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Does a multi-sectoral design improve indicator-based forecasts of the GDP growth rate? Evidence from Switzerland

Michael Graff

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Abstract

This article presents a multi-sectoral composite indicator for the Swiss GDP growth rate, targeting a lead of two quarters. The in-sample period ranges from 1991 to 2002 and 14 data points are reserved as out of sample to assess the forecasting performance. The results appear promising, in terms of both phase and amplitude. Comparisons with two other uni-sectoral composite leading indicators for the same reference series–the traditional KOF (Konjunkturforschungsstelle) barometer as published until March 2006 and a uni-sectoral composite indicator computed from the same indicators as the multi-sectoral instrument–show that the new approach is superior to the alternatives, which is due to both its broader information basis as well as to the structure that is imposed by the multi-sectoral design. Yet, there are pronounced differences regarding the accuracy of the sectoral forecasts, so that there is scope for improvement.

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Notes

[1] KOF stands for ‘Konjunkturforschungsstelle’ (Swiss Economic Institute) at ETH Zurich.

[2] The analysed data set is available from the author upon request.

[3] The definitions are based on the European System of Accounts (ESA 95), which since 2004 also constitutes the framework for the official Swiss GDP statistics (Bundesamt für Statistik, 2003). Note that ESA 95 records real growth rates as chain indices referring to the prices of the previous year.

[4] Some studies refer to the first provisional values of a reference series throughout to ensure uniformity over the whole sample period; see, e.g. ARTIS (1996). However, this should be a last resort when a forecasting instrument aims at a reference series that undergoes changes in definition through time, so that the initially published provisional data are a shortcut to ensure congruence of forecasted and reference series. Normally, as long as the provisional data are informationally efficient in the sense that the expected value of future revision is zero, a leading indicator targeting provisional data would not aim at the ‘true’ series, but rather at its best estimate that will eventually become available, i.e. the final data, together with the revisions to the provisional data releases. However, if the expected value of the latter equals zero, the target series will in fact be the former. Furthermore, as long as the official provisional data are the best forecasts of the final data available in real time, they constitute the proper reference series for out-of-sample evaluations, even when this implies that these analyses may be subjected to future revisions.

[5] For a comparable bivariate selection process, also see Etter and Graff (2003) and Graff and Etter (2004).

[6] These were three monthly time series from the KOF manufacturing industry survey (the annual change of incoming orders, the change of the order backlog compared to the previous month and the expected purchase of intermediate goods) as well as three quarterly series (the judgement of wholesale inventories, the real order backlog in the construction sector compared to the previous year and the evaluation of the financial situation in the coming 12 months from the Seco consumer sentiment survey). The qualitative items from the KOF surveys were quantified as balance indicators (percentage 'plus' less percentage 'minus').

[7] This, presumably, has to be understood as a precautionary measure, as the press statements always emphasized that the barometer should forecast the direction, but not the level of the GDP growth rate.

[8] In particular, when the monthly series of traditional KOF barometer is aggregated into quarterly frequency by taking the mean values over the months of a quarter, a cross correlogramme with the reference series covering 1991Q1 to 2002Q4 reveals the highest correlation when the series are synchronized.

[9] On the concept of efficiency relating to forecasts, see Granger and Newbold (1973). A multiple regression of the reference series on the traditional KOF barometer, advanced two quarters, and on the growth rate of real added value in the financial sector, yields a significantly positive coefficient for the barometer (1.15, t = 7.32). The coefficient for the financial sector, however, is also significantly positive (0.28, t = 4.56), confirming that the available set of information is under-utilized. Notably, this method does not indicate inefficiency of the traditional KOF barometer regarding the construction sector; the respective coefficient is insignificant, the point estimate negative. However, this is an expected result, since the construction sector is already reflected in the traditional KOF barometer. Indeed, the negative point estimate can be attributed to the fact that the construction sector as one of six indicator series is rather over-represented; its share in Swiss GDP during the 1990s was 5–6%, which is far from 17% (one-sixth).

[10] The regression of the reference series R on the traditional KOF barometer B, advanced two quarters, transforming the traditional KOF barometer into the scale of the GDP growth rate, yields $R_t = 1.47 + 0.81\ B_{t-2}$.

[11] For a nonlinear composite business cycle indicator, see ÖCAL (2006).

[12] From other leading indicators for GDP known to us, such as ‘bottom up’ approach is otherwise only implemented in the Economic Barometer of the German Institute for Economic Research (DIW: Deutsches Institut für Wirtschaftsforschung) in Berlin. A significant difference, however, is that for estimates of data points at the right margin, the DIW refers to univariate sectoral time series methods, while we exclusively rely on indicator models.

[13] This is why the traditional KOF barometer included a series from the construction sector as one of six indicators. However, since no explicit sectoral modelling was performed, the construction sector cycle enters with a weight that is determined from the correlation matrix of the indicators. In contrast to this, the new multi-sectoral approach will consider the sectoral cycles according to their shares in GDP.

[14] The SD of the annual growth rate of the quarterly series NOGA 45 (for which estimates have recently been published by the Seco) is 10.9% (mean 3.2%); after deduction of the FISIM the SD jumps to 29.7 (mean 9.0%). On the other hand, SD for the construction sector amounts to only 3.2% (mean −1.5%), so that the contribution of this sector to variance of GDP growth is in fact less than that of the financial sector without FISIM.

[15] This concerns 12 of the 22 series that finally enter into the composite indicator.

[16] For a similar approach, see Entorf (1993).

[17] See, among others, Etter and Graff (2003), Graff and Etter (2004) and Gayer (2005).

[18] When the resulting sets were empty, the search was extended to monthly indicators with a lead of down to four months, which were aggregated into quarterly series by referring to the first monthly value of the previous quarter. This concerns one of the 22 indicators that enter into the composite indicator. When this search still did not identify indicators satisfying the correlation cut-off criteria, the minimum lead was shortened to one quarter, which affected five of the indicators that were finally selected. The phase shift at the right margin resulting from this gradual ‘watering down’ of the minimum lead requirement is analysed in Section VI.

[19] The variables entering into the principle components and their transformations are described in the Appendix.

[20] For extractions of more than one factor, reflecting a multi-dimensional design, see, e.g. NATH (2004).

[21] Care was taken to use only coincident or lagging, but not potential leading indicators, for the quarterly breakdown of the reference series, since the indicators chosen for this purpose cannot at the same time be selected as leading indicators. Otherwise, the cross correlation-based selection criteria could mistake variables as leading indicators, which replicate the reference series in the seasonal spectrum rather than in lower frequencies, since their seasonality is the same as that of the reference series by construction. For the financial sector module, we refer to the three quarterly indicators from the Swiss banking statistics; the revenue from (1) the interest spread, (2) fees for banking services and (3) commissions.

[22] For the quarterly breakdown, we used the software 'EcoTrim', which is provided by Eurostat.

[23] These estimates were not available at the time of the in-sample computations.

[24] The four series are the gross profit compared to the previous quarter ($\lambda = 2$), the demand for banking services from foreign customers compared to the previous quarter ($\lambda = 1$), the revenue from commissions compared to the previous quarter ($\lambda = 1$) and the volume of private assets compared to the previous quarter ($\lambda = 1$).

[25] The longer series are the year-on-year growth rate of M2 ($\lambda = 2$), the volume of credit outstanding ($\lambda = 7$) and the growth rate of the Swiss share market SPI index compared to the previous year ($\lambda = 1$).

[26] Here, we rely on the SFSO sales index for the construction sector. As this series does not go back beyond 1996, for earlier years we refer to the Swiss Society of Constructors' data on construction activity.

[27] The indicators are construction activity compared to the previous year ($\lambda = 4$), expected employment in the construction sector ($\lambda = 4$) and the order backlog in the planning sector in months ($\lambda = 4$).

[28] This may partly be due to the difficulty to construct a plausible quarterly reference series in the first place.

[29] Note that this finding has an important consequence. Based on the residual series of core-GDP, a search for leading indicators will tend to identify series that are relative

insensitive with respect to the financial sector. This is desirable, since our multi-sectoral approach aims at capturing the financial business cycle separately and then to incorporate it into the overall indicator, weighted appropriately with the sector's share in GDP.

[30] The indicators are the expectations regarding incoming orders ($\lambda = 2$), production ($\lambda = 2$) and purchases of intermediate goods ($\lambda = 2$) in the following 3 months.

[31] The indicators are revenue compared to the previous year ($\lambda = 3$) and the change of the assessment regarding the level of employment compared to the previous year ($\lambda = 2$) in the hotel and restaurant industry, the change of expected sales in the retail trade nonfood sector compared to the previous year ($\lambda = 2$), the expectations regarding the future economic situation ($\lambda = 2$) the assessment of the economic situation as favourable for larger purchases ($\lambda = 2$) as well as the annual growth rate of the passenger car import value ($\lambda = 1$).

[32] In order to extract the relevant information for Swiss exports from these surveys, we identify the five most important export destinations (the four neighbouring countries Germany, France, Italy and Austria as well as the United Kingdom) and calculate, on a yearly basis, the shares of these destinations in Swiss overall exports. With these shares, we weight the survey results from these countries. Stable leads before the growth rate of the Swiss core-GDP show up for the weighted European production expectations ($\lambda = 2$) and for the weighted European incoming orders during the preceding months ($\lambda = 1$). A third series with a stable lead is the change of the order backlog compared to the previous year in Germany ($\lambda = 2$).

[33] Due to the difficulty in estimating a plausible quarterly breakdown of NOGA 45 for the years before 1997 (see section ‘Construction sector module’), we calculate the pre-1997 growth rate for the construction sector directly from the yearly data reported in the SFSO production account.

[34] Since ESA 95 reports real growth rates as chain indices referring to previous year's prices, the sectoral shares for aggregation refer to year $t - 1$.

[35] For the earlier years, the results are somewhat less convincing. The most plausible explanation is that this is due to the fact that the composite indicator is comprising an increasing number of input variables as one moves to the right on the time axis because some of the survey data are not available for the earlier years. As a

consequence, the set of information on which the composite indicator is based is increasing through time, which can be expected to improve its performance.

[36] Dynamic factor analysis goes back to SARGENT AND SIMS 1977) and Geweke (1977). Applications in the field of economic leading indicators are found, among others, in Stock and Watson (1999), Forni et al. (2001), Bandholz and Funke (2003), Nath (2004) as well as in van Nieuwenhuyze (2005).

[37] For a similar exercise, see Pons (1999).

[38] Yet, a correlation coefficient of 0.64 shows that no less than 40% of the variance ($0.64^2 = 0.41$) of the Swiss 1991–2002 core-GDP business cycle can ex post be reproduced with a few indicators from other European countries, confirming that important business cycle impulses for Switzerland stem from abroad.

[39] See Davidson and MacKinnon (1981) and Mizon and Richard (1986).

[40] See Clark (2004).

[41] The profession has recently become increasingly aware of the filtering problem; see e.g. ORPHANIDES AND VAN NORDEN (2002), Graff (2004) and Troy et al. (2007).

[42] As explained in Section IV, 12 of the 22 series that enter into the composite indicator are affected by seasonality, which is purged by the Census X11 seasonal filter. In the long run, this filter may also lead to data revisions, as it adapts to potential changes in the seasonal pattern. However, the resulting revisions are trivial compared to those resulting from symmetrical low-pass filters, and they are not focused on the right margin of the series, so that the end point instability due to the seasonal filter is negligible.

[43] It remains an open question whether revisions to the principle components improve or worsen the forecasting properties. An adaptation of the measurement model to changes in the data could, in principle, be a desirable characteristic. To enhance this feature, a ‘learning model’ would compute principle components from a relative short sample period with a constant number of observations that is moving forward as time passes. On the other hand, one can get rid of this source of revisions by computing the loadings in sample and fixing them rather than running subsequent principle component analyses with an increasing number of observations. However, due to limitations of space, we shall leave theses simulations for another paper.

[44] This affects the financial sector principle component based on the recently launched KOF banking survey.

[45] See Stulz (2005) for a similar conclusion.

[46] Regarding statistical significance, the multi-sectoral composite indicator is superior to the traditional KOF barometer. The t-statistics are 4.04 versus −0.82 ex post and 4.10 versus −1.50 in real time, referring to specification (4). As can be expected according to Table 5, the difference between the new instruments is less pronounced. The t-statistics comparing the multi-sectoral composite indicator to the uni-sectoral composite indicator are 2.58 versus −1.51 ex post, 2.43 versus −1.35 in quasi-real time, 2.10 versus −1.51 in real time simulated with specification (3), and 1.62 versus −1.50 in real time simulated with specification (4). Note that only the last test fails to meet the conventional 5%-significance level. Yet, as 14 data points constitute a very small sample, the empirical evidence taken together points towards superiority of the multi-sectoral structure.

[47] For the construction module, the real time simulations (3) and (4) are identical, due to the fact that in this module all indicator series have a lead of four quarters, so that there are no missing end points in real time.

[48] Interestingly, the out-of-sample forecasting accuracy in the financial sector module in quasi-real time is better than ex post. Now, recall that the measurement model for this module consists of two principle components: one extracted from long time series of monetary and financial indicators, and the other one from rather short series taken from the KOF banking survey launched in 2000. Accordingly, the additional out-of-sample data points have a comparatively high potential to change the loadings of the shorter principle components, which is obviously what has happened. The resulting end point instability, however, helped improve the quasi-real time forecasts, which may come close to what we called a ‘learning model’ (see footnote 42). Yet, with only 14 data points we are reluctant to push the interpretation too far and leave the assessment of an indicator model based on ‘learning principle components’ for another study.

[49] In May 2006, the traditional KOF barometer was replaced by a multi-sectoral barometer that is designed along the lines presented here, though with a number of details modified (KOF, 2006). The out-of sample data that will get available with the passing of time will allow analyses similar to these in a couple of years.

[50] The number of papers that pool large numbers of more or less related economic time series into composite indicators without imposing a particular economic structure is large and growing; see among others, Stock and Watson (1999), Artis et al. (2001), Forni et al. (2001), Banerjee et al. (2003), Gayer and Genet (2005), Kholodilin and Siliverstovs (2006) and Troy et al. (2007).

Jan P. A. M. Jacobs et al.
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