Estimating a real-time business conditions index for Romania[1,2]

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Abstract

We estimate a real-time (daily) business conditions index using a dynamic factor model that explicitly incorporates economic data measured at different frequencies. We also take advantage of the flexible structure of the model to create a small open economy setup. The indicator estimated on Romanian data gauges business conditions in an efficient and timely manner, being successful in filtering the information provided by a set of representative variables characterising risk aversion, labour market conditions, investors' confidence, industrial production and retail sales. These variables help in shaping the leading feature of the indicator, which has the potential to anticipate turning points in real activity. Moreover, the high correlation between the indicator and quarterly GDP growth recommends its use as a key synthetic variable in near term GDP forecasting models, especially within a central bank inflation forecast exercise.

JEL Classification: C32, E32, O11

Keywords: dynamic factor model, business cycle, macroeconomic forecasting

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1. Introduction

In this paper we estimate a real-time index by means of a dynamic factor model. We apply this methodology on Romanian data, taking advantage of the flexible structure of the model to use a setup for a small open economy.

Real-time measurement of business conditions aids to the optimality of business and financial decisions and to the implementation of economic policies. In this context, the availability of a high-frequency indicator is of paramount importance not only for the private sector, but also at institutional level, especially since official business cycle chronologies and underlying statistical data are published with a considerable lag.

Academic and applied research comprises a large variety of business cycle indices, which differ with respect to the methodology employed, the numbers of series used or the frequency of the resulting index. Stock and Watson (1988, 1989) contributed to formalising the methodology by estimating an index of the aggregate economic activity treated as an unobserved component, concurrently spurring the interest of academics in the study of business cycles. Afterwards, Stock and Watson (1999) put forward an index of aggregate economic activity, used as a determinant of inflation within the Phillips curve instead of unemployment. Their index of aggregate economic activity is extracted using principal component analysis and can be interpreted as an index of real economic activity. Subsequently, papers such as Mariano and Murasawa (2003), Aruoba *et al* (2009), Bsiwas *et.al* (2012) or Kumar (2013) further developed the estimation methodologies with regard to business cycle indices.

Among the aforementioned works, Aruoba, Diebold and Scotti (2009) – ADS stands out benefitting from the following traits: (i) it belongs to the class of factor models, capturing the latency of business conditions; (ii) it explicitly incorporates indicators measured at different frequencies and (iii) it estimates business conditions using the *Kalman filter*. Emphasizing the features of the ADS model within the business cycle literature we note that Stock and Watson (1989) do not use high-frequency indicators, Evans (2005) methodology is not based on factor models, Mariano and Murasawa (2003) use approximate techniques and Proietti and Mauro (2006) use a non-linear approach.

The above mentioned advantages of the ADS model led us to select it in constructing a real-time business conditions index for Romania. To our knowledge, this is the first index of this kind estimated for Romania[3]. Among others who use the ADS model for estimation of business conditions notable contributions come from the Central Bank of Canada, Kumar (2013), and the Central Bank of India, Biswas *et al.* (2012).

Worldwide, business cycle dating is undertaken by a relatively small number of institutions. In the US, business cycles are officially monitored by the *National Bureau of Economic Research* (NBER), both at monthly and quarterly frequency. However, NBER does that with an at most two-year lag, hence the necessity of measuring business conditions by means of a

[3] Muraru A. (2015) estimates a monthly financial conditions index for the Romanian economy that can also be used in forecasting exercises.

higher-frequency index. For this purpose, economic activity as a whole is generally reflected by the *comovement* of many variables, rather than by the association with a single variable, be it GDP, industrial production or employment[4]. NBER has calculated a series of business cycle indices starting with the 1960s, based on the work of Burns and Mitchell (1946). Depending on the individual behaviour of the series, these indices could be leading, lagging or coincident[5]. Later on, the *Bureau of Economic Analysis* and *The Conference Board*[6] took over the calculation and publication of official business cycle indices for the US. *The Conference Board* computes a composite coincident indicator that reflects aggregate economic activity. Disregarding the type of the variable considered (coincident or not), the aggregation into an index has the benefit of synthesizing overall economic developments, mitigating at the same time volatility of individual indicators. The turning points in the composite coincident index computed by *The Conference Board* broadly match those identified by NBER. The indicator's performance on identifying turning points is high – 8 out of 13 turning points being identical with those of NBER[7].

Another indicator, the *Chicago Fed National Activity Index* (CFNAI), is built using a similar methodology as the index of economic activity developed by Stock and Watson (1999). CFNAI offers a broad picture of the real activity, tracking recessions and expansions, as well as the build-ups and slowdowns in inflationary pressures.

For the euro area, the Business Cycle Dating Committee within the *Centre for Economic Policy and Research* (CEPR) dates quarterly turning points using a definition of a recession similar to that of NBER[8]. In addition CEPR and the Central Bank of Italy (following Altissimo *et al*., 2007) are in charge with the publication of a monthly indicator of aggregate economic activity within the euro area (€-coin), based on a generalized dynamic factor model[9]. In contrast to the indices introduced by NBER, the €-coin is an estimate of the underlying growth, free from short-run fluctuations, thus being a reliable assessment of the euro area economic outlook.

The rest of paper is structured as follows: in section 2 we present the dynamic factor model specified following Arouba *et al*. (2009), section 3 presents the empirical application on Romanian data, while the last section concludes. Further details regarding the previously mentioned indicators, the data sets used to compute them, as well as estimation results are presented in Appendix A.

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[4] As defined by Burns and Mitchell (1946), "*Business cycles are a type of fluctuations found in the aggregate economic activity of nations, […] a cycle consists of expansions occurring at about the same time in many economic activities, followed by similarly general recessions*".

[5] For example, by construction a coincident indicator is a measure of current aggregate economic activity, while a leading indicator is based on series that tend to fluctuate ahead of the overall economy.

[6] *The Conference Board* is an independent public institution whose attributions include, starting with 1995, the calculation and publication of official *leading, lagging* and coincident indicators for the US. Previously these tasks belonged to NBER and subsequently to the *Bureau of Economic Analysis* (between 1972 and 1995).

[7] Generally deviations are within a 3-month lead/lag from NBER turning points.

[8] http://cepr.org/content/business-cycle-dating-committee-cepr-and-nber-approaches

[9] This model is implemented also within the Hungary's Central Bank, in the form of a coincident indicator of economic activity (HuCoin). Its analysis is published quarterly in the Inflation Report.

2. The model

In order to design an aggregate business conditions index for Romania and to track it at high frequency we used the methodology of Aruoba *et al.* (2009). The modelling framework is based on a dynamic factor model at daily frequency that builds upon the assumption that the business conditions are evolving daily, even though they are not observed at a daily frequency. In implementing the model, the state variable corresponding to business conditions is assumed to fallow an autoregressive process of order 1- AR(1):

$$x_t = \rho x_{t-1} + e_t \tag{1}$$

where x_t represents the underlying business conditions at day t, which evolve daily.

The observed variables are contemporaneously affected by both the state variable and their own lag as specified in their law of motion. The treatment applied to each of the observed variables depends on the data type. It matters whether it is a stock or a flow variable, as we will elaborate next.

In this paper, most of the variables are observed at a monthly or quarterly frequency, although it can be assumed that they evolve daily. This feature is embedded into the analytical framework by including an additional daily variable $\tilde{y}_t^i$ denoting the same variable y_t^i, but observed at a lower frequency. The relationship between y_t^i and the additional variable is determined by the type of the variable – stock or flow– included in the data set. Therefore, at any moment in time (i.e. day) t y_t^i is observed (in this case $\tilde{y}_t^i = y_t^i$ for stock variables and $\tilde{y}_t^i = \sum_{j=0}^{D_i-1} y_{t-D_j}^i$ for flows) or unobserved, in which case $\tilde{y}_t^i = NA$ (missing value).

For monthly or quarterly stock variables, the measurement equations have the following form:

$$\tilde{y}_t^i = \begin{cases} y_t^i = \beta_i x_t + \gamma_{i1} \tilde{y}_{t-D_i}^i + u_t^i, & \text{if } y_t^i \text{ is observed at day } t \\ NA \end{cases} \tag{2}$$

where D_i depends on the frequency of the variable (28-31 days for monthly data, 90-92 days for quarterly data, respectively).

For monthly or quarterly flow variables, the additional variable $\tilde{y}_t^i$ cumulates the unobserved daily values throughout the month or the quarter, hence the need to define a cumulator variable[10] to handle the temporal aggregation of flow data:

$$C_t = \xi_t C_{t-1} + x_t \tag{3}$$

where ξ_t represents an indicator variable which takes as input values 0 in the first day of the period (i.e. a month or a quarter) and 1 otherwise (for the rest of the days). Therefore, the measurement equation for the flow variable $\tilde{y}_t^i$ becomes:

$$\tilde{y}_t^i = \begin{cases} \beta_i C_t + \gamma_{i1} \tilde{y}_{t-D_i}^i + u_t^{*i}, & \text{if } y_t^i \text{ is observed at day } t \\ NA \end{cases} \tag{4}$$

[10] This approach has been introduced by the authors afterwards and is detailed in Aruoba *et al.* (2013).

where u_t^{*i} is the sum of the u_t^i shocks over the reference period.

In the case of daily observed variables, the law of motion is given by the following two equations:

$$\tilde{y}_t^i = \beta_i x_t + v_t^i \tag{5}$$

$$v_t^i = v_{t-1}^i + \vartheta_t^i \tag{6}$$

In the empirical application of this paper most of the variables are transformed in growth rates (monthly or quarterly) and each of them has and associated flow measurement equation (independently of their individual type). On the other hand, variables such as interest rates, spreads and the economic sentiment indicator have been included in levels, with corresponding stock measurement equations.

This model could be expanded by adding a constant, more lags and/or a set of exogenous variables[11].

The model has a state-space representation, suitable for the estimation of unobserved variables using the Kalman filter. This procedure returns the most likely path for the variables conditional on the observable data, the structure of the model and the set of parameters:

Measurement equations: $$Y_t = Z\alpha_t + \Gamma w_t + \varepsilon_t \tag{7}$$

Transition equations: $$\alpha_{t+1} = T\alpha_t + \eta_t \tag{8}$$

$$\varepsilon_t \sim N(0, H), \eta_t \sim N(0, Q), t = 1, \ldots, \tau,$$

where (7) represents the set of measurement equations designed to link the observed variables (denoted by Y vector) to both the unobserved ones (state variables) α and the exogenous series w (i.e. variables which are not directly linked with the state). The estimation procedure based on the Kalman filter allows for missing values of monthly or quarterly observed variables (corresponding to the days when these are not measured; by convention we assume that monthly variables are observed in the last day of the month, while the quarterly data in the last day of the quarter). The α vector includes the business condition index which evolves at a daily frequency and also the cumulating variables needed for the temporal aggregation. The model's set of parameters (Z, Γ, T) and the variance-covariance matrices (H, Q) are estimated using the Kalman filter.

[11] In Aruoba *et al.* (2009) the exogenous variables can be used for trend modelling if the observed variables are analysed in levels. The downside of this approach resides in multiplying the estimated parameters. Although the authors present the model with exogenous variables, their empirical application is based on a simplified version of the model using filtered data. The current framework of the indicator uses variables that are expressed in log-difference, the need for trend modelling being eliminated.

3. Empirical application

a. Data

Regarding the selection of variables, other authors chose to look at either small or large data sets. The index of coincident indicators developed by Stock and Watson (1989) is based on industrial production, real personal income less transfer payments, real manufacturing and trade sales and employee-hours in non-agricultural establishments. The coincident index computed by *The Conference Board* is also based on a small set of indicators. Mariano and Murasawa (2003) encompass indicators at mixed frequencies. Their data set consists of the four series used by Stock and Watson (1989), complemented by quarterly GDP. On the other hand, Stock and Watson (1999) index of aggregate economic activity is based on 168 indicators, while CFNAI is estimated based on the first principal component of 85 economic activity series.

In our application, we use a small data set, similar to that used in Aruoba *et al.* (2009)[12]. Hence, in the first stage of this exercise we included variables such as: GDP (quarterly frequency), industrial production, employees in the private sector (monthly frequency) and CDS – *Credit Default Swap* (daily frequency).

In order to adapt the model to the features of the Romanian economy, the data set was subsequently augmented by adding a group of variables in line with the business cycle literature. Therefore, in the monthly data set we added variables such as the real average wage in the private sector (deflated by CPI), retail trade turnover (except for motor vehicles and motorcycles) and the economic sentiment indicator. Moreover, given the importance of the external demand for the Romanian (small open) economy, an effective external demand measure[13] was added as an exogenous variable, measured at quarterly frequency. We also checked the impact of including daily variables such as: the risk premium – *option adjusted spread* (OAS), the yield curve term premium (the spread between long and short term government bonds) and the 3-month interbank interest rate – ROBOR 3M, which we eventually included in the data set together with CDS. The estimation results were similar when using any of the other two variables.

Before proceeding with the state-space model estimation, the variables were transformed as follows: (i) growth rates (log-difference or change in level) were computed, except for the economic sentiment indicator, interest rates and spreads (the risk premium included), which were introduced in levels and (ii) the data set was standardized. The range was set between January 2005 and July 2015 due to the availability of the variables to be included and the need of bypassing the extreme values from the early 2000, partly caused by the transition process towards a truly business economy.

For the econometric exercise, we found important to mark a period of extreme values (outliers), between 17-23 October 2008, in the case of ROBOR 3M (higher values compared

[12] Aruoba et al. (2009) use initial jobless claims, GDP, payroll employment, industrial production, personal income less transfer payments and manufacturing and trade sales.
[13] Approximated by the effective EU GDP indicator, which is calculated based on the breakdown of Romania's exports by EU Member State.

to a threshold set to 25%). As a consequence, we choose to implement a procedure that excludes these values from the estimation process, replacing them with missing values. This procedure is referred to as a *trimmed regression*[14] (for details, see Ruppert and Carroll (1980) and Zaman *et al.* (2000)). The differences stemming from choosing to apply the trimming procedure are detailed in the next subsection.

b. Results

General considerations

The analysis of the indicator is performed concurrently with the dynamics in economic activity, reflected by real GDP, as well as with a group of variables underlying business conditions (such as risk aversion, financing costs, labour market indicators, economic sentiment indicators, prices or exchange rate dynamics). The average value of the indicator is by construction equal to zero. Positive values suggest favourable business conditions (better than average), while negative ones point to worse than average conditions.

The estimation reflects the importance of both the daily variables and the economic sentiment indicator for the evolution of the business condition index (given the highly absolute values of the associated coefficients). Most of the coefficients are statistically significant at a 5% threshold, except for the lags of GDP and industrial production. We also underline the coefficient associated with effective external demand (YSTAR_EF - that enters the model as an exogenous variable in the real GDP equation), which is positive and statistically significant at 5%, confirming the relevance of the small open economy setup. Details regarding the coefficients of each observed variable are reported in Appendix B.

The trimming procedure used for the outliers results in significant improvements in fitting the observed data, evaluated in terms of the model's likelihood (see Appendix B). During 17-23 October 2008 the index exhibits a different pattern, reflecting a massive deterioration of the business conditions in Romania. The analysis of the estimated coefficients reveals a smaller value associated with ROBOR 3M when using the trimming procedure that triggers absolute high values for the state variable.

Analysis of the real-time indices in parallel with other macroeconomic variables

During the last ten years, the dynamics of the indicators (see Figure 1) can be described as follows: (i) 2005-2007 – significantly high positive values; (ii) 2008-2009 – deterioration, moderate in the first half of 2008 and then sharply into negative territory; (iii) 2010-2012 – discontinuous recovery signs, with values close to zero; (iv) 2013-2015 – moderately positive values (with the lower bound of the 90% confidence interval being very close to zero), but smaller than the ones seen before the recession. The indicators swings generally overlap the dynamics of real GDP: the boom of 2005-2008, a sharp recession in 2009 and 2010 and a moderate recovery in 2011-2012 followed by the consolidation of growth in 2013-2015.

[14] The steps followed within the methodology are: 1) replacing the values higher than the threshold (chosen to be 25%) with missing values (NA); 2) the coefficient estimation of the state-space model; 3) recovering the true values (in this exercise the extreme values for ROBOR 3M); 4) the estimation of the state variable.

Given the similar pattern of the real-time indices, we decided to focus on only one of them, in particular on the one obtained by applying the trimming procedure. This choice is also supported by superior results in terms of the goodness of fit of the model: a higher value for the likelihood function and, respectively, a lower number of iterations needed for the convergence of the likelihood maximization algorithm.

Before 2008, also due to strong economic growth of Romania's foreign partners and the pro-cyclical stance of the fiscal policy, large internal and external unbalances built up (fiscal deficit, current account deficit, high inflation – on the back of excess demand, as well as a widening gap between wages and productivity[15]). This is pointed out by a substantial deterioration of risk aversion at the onset of the crisis. Consequently, we see a significant drop of the ADS index in 2008 (positive diminishing values) and 2009 (significantly negative values), in parallel with the signals given by the variables in the model (in particular, the daily variables and the confidence indicator). The subsequent correction of internal macroeconomic imbalances and the moderation of global tensions, also due to the agreements with international financial institutions, lead to an improving set of macroeconomic indicators (consolidation of economic activity, coupled with improving external equilibrium[16], relatively stable currency and low inflation), also reflected by the re-assessment of the Romanian sovereign rating as *investment grade*[17] and the long term interest rates[18]. During this period, the indicator hovers around zero, with temporary increases or even decreases, against the background of the fragile growth of external partners.

In the last two years, positive values of the index suggest favourable business conditions, albeit with a smaller intensity than before the financial crisis. This may point to a series of structural rigidities. Investors may perceive this as a risk factor that highlights the need for structural reforms, with potentially stimulating effects on investments and competitiveness.

The analysis underlines the leading feature of the indicator with regard to turning points in real economic activity, especially around the start of the recession. During 2008, the deterioration of the indicator, due to worsening risk perception and weakening external demand, is visible before the peak from 2008 Q3, as identified with the MBBQ algorithm. Afterwards, the negative development of the indicator is reflected by diminishing employment, industrial production and retail sales. The leading trait of the ADS index is visible as it improves before the trough identified in 2010 Q3, a feature coming from its underlying data set: even if some variables are coincident (labour market, production, retail sales), others are leading – in particular the financial variables and the confidence indicators. The leading characteristic of the indicator is amplified by its high frequency (by construction) as compared to the real economy series.

[15] During the booming phase, wages have substantially increased in Romania. The subsequent deceleration during the economic crisis was also due to a more efficient production processes imposed by financial constraints.

[16] During 2013-2014, the cohesion and structural funds were significant, allowing for new resources to be directed from the financial account to external reimbursements, thus compensating for non-residents deposit withdrawals.

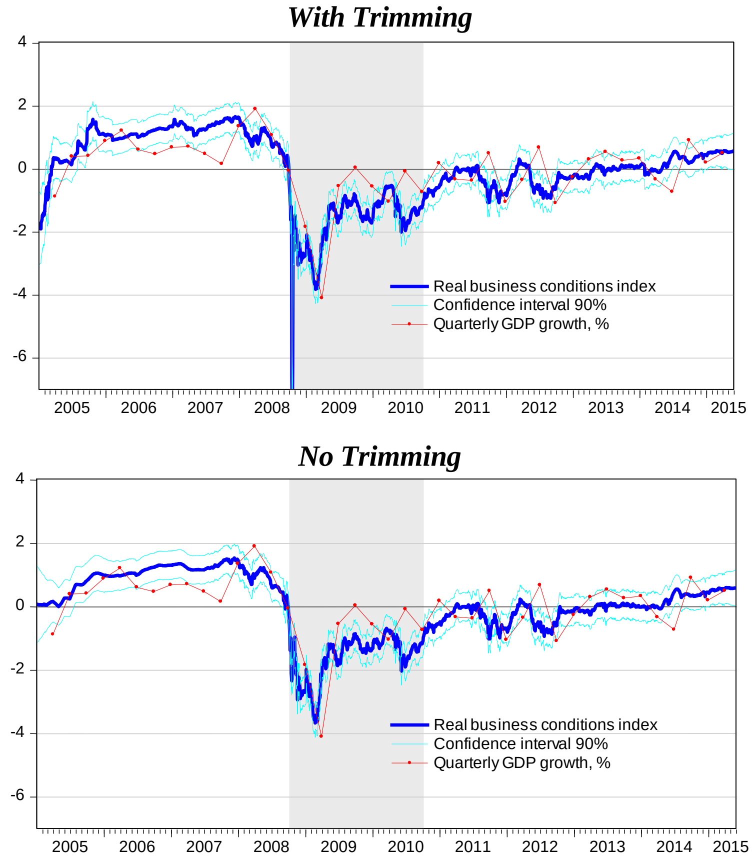
[17] The risk perception associated to the Romanian economy has improved during 2013-2014. In this context, during 2014, the Romanian sovereign debt rating was re-established into the investment grade category, starting with the S&P upgrade. Moody's and Fitch attributed this risk category to Romania in October 2006 and July 2011, respectively.

[18] Long term interest rates (10 years) went down significantly during 2010-2014.

The correlation of the index with real GDP growth and with the output gap

The indicator is useful in *nowcasting* the real economy, a feature highlighted by the significant positive correlation[19] with quarterly real GDP growth (see Figure 2). Moreover, the correlation with the change in the output gap (estimated using a HP filter) is significantly positive, meaning that the indicator points out the direction of the output gap. The latter information may be extremely useful for monetary policy as it assesses the variation in inflationary pressures stemming from the real economy.

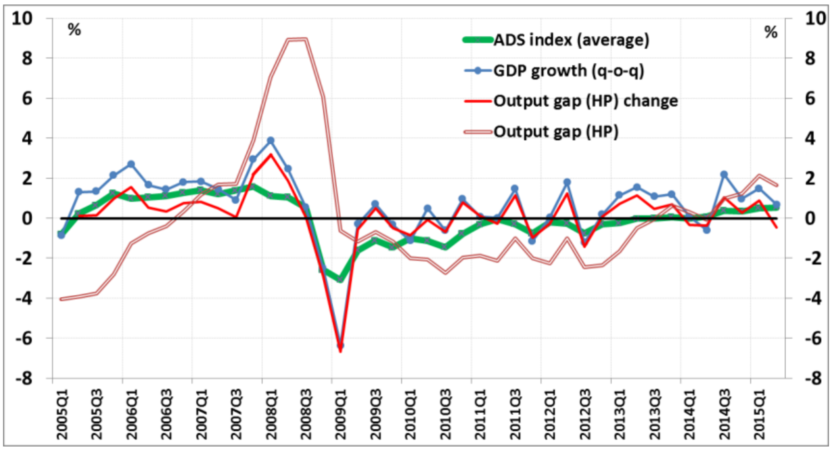
Figure 1: ADS indices, the 90% confidence intervals and the quarterly growth of GDP (standardized series). The daily variables are CDS and ROBOR 3M.



Note: The shaded interval shows the economic recession identified with the modified Bry and Boschan Quarterly algorithm (MBBQ). Details on this algorithm can be found in Grigoraș and Stanciu (2015).

[19] The bounds of the confidence interval of the correlation coefficient are computed as in Bonett and Wright (2000).

Figure 2: ADS index (quarterly average), the quarterly increase in GDP, the output gap (HP filter) and the change in the output gap. Estimates are obtained using the trimming procedure.



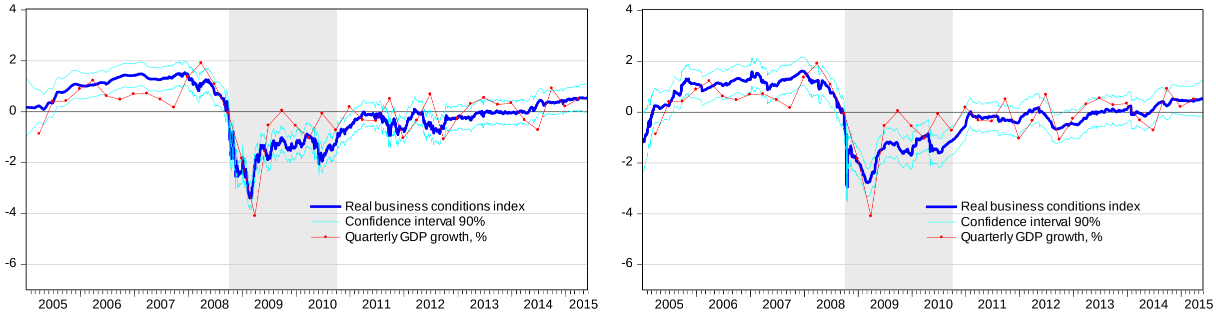
	Correlation coeff.	Confidence interval 95%	
GDP growth (q-o-q)	**0.82**	0.69	0.90
Output gap (HP)	**0.28**	-0.03	0.54
Output gap (HP) change	**0.74**	0.56	0.85

Note: Without trimming, the correlation coefficients are only marginally lower.

c. Robustness checks

We checked the robustness of the indicator by: (i) including only one daily variable and (ii) excluding the quarterly dynamics of GDP from the model. Figure 3 shows a similar pattern of the indicator irrespective of the daily variable in use (CDS *versus* ROBOR 3M). Differences are visible only in terms of local variability. The first indicator (CDS) shows a higher volatility in the post-crisis period, while the second one (ROBOR 3M) is more volatile in the expansion phase. The second robustness check was based on excluding the quarterly dynamics of GDP from the model. Results are not visibly different, and the corresponding coefficients are similar in magnitude. A possible explanation is that the relatively low frequency of GDP as compared to the other variables offers limited scope to influence the state variable. This is also indicated by the very low corresponding coefficient.

Figure 3: ***ADS index (quarterly average) and the (standardized) quarterly GDP growth. The daily variable is CDS (left panel) or ROBOR 3M (right panel), respectively.***



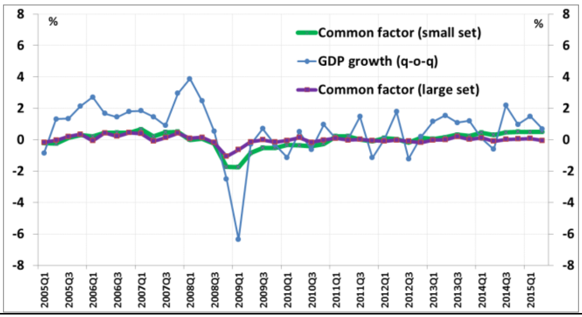
Note: Results are obtained without applying the trimming procedure (in the case of ROBOR 3M).

d. Comparative analysis

We extended the robustness analysis presented in the previous section by comparing the indicator with a common factor obtained by means of a *plain vanilla* principal component analysis. The first step consisted of the extraction of a single common factor from two sets of monthly variables: a small set and a large set, both presented in Appendix C. The comparison between the indicator and the common factor was ensured by using the variables chosen to construct the real-time business index as the small set (except for the quarterly GDP growth and the external demand, observable at a quarterly frequency). Results are shown in Figure 4. The common factors obtained by the principal component analysis are presented in terms of 3-month moving averages to smooth their volatility.

The comparative analysis suggests a similar profile of the common factors and the ADS index, respectively. Still, there are visible differences in terms of magnitude and volatility. Similarly to the ADS index, the common factors have a leading profile. For example, during the financial crisis, the common factors show deteriorating signs starting March 2008; the ADS index shows deteriorating business conditions even from the beginning of 2008, also due to its daily frequency. The characteristics of the data set used for the extraction of the common factors gives way to a different behaviour in some specific periods: during 2008-2010, the magnitude of the common factor based on the extended data set is smaller; in the recent periods, the factor based on the extended data set suggests a more gradual recovery, due both to the spectre and the number of containing variables that may show mixed signals. As for the correlation between the common factors and the quarterly dynamics of GDP, it is lower than the ADS index, pointing to a comparative advantage of the latter versus the purely-statistical procedure of principal components analysis.

Figure 4. ***Comparative analysis – principal components versus ADS***



Common factor (small set)

	Correlation coeff.	Confidence interval 95%	
GDP growth (q-o-q)	**0.72**	0.53	0.84
Output gap (HP)	**0.00**	-0.30	0.31
Output gap (HP) change	**0.70**	0.50	0.83

Common factor (large set)

	Correlation coeff.	Confidence interval 95%	
GDP growth (q-o-q)	**0.71**	0.51	0.83
Output gap (HP)	**-0.09**	-0.38	0.22
Output gap (HP) change	**0.67**	0.46	0.81

4. Summary and conclusions

The real-time business conditions index for Romania built with the ADS (2009) model is able to properly filter the information provided by a set of representative variables characterising the Romanian economy. These refer to risk aversion, labour market conditions, confidence indicators, industrial production and the retail sales. The high correlation between the indicator and the quarterly GDP growth, as well as the ability to grasp the relevant information regarding economic conditions recommends it as a suitable synthetic variable in near-term GDP forecasting.

The empirical application underscores the importance of the daily and the economic confidence variables, as well as the choice of a small open economy setup. Results are robust to model specification (using alternative daily variables or excluding GDP from the model). The procedure based on principal components confirms the consistency of the ADS index, given that the common factors have a similar profile. However, the ADS index has a number of advantages: a higher degree of correlation with the quarterly dynamics of GDP (despite a smaller set of variables) and a higher updating frequency.

We highlight the leading feature of the indicator with respect to turning points in real economic activity. For example, its significant deterioration in the first quarters of 2008 is visible before the large drop in economic activity in 2008 Q4. In the last quarters of the sample, the positive values of the indicator point to an improvement in business conditions, due to a recovery of the economic sentiment, a good risk perception and favourable financing conditions. In terms of policy, the consolidation of the indicator in positive territory is conditioned on measures that support investment, competitiveness, stabilisation of legal and fiscal frameworks, as well as the need to reinforce structural reforms implementation.

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Appendix A: Summary of the different approaches aimed at computing a business conditions/ cycle indicators

Indicator (source)	Data set	Data treatment	Methodological notes	Interpretation
Index of aggregate activity Stock and Watson (1999) (based on168 economic indicators)	168 economic indicators comprising: real activity, interest rates, monetary variables and prices	Non-stationary series are differenced (assuming no cointegration).	The index is computed based on factor models, over the entire set, or over sub-sets.	Cyclical behaviour is stronger than that of unemployment. The identified common factors are *leading* with respect to unemployment data.
Chicago Fed National Activity Index (CFNAI) (based on 85 economic activity series)	**85 monthly series** divided into 4 categories: - Production and income (23 series); - Employment and unemployment (24 series); - Personal consumption and housing (15 series); - Sales, orders and inventories (23 series).	Data is expressed in real terms. Prior to estimation the series are stationarised (except for indices, analysed in levels[20] or logarithm[21]) by: - Simple difference - Log difference In addition the series are standardised. Ultimately the index itself is standardised.	The methodology resembles that of Stock and Watson (1999) and consists of extracting a common factor.	An index of 0 corresponds to the average long-term growth rate. For the CFNAI-MA3 index values: (i) < -0,7 following an expansion – high probability of recession; (ii) > -0,7 following a recession – high probability of ending the recession; (iii) > 0,2 – increased/ significant probability of ending a recession; (iv) > 0.7 for more than 2Y of expansion – rising probability of inflationary pressures; (v) > 1 – high probability of inflationary pressures.
€-coin, CEPR, based on Altissimo *et al.* (2007)	145 variables: industry (41), prices (24), financial indicators (25), demand (14), surveys (25), trade (9), labour market (7)	The series are standardised (a common feature of factor models).	The dynamic factor model in generalised form as suggested by Forni *et al.*(2000)	€-coin captures underlying GDP growth, in correlation with a large data set and avoiding end-sample issues pertaining to univariate filters.
The index of coincident economic	4 monthly indicators have been used: industrial	Log differenced series.	The variables are the ones used by the *US Department of Commerce*	In the model specification, each variable is contemporaneously determined by the

[20] ISM Manufacturing: PMI Composite Index SA, 50+=Econ Expand, ISM Manufacturing: Production index SA, 50+ = Econ Expand, ISM Manufacturing: PMI Employment Index. PMI indices are already standardised – values greater than 50 correspond to an expansion, while the ones below 50 correspond to a decline.

[21] The data can be interpreted as the flow of new housing: Housing Starts SAAR, Thousands of Units, Housing Units Authorized by Building Permits SAAR, Thousands of Units, Housing Starts: West SAAR, Thousands of Units, Housing Starts: South SAAR, Thousands of Units, Housing Starts: Midwest SAAR, Thousands of Units, Housing Starts: Northeast SAAR, Thousands of Units, Manufacturers' Shipment of Mobile Homes SAAR, Thousands of Units.

indicators Stock and Watson (1989) (based on 4 series)	production, real personal income less transfer payments, real manufacturing and trade sales, employee-hours in non-agricultural establishments;		(DOC) in the computation of an index of real economic activity.	unobserved component. The index is presented in levels (with a fixed base in 1967), and its profile is analysed in correspondence with NBER turning points. Also the dynamics of the index is closely related to that of Gross National Product.
Coincident index of business cycles, as per Mariano and Murasawa (2003)	**Monthly frequency:** - Industrial production; - Personal income less transfer payments; - Manufacturing and trade sales; - Employees on non-agricultural payrolls; **Quarterly frequency:** GDP.	The series used in estimations are expressed as growth rates (log difference) and are partially standardised (mean-adjusted, but the variance can be different than 1).	This paper is a forerunner of the index computed in Aruoba, Diebold, Scotti (2009), in the sense that it uses mixed frequency and it includes GDP data.	The index can be interpreted as a monthly GDP.
Aruoba-Diebold-Scotti (ADS) Business Conditions Index (based on 6 economic indicators)	**Daily frequency** - *Yield curve term premium*, i.e. spread between 10Y and 3M US Treasury yields (not currently used). **Weekly frequency** - Initial claims for unemployment insurance. **Monthly frequency** - Employees on non-agricultural payrolls; - Industrial production; - Personal income less transfer payments; - Manufacturing and trade sales; **Quarterly frequency** - Real GDP.	Initially filtered values were used. Subsequently, M-o-M growth rates were preferred (log difference) for all variables except for initial jobless claims (a proxy for newly unemployed). The index is inherently standardised, by the way the model is defined.	Taking into account weekly data brings a substantial amount of information, unlike the case of the daily data.	Mostly with regard to peaks in real activity, the index can be considered as leading. It is a high-frequency *nowcast* of NBER's methodology; The index is updated on a weekly basis; Positive values indicate above average business conditions. Values can be compared between different time periods. For example, values lower than -4 shows worse business conditions with respect to the period from the international financial crisis.

ADS application for India (based on 4 series)	**Quarterly frequency** - Non-agricultural GDP; **Monthly frequency** - Industrial production; **Bi-monthly frequency** - M1; **Daily frequency** - *Yield curve term premium* (spread between 10Y and 3M bond yields).	Data are seasonally adjusted (using X12) and filtered (using the HP filter).	The model was defined in *state-space* form following Arouba, Diebold, Scotti (2009). The state variable and observed variables follow an AR(1) process. The daily variable does not follow an autoregressive process, but rather its innovations do so.	The interpretation is similar to that of the ADS index.
ADS application for Canada (based on 4 series)	The data used have a **monthly frequency (including GDP)** - Employment; - Manufacturing sales; - Retail sales - GDP.	Variables are expressed as Y-o-Y growth rates.	The methodology follows that of ADS. The index has a weekly frequency, based on the data release calendar (information is being updated weekly). The interpretation takes into account that the mean value is 0. Positive values show (similarly to the ADS index) business conditions above average, meanwhile negative values encompass below average conditions.	The index is leading as compared to GDP growth, anticipating turning points. In order to validate the accuracy of the model the index is aggregated at monthly frequency and a correlation coefficient is computed between each series and the ADS index. Compared to the first principal component (whose frequency is limited by that of the series used), one can observe the *leading* feature of the ADS index.
The composite coincident indicator computed by *The Conference Board*	**Monthly** frequency**:** - Employees in non-agricultural payrolls; - Personal income less transfer payments ; - Industrial production; - Manufacturing and trade sales.	M-o-M growth rates; for series expressed as percentages simple difference is used, meanwhile for ever other series a symmetric percentage change is computed	The methodology has five steps: (i) monthly growth rate is computed for each series[22]; (ii) series are standardised[23]; (iii) components are summed up; (iv) a preliminary level is computed, with the first observation=100; (v) the index is rescaled to obtain the desired reference year.	The composite coincident indicator of *The Conference Board* is very well synchronised with NBER turning points (8 out of 13 turning points are a perfect match; otherwise there is a maximum 3-month lead/lag in between them).

[22] $r_{i,t} = 200 \times \frac{(X_{i,t}-X_{i,t-1})}{(X_{i,t}+X_{i,t-1})}$.

[23] The standardisation factor controls for the way in which monthly developments in individual series impact the developments of the index. Adjustments are made to reduce individual volatility within subcomponents (based on the inverse standard deviation of the symmetrical percentage change). Factors are standardised and rescaled in order to add up to 1.

Appendix B: Estimation results

Daily variables – CDS & ROBOR3M, With trimming

	Coefficient	Std. Error	P-value
CDS	0.72	0.12	0.00
EMPR	-0.01	0.00	0.02
CA_RETXAUTO	-0.02	0.00	0.00
Y	-0.01	0.00	0.00
YSTAR_EF	0.41	0.14	0.00
YIND	0.00	0.00	0.14
BS_ESI_I	-0.20	0.06	0.00
WGPR_R	-0.01	0.00	0.00
ROBOR3M	0.09	0.03	0.00
Log likelihood	7454.93	AIC	-5.54

Daily variables – CDS & ROBOR3M, No trimming

	Coefficient	Std. Error	P-value
CDS	0.72	0.17	0.00
EMPR	-0.01	0.00	0.03
CA_RETXAUTO	-0.02	0.00	0.00
Y	-0.01	0.00	0.00
YSTAR_EF	0.42	0.14	0.00
YIND	0.00	0.00	0.14
BS_ESI_I	-0.21	0.06	0.00
WGPR_R	-0.01	0.00	0.00
ROBOR3M	0.33	0.10	0.00
Log likelihood	3575.80	AIC	-2.65

Daily variable – CDS only, No Trimming

	Coefficient	Std. Error	P-value
CDS	-0.70	0.20	0.00
EMPR	0.01	0.00	0.03
CA_RETXAUTO	0.02	0.00	0.00
Y	0.02	0.01	0.03
YSTAR_EF	0.41	0.14	0.00
YIND	0.00	0.00	0.21
BS_ESI_I	0.22	0.09	0.01
WGPR_R	0.01	0.00	0.00
Log likelihood	2341.34	AIC	-1.90

Daily variable – ROBOR 3M only, No Trimming

	Coefficient	Std. Error	P-value
ROBOR3M	-0.59	0.24	0.02
EMPR	0.01	0.00	0.03
CA_RETXAUTO	0.02	0.00	0.00
Y	0.02	0.01	0.04
YSTAR_EF	0.42	0.14	0.00
YIND	0.00	0.00	0.34
BS_ESI_I	0.20	0.08	0.01
WGPR_R	0.01	0.00	0.01
Log likelihood	2404.30	AIC	-1.78

Appendix C: The variables included in the alternative assessments based on the principal components models

Indicator	Variable description	Transformation
	Small data set	
EMPR	Employees, private sector	Log-difference
YIND	Industrial production	Log-difference
CA_RETXAUTO	Retail sales turnover index (except for motor vehicles and motorcycles)	Log-difference
BS_ESI_I	Economic sentiment indicator, Romania (balance seasonally adjusted)	Change in level
WGPR_R	Gross wage in private sector, real	Log-difference
ROBOR3M	3 months interbank interest rate (ROBOR, Romanian Interbank Offer Rate)	Level
CDS	Credit default swap, 5Y, Romania	Level
	Large data set	
YIND	Industrial production	Log-difference
YINDEU	Industrial production in EU	Log-difference
YINDMAN	Industrial production in manufacturing	Log-difference
YINDELT	Industrial production in electric and thermal energy	Log-difference
YINDEN	Industrial production in energy	Log-difference
YINDEX	Industrial production in mining and quarrying	Log-difference
YINDDG	Industrial production of durable goods	Log-difference
YINDIG	Industrial production of intermediate goods	Log-difference
YINDKG	Industrial production of capital goods	Log-difference
YINDNDG	Industrial production of nondurable goods	Log-difference
CA_RETXAUTO	Turnover volume index of retail trade (except for motor vehicles and motorcycles)	Log-difference
CA_AUTO	Turnover volume index of wholesale and retail, maintenance and repair of auto-moto	Log-difference
CA_FUELS	Turnover volume index of retail sale of fuels for cars	Log-difference
CA_FOOD	Turnover volume index of retail sale of food, beverages and tobacco	Log-difference
CA_NFOOD	Retail sale of non-food products (including fuel)	Log-difference
CA_YINDMAN	Turnover volume index in industry – manufacturing (domestic market)	Log-difference
CA_YINDEX	Turnover volume index in industry – mining and quarrying (domestic market)	Log-difference
CA_YINDDG	Turnover volume index in industry – durable consumer goods (domestic market)	Log-difference
CA_YINDIG	Turnover volume index in industry – intermediate goods (domestic market)	Log-difference
CA_YINDKG	Turnover volume index in industry – capital goods (domestic market)	Log-difference
CA_YINDNDG	Turnover volume index in industry – non-durable consumer goods (domestic market)	Log-difference
BS_CCI_BAL	Construction confidence indicator, Romania (balance seasonally adjusted)	Change in level
BS_ICI	Industrial confidence indicator, Romania (balance seasonally adjusted)	Change in level
BS_RCI	Retail confidence indicator, Romania (balance seasonally adjusted)	Change in level
BS_CSMCI	Consumer confidence indicator, Romania (balance seasonally adjusted)	Change in level

BS_SCI	Services confidence indicator, Romania (balance seasonally adjusted)	Change in level
BS_ESI_I	Economic sentiment indicator, Romania (balance seasonally adjusted)	Change in level
ESI_EU	Economic sentiment indicator, EU (balance seasonally adjusted)	Change in level
OIL_BRET_U	Europe Brent Spot Price FOB, average	Log-difference
ROBOR3M	3 months interbank interest rate (ROBOR, Romanian Interbank Offer Rate)	Level
CDS	Credit default swap, 5Y, Romania	Level
EURUSD, S	EUR/USD exchange rate, EUR/RON exchange rate	Log-difference
BPI	Building permits 1000 square meters	Log-difference
CPI_U	Consumer price index, total (CPI)	Log-difference
EMPR	Employees, private sector	Log-difference
EMI	Employees, industry	Log-difference
UILOM	Unemployment rate (ILO)	Change in level
WGI_R	Gross wage in industry, real	Log-difference
WGPR_R	Gross wage in private sector, real	Log-difference
LWI	Industry labour productivity	Log-difference
CONSTR	Construction works index	Log-difference
CONSTR_NEW	New construction works index	Log-difference
CONSTR_RK	Capital repairs construction works index	Log-difference
CONSTR_RC	Current repairs construction works index	Log-difference
XBP6	Export of goods and services, fob (BoP data, current prices)	Log-difference
MBP6	Import of goods and services, fob (BoP data, current prices)	Log-difference
NDA	Net domestic assets	Log-difference
CREDITPOP_R	Households loans, real	Log-difference
CREDITSN_R	Corporate loans (non-financial corporations and non-monetary financial institutions), real	Log-difference