of Economic Experts. Address: Gustav-Stresemann-Ring 11, 65189 Wiesbaden, Germany. E-mail: sebastian.weiske@svr-wirtschaft.de.

1 Introduction

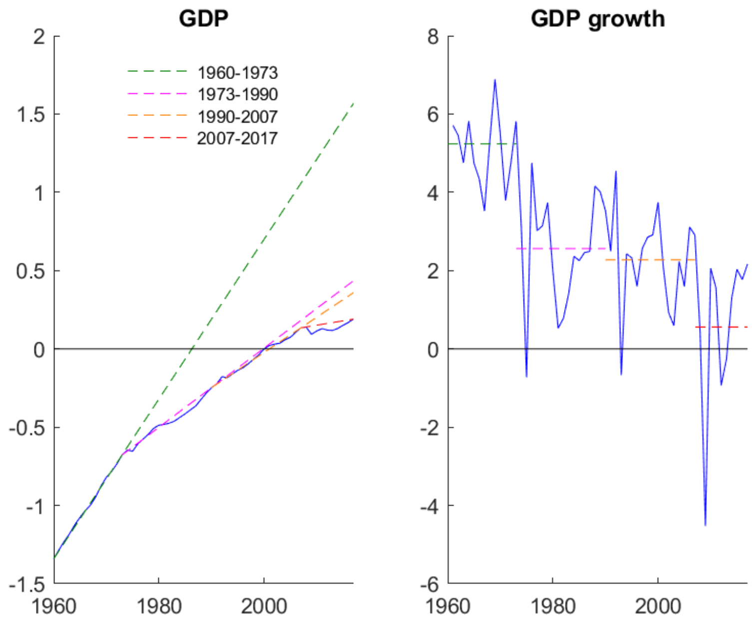
The output gap is an important figure in macroeconomics. It measures the percentage deviation of gross domestic product (GDP) from its potential level. The output gap informs about (i) the current stage of the business cycle, (ii) the amount of slack in the economy and (iii) the inflationary pressure to be expected. Output gaps are further used in surveillance of fiscal rules (Deutsche Bundesbank, 2014).

But the usefulness of the output gap for economic policy is limited by the difficulties of obtaining reliable real-time estimates (Orphanides and van Norden, 2002). Measuring the output gap in real time requires distinguishing permanent (structural) from temporary (cyclical) factors. Very often it is not obvious whether changes in economic activity are permanent or temporary. This makes the estimation of the output gap a relatively difficult task. Coibion et al. (2017) find for the United States that different estimates of potential GDP tend to react to demand shocks, which should have no impact on the potential in theory.

In 2017, GDP in the euro area (12 countries) was 16 percent below its pre-crisis trend between 1990 and 2007. This may suggest that a significant amount of slack has remained in the economy. Such an extrapolation of linear growth trend ignores, however, that trend or potential growth is changing over time. In fact, trend growth has fallen over the last decades (Figure 1). Compared with the extrapolated growth path between 1960-1973, when average growth was about five percent, today's GDP level is 75% lower. Such a number would be hardly considered a reasonable estimate of the output gap.

The secular decline in productivity growth is well documented for many industrial countries, among others the United States (Fernald, 2015). Studies that filter GDP using an unobserved components model find evidence for a significantly lower trend growth rate in the United States compared to the early 2000s (Luo and Startz, 2014; Antolin-Diaz et al., 2017; Grant and Chan, 2017). Recently, GDP growth in the United States and the euro area has rebounded somewhat, but it remains an open question whether this development is permanent.

There are different estimation methods for the output gap. An approach used by many international organizations builds on an aggregate production function. Potential GDP is decomposed in its production inputs, mainly capital and labor, and a residual - total factor productivity (TFP). Labor input, in particular, is modelled in great detail. See for example Breuer and Elstner (2017). Other approaches determine the trend of GDP instead of its potential, using standard filter methods (Hodrick and Prescott, 1997; Baxter and King, 1999; Christiano and Fitzgerald, 2003). GDP is decomposed in a trend and in



y-axis, left: $\ln(GDP_{2010}) = 0$. y-axis, right: percent. Euro area (12 member states, including West-Germany until 1991). Solid line, left: $\ln(GDP_t)$. Solid line, right: $\Delta \ln(GDP_t)$. Dashed lines: Trend GDP (growth).

Figure 1: GDP Growth Trends in the Euro Area

a cyclical component, which serves as a proxy for the output gap. Both approaches have in common that their real-time estimates undergo significant revisions over time.

One way to obtain more reliable estimates is to use indicators, in particular business surveys, that are not subject to large revisions, unlike data from national accounts, such as GDP for example. In these surveys companies are asked, among others, about their current level of capacity utilization or whether insufficient demand is limiting their production. These indicators can be used together with GDP data for the estimation of the output gap (ECB, 2015; IfW, 2018).

This paper considers a wide range of indicators that should provide useful information about the business cycle. These indicators include business survey data, sentiment indicators, investment and unemployment rates, different inflation measures and recession indicators such as the wage share or the term spread. In total, 37 different indicators are used in estimation. They are aggregated using two different weighting schemes. First, the correlation of each indicator with the output gap in the past is calculated. Indicators are then weighted based on these correlations. Second, a factor model approach is employed. This method has been proposed for estimation of the output gap using many different indicators (Pybus, 2011). The factor is estimated via principal components.

The output gap is estimated for Germany, France, Italy and Spain over the period 1991Q1 to 2018Q3. Estimates point to a positive output gap for all four countries in 2018. Results for both weighting schemes are very similar. They suggest that the economic expansion in the euro area, like in the United States, is already advanced. This does not necessarily mean, however, that a downturn or a recession is about to come. For the euro area the results suggest that growth rates of more than two percent as in 2017 should not be expected in the medium term unless potential growth rebounds.

A real-time analysis shows that the estimates from the factor model undergo only minor revisions over time, whereas the estimates from the European Commission, the IMF, or the OECD have been much less reliable in the past. For France, Italy and Spain differences are large, whereas for Germany the factor model provides no improvement compared to the estimates from the institutions. In particular, the model is able to account for the economic boom phases 2000/01 and 2006/07 in real time. One reason is the use of survey data, which is in general not subject to revisions. Another reason is that the factor model exploits the cross-section dimension of the data, while filter methods face the problem that data points at the end of the estimation period receive a large weight, which may result in sizable revisions later. For Spain, the factor model estimates are nevertheless subject to considerable revisions. This is mainly due to the fact that the estimated factor is scaled to the standard deviation of the output gap estimates from international institutions. This standard deviation has steadily increased for Spain over the last 15 years. With a constant scaling factor, the revisions of the factor model estimate would have been much smaller.

A major drawback of indicator-based output gap estimates is that the interpretation of the implied potential growth rate is rather difficult. First, in contrast to the production function approach based on growth accounting, the composition of potential growth is unclear. Second, the potential growth rate implied by the output gap estimate is generally very volatile. In this paper, I propose a way to smooth the implied potential growth rate. In particular, the 7-year moving average of the unsmoothed potential growth rate is calculated. This moving average is then used to recalculate the output gap. This results in a smoother and more realistic potential growth rate, which can be more easily interpreted. The real-time performance of the factor model is only slightly affected by this smoothing.

Section 2 describes the indicators and presents two different weighting schemes for estimating the output gap. Section 3 evaluates the performance of the factor model in real time. Section 4 considers some robustness checks. Section 5 concludes.

2 Estimating the output gap

There are several studies that use business survey data, such as the fraction of industrial firms reporting insufficient demand (ECB, 2015) or the current level of capacity utilization in manufacturing (IfW, 2018), in order to estimate the output gap. Pybus (2011) uses slightly more than 10 indicators in his output gap estimation for the UK, among others, several survey indicators, earnings growth, unit labor costs and the unemployment gap. De Waziers (2018) uses 8 different business cycle indicators in a study for Germany, France, Italy and Spain.

I follow these two papers and consider a large set of indicators that should provide useful information about the business cycle. Some indicators like the capacity utilization rate serve as a natural proxy for the output gap. Other indicators like investment have been found to be more volatile than GDP over the business cycle. Investment increases more strongly than output during expansions, whereas it experiences a larger drop during recessions. This pattern is consistent with business cycle theory. See for example King and Rebelo (1999). Investment as a share of GDP should therefore be positively correlated with the output gap. Sentiment indicators should also be procyclical, in accordance with modern demand-sided business cycle theories (Lorenzoni, 2009), whereas prices and wages should rise in response to positive output gaps, according to a standard Phillips curve relationship.

The different indicators can be grouped into six categories: (i) survey-based indicators in the industry sector, (ii) survey-based indicators in the service sector, (iii) investment rates from national accounts, (iv) economic sentiment indicators for different sectors, (v) various price and wage inflation measures and (vi) other indicators. Table 1 gives an overview about the 37 indicators that are used in estimation.

Some indicators are subject to trends and need to be detrended first, in order to extract their cyclical components. The detrending is done by substracting from a particular variable its 7-year moving average. There are of course more sophisticated filtering methods than this simple detrending. The advantage of a one-sided filter is that it is not subject to later revisions. Detrending concerns investment rates, core inflation, price deflators, unit labor costs and the unemployment rate. Not removing the trend components would leave these variables less useful for estimating the cyclical component of output.

This paper does not arbitrarily preselect indicators that seem to be best suited for estimating the output gap. The analysis in this paper instead relies on two different weighting schemes that follow the same idea: the output gap is obtained as a linear

Table 1: Indicators

Category	Indicator	Trend	Unit
Industry	Current level of capacity utilization	no	%
	New orders in recent months	no	balance
	Duration of production assured by current order books	no	months
	Export expectations for the months ahead	no	balance
	Assessment of current production capacity	no	balance
	Factors limiting the production - insufficient demand	no	%
	Factors limiting the production - shortage of labor	no	%
	Production development observed over the past 3 months	no	balance
	Employment expectations over the next 3 months	no	balance
	Assessment of order-book levels	no	balance
	Assessment of the current level of stocks of finished products	no	balance
	Production expectations over the next 3 months	no	balance
	Selling price expectations over the next 3 months	no	balance
Services	Business situation development over the past 3 months	no	balance
	Evolution of demand over the past 3 months	no	balance
	Expectation of the demand over the next 3 months	no	balance
	Evolution of employment over the past 3 months	no	balance
	Expectations of the employment over the next 3 months	no	balance
	Expectations of the prices over the next 3 months	no	balance
Investment	GFCF: total assets (% of GDP)	yes	%
	GFCF: machinery and equipment and weap. sys. (% of GDP)	yes	%
	GFCF: total construction (% of GDP)	yes	%
Sentiment	Economic sentiment indicator	no	balance
	Construction confidence indicator	no	balance
	Industrial confidence indicator	no	balance
	Retail confidence indicator	no	balance
	Consumer confidence indicator	no	balance
	Services confidence indicator	no	balance
Prices/Wages	Consumer prices: all items non-food, non-energy (y-o-y change)	yes	%
	Unit labor costs: based on persons (y-o-y change)	yes	%
	Implicit price deflator: GDP (y-o-y change)	yes	%
	Implicit price deflator: private consumption (y-o-y change)	yes	%
	Implicit price deflator: GFCF (y-o-y change)	yes	%
Other	Wage share: compensation of employees (% of GDP)	no	%
	Unemployment (% of active population)	yes	%
	Yield curve (10-y. gov. bond yield minus 3-m. interest rates)	no	pp.
	Composite Leading Indicator (OECD)	no	balance

GFCF: gross fixed capital formation. GDP: gross domestic product. The frequency of indicators is either monthly or quarterly. Investment and unemployment data is seasonally and calendar-day adjusted. Data on prices, wages and interest rates is unadjusted. The other data series are seasonally adjusted. Data detrended by one-sided 7-year moving average. Sources: European Commission, Eurostat, OECD.

combination of indicators. The two schemes differ with respect to the weights that are used in calculating the output gap. The first scheme weights indicators according to their correlation with the output gap in the past. Variables that were highly correlated with the output gap in the past obtain a large weight.[1] The second scheme weights indicators such that the total variance explained by a linear combination of indicators is maximized.

Correlation-weighted mean Table 2 shows the correlation of selected indicators with the output gap estimated by the European Commission in May 2018. The period considered is 1991-2010. Years later than 2010 are ignored in the calculation, given that real-time estimates of the output gap are subject to considerable revisions over time. Capacity utilization rates comove with the output gap. The correlation coefficients lie between 0.6 and 0.8. Other survey indicators also display a strong correlation with the output gap. Price expectations in the service sector, for example, have a correlation with the output gap of more than 0.8 in all four countries. There are differences between Germany and the other three countries regarding investment rates. In Germany, investment in equipment is highly procyclical (0.7), whereas investment in construction is more or less acyclical (0.2). By contrast, investment in construction is highly correlated with the output gap in France, Italy and Spain (0.7-0.9). Sentiment indicators also show a strong correlation and seem to be very informative about future output gaps. Price indicators, however, show only a small contemporaneous correlation with the output gap. Only for France and Spain, correlation coefficients are somewhat higher. Core inflation and unit labor costs are lagging behind the output gap. Indicators, such as the yield curve or the unemployment gap, are countercyclical. The unemployment gap is calculated as the deviation of the unemployment rate from its 7-year moving average. This is only a rough measure of the trend unemployment rate, or NAIRU. For Germany, this unemployment gap measure is hardly correlated with the output gap (-0.2), unlike for France, Italy and Spain (-0.9).

Indicators display different scales. Some are expressed as balances, others as percentages of GDP or as year-over-year growth rates. Therefore, indicators are normalized to zero mean and unit variance. For indicator i we have

$$x_{i,t}^{*} = \frac{x_{i,t} - \bar{x}_i}{\sigma_i}, \tag{1}$$

with $\bar{x}_i = \frac{1}{T}\sum_{t=1}^{T} x_{i,t}$ and $\sigma_i = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}(x_{i,t} - \bar{x}_i)^2}$. The correlation-weighted output

[1] Variables that display a strong negative correlation with the output gap obtain a large negative weight.

Table 2: Correlation of selected indicators with the output gap

Indicator	Germany			France			Italy			Spain		
	-1	0	+1	-1	0	+1	-1	0	+1	-1	0	+1
Capacity utilization	0.3	**0.6**	-0.3	0.5	**0.7**	0.4	0.6	**0.8**	0.3	0.8	**0.8**	0.5
Order-book levels	0.3	**0.3**	-0.5	0.6	**0.6**	0.0	0.6	**0.6**	0.0	0.7	**0.5**	0.3
Labor shortage	0.1	**0.5**	-0.1	0.4	**0.6**	0.5	0.7	**0.7**	0.5	0.7	**0.8**	0.7
Services: price expectations	0.2	**0.8**	0.1	0.6	**0.8**	0.4	0.7	**0.8**	0.5	0.9	**0.9**	0.8
Investment: equipment	0.4	**0.7**	0.1	0.5	**0.6**	0.2	0.6	**0.7**	0.4	0.6	**0.4**	0.1
Investment: construction	0.0	**0.2**	0.3	0.7	**0.9**	0.9	0.6	**0.8**	0.8	0.9	**0.9**	0.8
Sentiment: industry	0.3	**0.3**	-0.7	0.6	**0.5**	-0.0	0.6	**0.5**	-0.1	0.6	**0.4**	0.1
Sentiment: consumer	0.4	**0.4**	-0.4	**0.7**	0.6	0.2	**0.7**	0.5	0.2	**0.8**	0.5	0.1
Core inflation	0.0	**0.4**	0.5	0.4	**0.5**	0.7	-0.3	**0.0**	0.2	0.2	**0.4**	0.5
Unit labor costs	-0.3	**0.1**	0.7	0.4	**0.5**	0.8	0.2	**0.3**	0.6	0.6	**0.7**	0.7
Yield curve	-0.2	**-0.7**	-0.6	0.2	**-0.2**	-0.3	-0.4	**-0.7**	-0.6	-0.5	**-0.6**	-0.6
Insufficient demand	-0.3	**-0.5**	0.3	-0.5	**-0.8**	-0.4	-0.6	**-0.7**	-0.2	-0.8	**-0.8**	-0.7
Unemployment rate	-0.0	**-0.2**	0.1	-0.7	**-0.9**	-0.7	-0.7	**-0.9**	-0.8	-0.8	**-0.9**	-0.7

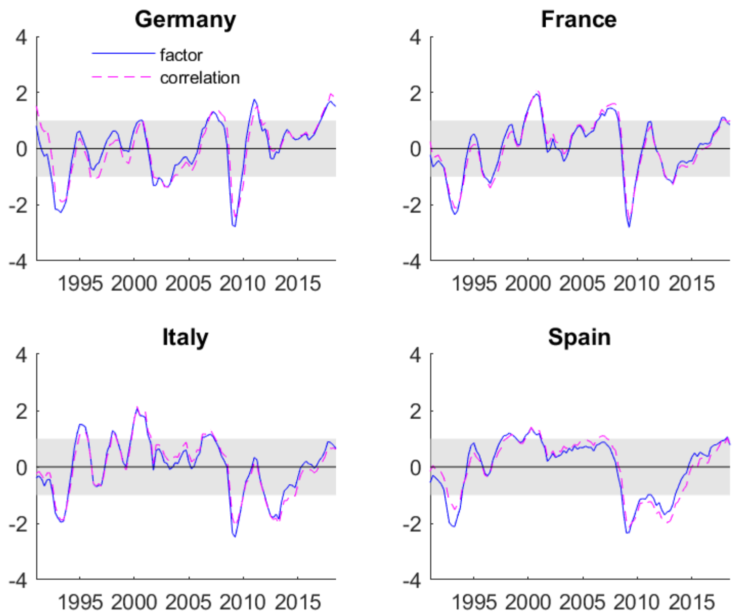
Correlation with the output gap estimate from the European Commission as of May 2018: $corr(x_{i,t+s}, \widehat{gap}_t^{EC})$ with $s = -1, 0, 1$. Period: 1991-2010. Contemporaneous correlations bold. Numbers ≥ 0.5 in green. Numbers ≤ -0.5 in red. Numbers rounded to one digit.

gap is calculated as follows

$$\widehat{gap}_t = \frac{\sum_{i=1}^{N} \varrho_i x_{i,t}^*}{\sum_{i=1}^{N} |\varrho_i|}, \tag{2}$$

where ϱ_i is the correlation between indicator i and the average output gap estimate from the European Commission, the IMF and the OECD as of 2018.

Figure 2 shows the resulting output gap estimates. Output gaps have all zero mean and unit variance. The estimates are consistent with business cycle chronologies for the euro area (CEPR, 2015) and Germany (SVR, 2017). Two boom periods are identified: 2000/01 and 2006/07. Currently, the estimated output gap for Germany reaches an all-time high. For the other three countries, output gaps are also relatively high, albeit still somewhat lower than during the early and mid 2000s. This is consistent with the view that the economic recovery in these countries is still lagging slightly behind Germany. The estimates also shed some light on business cycle asymmetries between the four countries. Despite the bust of the dotcom bubble in 2000 and the growth slowdown that followed in most advanced economies, output gaps for France, Italy and Spain remained positive during the early 2000s. At the same time, Germany had a significantly negative output gap. Large discrepancies between countries existed during the euro debt crisis 2009-2013. Output gaps remained in negative territory for many years in France, Italy and Spain and turned positive not before 2015, whereas the output gap has been positive in Germany for most of the time since the end of the recession 2008/09.



Output gap estimates $\widehat{gap}_t$ are normalized (zero mean and unit variance). Solid lines: estimate based on factor model. Dashed lines: estimate based on correlation weights. 1991Q1-2018Q3.

Figure 2: Estimated Output Gaps

Factor model For many years factor models have been used in macroeconomic forecasting (Stock and Watson, 2002). They allow for incorporating a large set of variables, while keeping the econometric model parsimonious. By that they proved to be an efficient forecasting tool. But factor models can also be used for estimating the output gap (Pybus, 2011). The idea is to identify the linear combination of indicators that accounts for the maximum of the total variance.

Let $X^* = \begin{bmatrix} x_1^* & \dots & x_t^* & \dots & x_T^* \end{bmatrix}$ with $x_t^* = \begin{bmatrix} x_{1,t}^* & \dots & x_{i,t}^* & \dots & x_{N,t}^* \end{bmatrix}'$ be the matrix containing the normalized indicators. The output gap from the factor model is the first principal component of system X^*

$$\widehat{gap}_t = w' x_t^*, \tag{3}$$

where the factor loadings $w = \begin{bmatrix} w_1 & \dots w_i & \dots & w_N \end{bmatrix}'$ are chosen to maximize the variance of the factor $w'X^*$

$$w = \arg\max_{\omega}\{\omega'\Sigma\omega\}, \tag{4}$$

subject to $\sum_{i=1}^{N} \omega_i^2 = 1$. Here, $\Sigma = \mathbb{E}[X^*(X^*)']$ denotes the covariance matrix of X^*.[2]

[2]The factor loadings w' can be found through a eigendecomposition of the covariance matrix $\Sigma = \Gamma\Lambda\Gamma'$,

Table 3: Factor loadings and variance explained

Indicator	GER	FRA	ITA	ESP
Capacity utilization	0.19	0.17	0.20	0.18
Order-book levels	0.23	0.21	0.23	0.20
Labor shortage	0.16	0.10	0.16	0.11
Services: price expectations	0.19	0.17	0.16	0.17
Investment: equipment	0.12	0.14	0.20	0.16
Investment: construction	0.09	0.10	0.13	0.17
Sentiment: industry	0.23	0.21	0.22	0.20
Sentiment: consumer	0.21	0.19	0.17	0.18
Core inflation	-0.06	0.03	-0.04	0.02
Unit labor costs	-0.12	0.00	-0.01	0.15
Yield curve	0.00	0.02	-0.08	-0.04
Insufficient demand	-0.20	-0.18	-0.19	-0.18
Unemployment rate	-0.06	-0.13	-0.11	-0.19
Variance explained by output gap	0.50	0.54	0.51	0.61

GER: Germany, FRA: France, ITA: Italy, ESP: Spain. Factor loadings: w_i. Variance explained by first principal component $\frac{\lambda_1}{\sum_{i=1}^{N}\lambda_i}$, where λ_1 is the largest eigenvalue from the eigendecomposition $\Sigma = \Gamma\Lambda\Gamma'$, where $\Sigma = \mathbb{E}[X^*(X^*)']$.

The output gap is thus the linear combination of indicators with maximum variance. Table 3 shows some of factor loadings. The estimated output gaps account for slightly more than 50% of the total variance of indicators for the countries considered in this analysis.[3] The remaining variance of indicators can thus be interpreted as idiosyncratic variations that are unrelated to the business cycle, as measured by the output gap. Estimates based on the factor model are very similar to the correlation-weighted estimates (Figure 2).[4]

For a reasonable interpretation of the estimated output gaps two practical issues need to be addressed. The first issue concerns the scaling of the output gap, the second issue is about the implications for potential growth.

Scaling The estimates of the output gap so far allow for qualitative statements ("The output gap is historically high/low."). But they do not allow for quantitative statements ("The output gap is at X%."). For a better interpretation, estimates can be scaled to match the standard deviation of output gaps from international institutions. Let $\widetilde{\sigma}$ be the

where Λ is a diagonal matrix containing the eigenvalues in descending order and Γ is a matrix containing the corresponding eigenvectors. The sample covariance matrix is $X^*(X^*)'/T$. The principal factor loadings w' equal the eigenvector associated with the largest eigenvalue λ_1.

[3]The variance of X^* that is explained by the first principal component is given by $\frac{\lambda_1}{\sum_{i=1}^{N}\lambda_i}$.

[4]An expectation-maximizing algorithm is used in order to deal with missing observations (Stock and Watson, 2002).

average standard deviation of the output gap estimates from the European Commission, the IMF and the OECD. The scaled output gap is then $\widehat{gap}_t^{scaled} = \tilde{\sigma}\widehat{gap}_t$. See for example Pybus (2011). For 2018, this results in output gaps of 2,6% for Germany, 1,9% for France, 2,3% for Italy and 5,1% for Spain. These numbers are considerably higher than the estimates from the international institutions.[5] The large number for Spain reflects the high standard deviation of the output gap.[6] Using a scaling factor of two for all four countries would yield output gap estimates of 3,1% for Germany, 2,5% for France, 2,2% for Italy and 2,6% for Spain.

Smoothing A problem with indicator-based output gaps is that the implied potential growth rates are very volatile and hard to interpret (Pybus, 2011; De Waziers, 2018). This unappealing feature of indicator-based estimates can be addressed by the following procedure. First, consider the growth decomposition of GDP

$$\Delta y_t = \Delta g_t + \Delta\widehat{gap}_t, \tag{5}$$

where $y_t = \ln(Y_t)$ is the logarithm of GDP, $g_t = \ln(G_t)$ is the logarithm of the trend component (or potential), and $\widehat{gap}_t = \ln(Y_t/G_t)$ is the scaled output gap from above. The implied potential growth estimate, Δg_t, is the difference between the GDP growth rate, Δy_t, and the percentage point change in the estimated output gap, $\Delta\widehat{gap}_t$. Second, a new series for potential growth is constructed as follows

$$\Delta g_t^{ma} = \frac{1}{2q+1}\sum_{s=-q}^{q}\Delta g_t, \tag{6}$$

where Δg_t^{ma} is the two-sided moving average of the unsmoothed potential growth rate Δg_t. The length of the smoothing window can be set to 7 years (28 quarters), for example. Third, the smoothed output gap is then calculated recursively

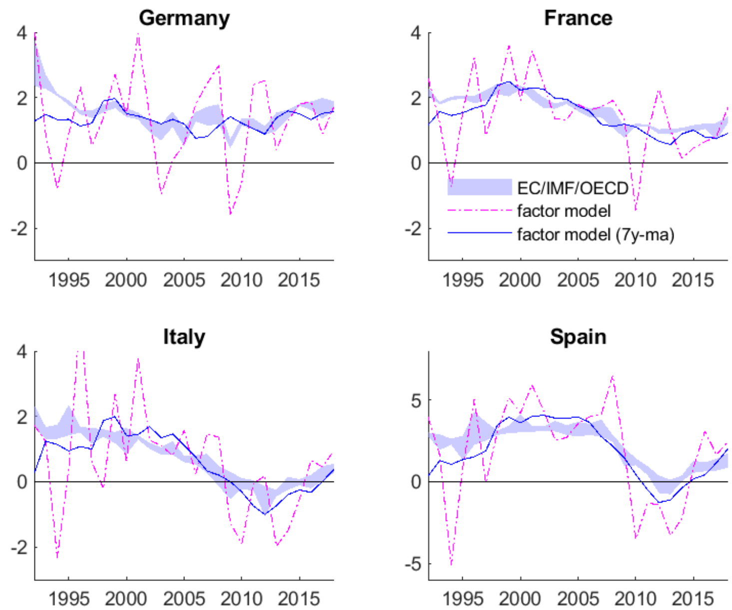
$$\widehat{gap}_t^{smooth} = \Delta y_t - \Delta g_t^{ma} + \widehat{gap}_{t-1}^{smooth}, \quad t \geq 2, \tag{7}$$

with $\widehat{gap}_1^{smooth} = \widehat{gap}_t$. In a final step, the output gap is demeaned and rescaled.

Output gap estimate are now consistent with a smooth profile of potential growth, similar to the estimates from international institutions (Figure 3). The estimates differ,

[5] The most recent estimates from the European Commission / the IMF / the OECD are 0,4%/1,2%/1,8% for Germany, 0,1%/0,1%/-0,6% for France, -0,1%/-0,8%/-0,5% for Italy and 1,4%/0,2%/-1,1% for Spain.

[6] The average standard deviation of the output gap (1991-2018) across institutions is 1,6 for Germany, 1,5 for France, 2,1 for Italy and 3,9 for Spain.



y-axis: percent. Shaded areas: bandwidth of potential growth estimates by the European Commission, the IMF and the OECD as of 2018. Dashed lines: potential growth rate implied by unsmoothed factor-model estimate. Solid lines: smoothed estimate. Annual frequency.

Figure 3: Potential GDP Growth - Factor Model

however, in their assessment of the crisis impact on potential growth. In contrast to the estimates from the European Commission, the IMF and the OECD, the factor model suggests lower potential growth rates over the period 2010-2015, in particular for Italy and Spain. This also explains the differences in the current level of the output gap. According to the factor model, potential growth declined much more during the crisis than the estimates from international institutions suggest, which would mean that the weak economic performance in these countries was in part structural. In recent years, however, potential growth seems to have rebounded in Italy and Spain.

3 Real-time analysis

This section evaluates the performance of the factor model in real time relative to the output gap estimates from international institutions. For this purpose the common factor is estimated using (i) indicators that are not subject to revisions and (ii) available real-time data. In total, 30 time series are used in estimation. To make results comparable to the estimates from the autumn publications of the international institutions, the factor is estimated using an expanding window (1991Q1-2000Q3, 1991Q1-2001Q3, ..., 1991Q1-

Table 4: Revisions of output gaps

Estimate	Mean error				Mean absolute error			
	GER	FRA	ITA	ESP	GER	FRA	ITA	ESP
EC	**0.1**	1.6	1.2	1.0	**0.7**	1.6	1.3	2.4
IMF	0.7	1.3	1.7	1.8	0.9	1.3	1.7	3.0
OECD	1.1	1.8	1.6	1.1	1.2	1.8	1.6	2.9
Factor model	-0.3	**0.1**	0.7	**0.8**	0.8	**0.3**	0.9	2.3
Factor model (unsmoothed)	-0.2	0.2	0.9	1.2	1.2	0.5	1.2	2.6
Factor model (constant std.)	-0.3	**0.1**	**0.6**	1.3	1.2	0.5	**0.7**	**1.7**

Factor model based on 30 indicators. Output gap estimates are smoothed such that their implied potential growth rate correspond to the 7-year moving average potential growth rates implied by the unsmoothed estimates. For the constant scaling factor, the average standard deviation of output gap estimates from the European Commission, the IMF and the OECD as of autumn 2000 are considered. Estimation using expanding windows. First estimation window: 1991Q1-2000Q3. Vintages for real-time data: September 2000, September 2001, ..., September 2017. GER: Germany, FRA: France, ITA: Italy, ESP: Spain. Mean error: $\frac{1}{15}\sum_{t=2000}^{2014}(\widehat{gap}_t^t - \widehat{gap}_t^{2017})$. Mean absolute error: $\frac{1}{15}\sum_{t=2000}^{2014}|\widehat{gap}_t^t - \widehat{gap}_t^{2017}|$. $\widehat{gap}_t$ is the real-time output gap estimate and $\widehat{gap}_T$ is the ex-post estimate. Bold: smallest revisions across estimates.

2017Q3). Only data that is available at the respective dates is considered. Real-time data is from the OECD Revisions Analysis Database.[7]

Real-time estimates from the factor model are subject to smaller revisions than the estimates by the international institutions (Table 4). For France, Italy and Spain the model performs much better in terms of revisions than the institutions. Only for Germany, the model does not really provide an improvement compared to the institutions. This is mainly due to the fact that the revisions of their output gap estimates for Germany have been much smaller than for the other three countries.

The factor model would have been able to correctly identify a positive output gap in the boom years 2001 and 2007 (Table 5), whereas the international institutions announced a positive output gap only with some delay. The smoothing of the factor estimate has only a minor effect on revisions.[8] The scaling of the factor has a more substantial impact on revisions, in particular for Italy and Spain. This is because the output gap estimates from the institutions become more volatile in later vintages for these two countries. This implies a larger scaling factor in later vintages and substantial differences between real-time and ex-post estimates. Using a constant standard deviation would yield much

[7] 18 real-time vintages (September 2000, September 2001, ..., September 2017) of the following six variables are considered in estimation: gross fixed capital formation (relative to GDP), GDP deflator, consumer price index, harmonized unemployment rate, hourly earnings in manufacturing and the composite leading indicator. Prices and earnings are expressed as year-over-year growth rates. Investment rates and inflation measures (prices and earnings) are detrended using their 7-year moving averages.

[8] Revisions are likely to arise, because of the two-sided moving average (6) that used in order to smooth the potential growth rate implied by the output gap estimate.

Table 5: Real-time and ex-post estimates

Year	Estimate	Germany		France		Italy		Spain	
		RT	EP	RT	EP	RT	EP	RT	EP
2001	EC	-0.5	1.6	0.3	2.3	-0.3	2.1	0.2	3.6
	IMF	-1.5	1.4	-0.8	1.0	-2.0	0.4	0.0	2.7
	OECD	-1.1	0.5	0.4	1.9	-1.9	2.2	-0.1	2.6
	Factor model	-0.4	1.1	2.2	2.4	1.6	3.2	2.4	5.4
	Factor model (unsmoothed)	-0.1	-0.6	1.4	1.4	1.0	1.9	1.4	3.4
	Factor model (constant std.)	-0.4	1.1	2.2	2.3	1.6	1.8	2.4	3.0
2007	EC	0.3	1.8	-0.3	2.9	-0.8	2.5	-0.5	3.0
	IMF	-0.1	2.3	-1.2	1.8	-0.8	2.7	0.2	6.0
	OECD	0.0	2.7	-0.3	2.6	-1.1	2.7	-0.2	4.3
	Factor model	3.0	3.0	1.3	2.8	1.1	3.1	0.8	3.8
	Factor model (unsmoothed)	2.2	2.1	1.5	2.2	0.8	2.1	0.2	3.3
	Factor model (constant std.)	3.0	2.6	1.4	2.6	1.1	1.7	1.0	2.1

Factor model based on 30 indicators. Output gap estimates are smoothed such that their implied potential growth rates correspond to the 7-year moving average potential growth rates implied by the unsmoothed estimates. For the constant scaling factor, the average standard deviation of output gap estimates from the European Commission, the IMF and the OECD as of autumn 2000 are considered. RT: real time. EP: ex post. Real-time estimates from autumn 2001 and autumn 2007. Ex-post estimates: autumn 2017. Numbers ≥ 1 in green. Numbers ≤ -1 in red.

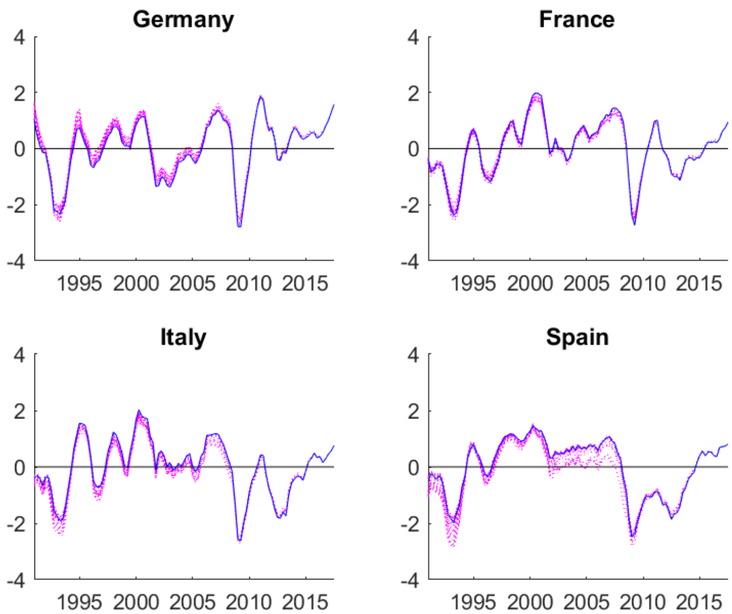
smaller revisions for Italy and Spain. Real-time estimates for Germany and France are very close to the ex-post estimates from the last vintage considered, whereas the differences for Italy and Spain can be quite large.[9] But the factor model would have still been able to identify the different business cycle phases in these countries in real time (Figure 4).

4 Robustness

Until now indicators are weighted depending on how correlated they were in the past with the output gap, or such as to maximize the total variance explained by their linear combination. One may have two concerns regarding this strategy.

First, indicators that neither comoved with the output gap nor with other indicators in the past, receive little weight in the estimation. It could be that some of them would lead to a very different assessment of the current output gap. Second, the weighting schemes considered so far may be inadequate. Instead of weighting indicators based on their correlation with the output gap in the past, indicators could be weighted according to the information that they contain about future price developments. Jarociński and

[9] The factor model would have not signaled a positive output gap for Germany in 2001, which is consistent with the view that the German economy was already in a downturn at that time. According to SVR (2017) the early-2000s recession in Germany started in 2001Q1.



Estimation using expanding windows. Vintages: September 2000, September 2001, ..., September 2017. Unsmoothed factor with zero mean and unit variance.

Figure 4: Real-time Estimates

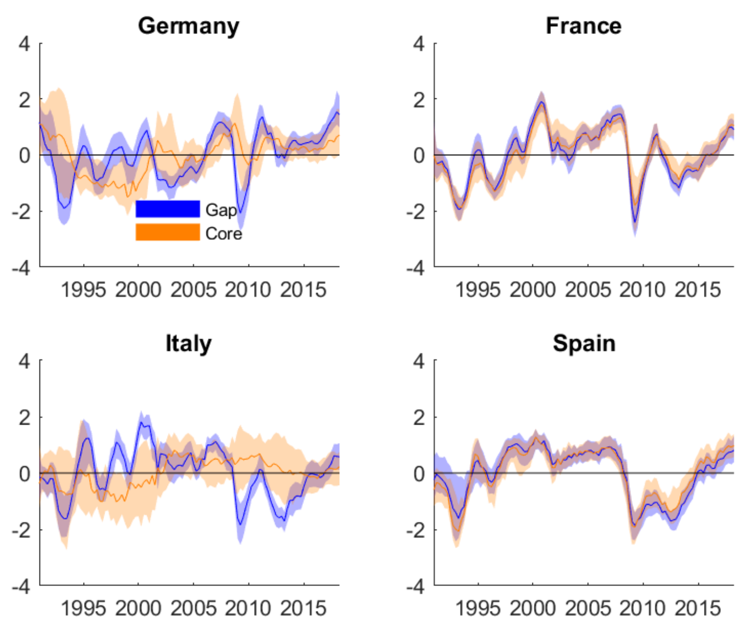
Lenza (2018), for example, estimate the output gap using an unobserved components model based on a Phillips curve relationship. Among a variety of models they choose the specification that yields the most accurate real-time inflation forecasts for the euro area. Table 6 presents indicators leading the core inflation rate. Not surprisingly, other price and wage measures including the first lag of the core inflation rate itself are among the indicators that seem to be informative about future changes in the core inflation rate.

In order to address these concerns, I consider the following procedure. Instead of condensing the different indicators to a single estimate of the output gap, different indicators are combined, in order to obtain a distribution of estimates. More precisely, out of a total of N indicators a subset of M indicators, with $1 < M < N$, is chosen and weighted according to equation (2). This is done for all possible combinations. With $N = 37$ and $M = 4$, this yields a total of $\binom{37}{4} = 66,045$ combinations. The resulting distribution helps assess the uncertainty surrounding the output gap estimates. Figure 5 shows the time-varying distribution of estimates for two different weighting schemes. The first one weights indicators according to their correlation with the output gap. In the second one indicators are weighted according to their correlation with the core inflation rate next year. For Germany the output gap estimates based on the second scheme lag somewhat behind the output gap estimates from the first scheme. For Italy the estimates from the

Table 6: Leading indicators for core inflation

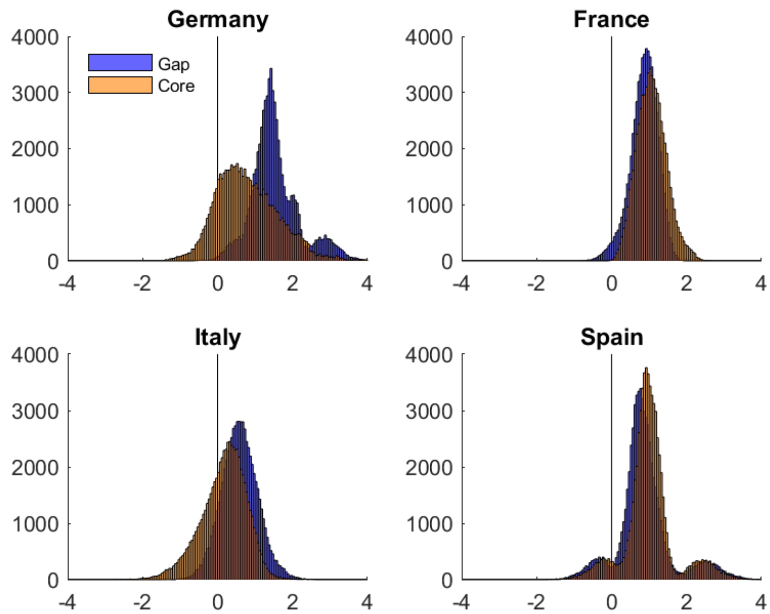
INDICATOR	GER	FRA	ITA	ESP
Core inflation	0.8	0.8	0.7	0.7
Unit labor costs	0.5	0.5	0.2	0.5
Deflator: investment	0.8	0.4	0.6	0.4
Deflator: consumption	0.5	0.5	-0.2	0.4
Production assured by current order-books	0.5	0.5	0.1	0.4
Investment: total	0.3	0.6	0.3	0.4
Services: price expectations	0.4	0.5	0.5	0.5
Sentiment: construction	0.4	0.7	0.4	0.4
Sentiment: retail	0.4	0.2	0.5	0.3
Unemployment rate	-0.4	-0.7	-0.4	-0.3

GER: Germany, FRA: France, ITA: Italy, ESP: Spain. Correlation of core inflation rate (in deviation from its 7-year moving average) with lagged indicator: $corr(x_{i,t-1}, core_t)$. Period: 1991-2010. Numbers ≥ 0.5 in green. Numbers ≤ -0.5 in red. Numbers rounded to one digit.



Shaded areas: 68th-percentiles. Solid lines: median. Estimates normalized (zero mean and unit variance).

Figure 5: Estimated Output Gap - Combinatorics



$\binom{37}{4} = 66,045$ combinations. Estimates for 2018Q3.

Figure 6: Distribution of Estimates - Combinatorics

second scheme hardly display any cyclical pattern. Interestingly, for France and Spain estimates from both schemes are very similar.

Figure 6 shows the distribution of estimates for 2018Q3. Under the first weighting scheme almost all estimates are positive, giving strong evidence for GDP being above its trend or potential. For France and Spain, estimates from the second weighting scheme also point to a positive output gap. For Germany and Italy, the results from the second weighting scheme are somewhat more mixed, although the majority of estimates is positive, too.

5 Conclusion

This paper evaluates indicator-based estimates of the output gap for the largest euro area economies. It combines business and consumer surveys with “hard” economic data on investment, prices and unemployment. The output gap is estimated for two different weighting schemes. The first scheme weights the different indicators according to their correlation with the output gap in the past. Highly procyclical indicators, such as the capacity utilization rate in manufacturing, as well as highly countercyclical indicators, such as the unemployment rate, receive a large weight. The second method identifies the output gap as the first principal component underlying the various indicators.

The results of this paper are as follows. First, output gap estimates for both weighting schemes are very similar. They suggest that output gaps for Germany, France, Italy and Spain are all positive now, reflecting that many indicators are at historical highs. This points to an already matured business cycle in the euro area. Second, estimates from the factor model turn out to be quite reliable in real time.

One of the most important figures in business cycle analysis, the output gap, is unobservable and difficult to determine. It seems thus reasonable that policy makers consider a wide range of estimates. This paper suggests that indicator-based estimates should be among them.

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