Towards the improvement of Eurostat's turning points coincident indicators

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1. INTRODUCTION

In the Eurostat's business cycle clock (BCC), the detection part (displayed in the form of a clock on the bottom left corner of the screen) is generated by a set of turning points coincident indicators. These coincident indicators have been designed to detect almost in real-time the occurrence of turning points in a reliable manner. This means that our indicators have been designed to be as much as possible timely and to minimize the probability of delivering false signals. The set of turning points coincident indicators (described in Anas et al. {1}) comprises 21 pairs of multivariate turning points coincident indicators detecting simultaneously turning points of the growth and the business cycle, (MSVAR-GCCI and MSVAR-BCCI, respectively) developed for the euro area and its member countries. Additionally, a univariate indicator detecting turning points of the acceleration cycle (ACCI) is available for the euro area. This paper describes some methodological and computational improvements recently introduced to enhance the timeliness and performance of our indicators.

2. METHODS

In this section we present some improvements recently introduced, which mainly concerns: i) The timeliness of the indicators (especially the MSVAR-GCCI and MSVAR-BCCI); ii) the stability of the signal (for the ACCI). Additionally, we discuss enhancements in the performance's monitoring of all coincident turning points indicators.

2.1. Improving timeliness

Our multivariate coincident indicators for simultaneous detection of growth and business cycle turning points are based on a Markov-Switching (MS) vector autoregressive model (MSVAR) including both soft and hard (officially Principal European Economic Indicators (PEEIs)) economic indicators. Since the timeliness of the variables included in the model is quite different, mainly but not only between hard and soft ones, our model needs also to manage a ragged-edge structure of the information . Unfortunately, this is not feasible with the current modelling approach so that it is necessary to choose which the last value to take in consideration in the model is. In the past, we decided to align the model to the last updated variable, the industrial production index (IPI) in our case. This approach privileges the reliability of the signal but surely not its timeliness. With this approach, the model computed at the end of month *m* produced filtered probabilities only until the month *m-2* (last month for which the IPI is available) and all more recent information was discarded. This is the case for the survey data, which are usually available until month *m*, but also the unemployment rate, which is available around the end of month *m* until month *m-1*. The pandemic and the associated recession have shown the importance of providing users with a more up to date cyclical information. In order to find a way to improve the timeliness of our indicators, we have considered two alternative solutions. The first one consists in removing from our model the constraint of aligning all component series to the less updated one. In such a way, the most up to date values of all components series will enter in the model. This solution has the advantage of using all available information and of reducing the use of forecasted probability privileging the filtered ones. The second solution considered consists in building up separate models for the most up to date variables, estimating from them updated filtered probability of such variables and using them as an input in our standard model to revise the filtered probabilities and thus constructing the cyclical indicators. This approach essentially follows the one proposed by Camacho et al. {2}. Beside its computational complexity, the main obstacle in implementing this solution is that the original specification allows only for the presence of two regimes in the factor model while in our MSVAR model we typically have four regimes to capture movements in the phases of the business and growth cycles, depending on countries characteristics. Even if we have not abandoned the possibility of farther investigating the second solution, we have then decided to implement the first one. In practice, we have decided to align the model to the release of the unemployment rate, which is the most up to date hard variable present in the model. In such a way, the new model for the month *m* returns filtered probabilities until the month *m-1* and not anymore *m-2* as in the previous specification.

2.2. Improving the stability of the signal

The ACCI is based on a simple univariate MS model, where the only involved variable is the Economic Sentiment Indicator (ESI). Recently, the procedure used to estimate the model underpinning the ACCI did not converge. This is due to the sharp decline observed in the ESI starting in April 2020, which resulted in the transformed ESI as input to the model (1-month change of the 6-month difference) to experience a drop corresponding to more than 10 standard deviations. This situation affected significantly the stability of the signal delivered by the ACCI. In order to cope with this limitation, after deep investigation of model characteristics and specificities, we decided to re-specify the MSI(3)-AR(0) model and to move to a state-dependent heteroscedastic model of the form: MSIH(3)-AR(0). Furthermore, to match as closely as possible the ACCI released so far, the definition of the ACCI has been changed to the sum of the filtered probabilities of the first two regimes, instead of the first regime alone considered before. With this new specification, the convergence problem has been fixed without adversely affecting the performance of the ACCI in detecting the historical turning points (Table 1).

2.3. Introducing new performance measures

We have used two well-known indicators in the business cycle literature to measure the performance of our turning points coincident indicators: the Brier's score and the concordance index. Nevertheless, both measures provide general information about how many observations are correctly classified as per the historical dating chronology but do not distinguish between type of signals. This must be considered with some caution, especially when the panel is unbalanced, which is often the case for the business cycle coincident indicator, due to the fact that economy most of the time is not in recession. We searched for additional performance measures enabling us to provide a much more complete picture of the overall performance and quality of our coincident indicators. The literature and practice on classifiers, especially in the machine learning area, present a number of performance measures complementing the already used ones for the business cycle, namely: precision, recall and F1 (the harmonic mean of precision and recall).

We specified first the assumption on the adopted classifier: it is set to 1 (recession/slowdown) if the probabilistic coincident indicator exceeds 0.5 and to 0 otherwise.

Then we considered the following additional metrics to assess the performance of classifiers:

- Precision = the number of true positives divided by the number of all positive (i.e. recession/slowdown/deceleration) returned by the classifier. Perfect precision corresponds to no false positive signals.
- Recall = the number of true positives divided by the periods that should have been identified as positive (i.e. recession/slowdown/deceleration). Perfect recall corresponds to no false negative signals.
- F1 = harmonic mean of precision and recall. In the initial application, precision and recall are evenly weighted; however, further different versions of F score can be considered assigning higher weight to precision or recall, depending on the appetite for false positive and false negative signals, respectively.

3. RESULTS

In this section, we briefly present some results supporting the improvements described in section 2.

3.1. Timeliness improvements

The impact of incorporating the most recent Unemployment Rate information and re-aligning the IPI is assessed by comparing the newly computed indicators with the coincident indicators computed as per the previous methodology. The analysis considers both the coincident indicators as released over time (and revised as per the 6-month revision horizon at each successive release) and the coincident indicators estimated as per the previous methodology in the latest available assessment (April 2020). This allows distinguishing the impact of the change in methodology and the cumulative impact from the dynamics of changing component variables. As expected, also due to the trade-off between timeliness and accuracy, a slight deterioration in the performance of the coincident indicators, as measured by the Brier's score and the Concordance index, has been observed for some Member States, which is largely compensated by the gain in terms of timeliness. This deterioration is not generalized and in few cases, like the euro area, an improvement was observed instead. In particular, for the euro area MSVAR GCCI and MSVAR BCCI, the following conclusions can be drown:

MSVAR GCCI:

- Performance marginally improved as measured by the Brier's Score the Concordance Index, when not considering the historically revised coincident indicator.

- The new coincident indicator does not give a false slowdown signal in 2005, which is the only false slowdown signaled by the previous model.

MSVAR-BCCI:

- The adoption of the new model results in a slight deterioration in model performance as measured by the Brier's Score and the Concordance Index, both considering the historically revised coincident indicator and the one estimated in the latest assessment.

  The new coincident indicator signals a false recession in 2002-2003, which was not originally identified by the previous model (as historically revised), but that is also signaled by the same model as computed in April 2020 (latest, as computed). Further analysis suggests that this false signal is not due to the change in model specification so that we could even conclude that the performance of the new indicators remains substantially the same.

3.2. Implementing the new performance measures

The computation of the new performance indicators enabled us to shed further light on the relative performance of our coincident indicators, as summarized below:

Table 1: Performance metrics for the ACCI

Metric	May 2020 ACCI	April 2020 ACCI	
	As Computed	As Computed	As Released (6-month Revised)
Brier's Score	.29	.23	.23
Concordance Index	.62	.68	.68
Recall	.88	.76	.81
Precision	.59	.66	.64
F1 Score	.71	.70	.72

Table 2: Performance metrics for the MSVAR GCCI

Metric	May 2020 MSVAR GCCI	April 2020 MSVAR GCCI	
	As Computed	As Computed	As Released (6-month Revised)
Brier's Score	.18	.19	.16
Concordance Index	.79	.79	.82
Recall	.65	.85	.77
Precision	.78	.68	.77
F1 Score	.71	.76	.77

Table 3: Performance metrics for the MSVAR BCCI

Metric	May 2020 MSVAR BCCI	April 2020 MSVAR BCCI	
	As Computed	As Computed	As Released (6-month Revised)
Brier's Score	.07	.07	.05
Concordance Index	.91	.92	.95
Recall	.74	.78	.71
Precision	.62	.61	.81
F1 Score	.67	.68	.76

The same performance measures have also been used to check the optimality of the 'natural' threshold of 0.5 for each detecting turning points indicator. The results obtained confirmed the validity of the 'natural' threshold for the ACCI and MSVAR GCCI, while for the MSVAR BCCI delays in detecting need further investigation.

4. CONCLUSIONS

In this paper we have shortly presented some recently improvements to our turning points coincident indicators together with some first results obtained.

REFERENCES

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