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INDICATOR BASED FORECASTING OF BUSINESS CYCLES IN AZERBAIJAN

F.MAMMADOV,

SH.ADIGOZALOV

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Abstract

This paper has attempted to construct leading indicator systems and based on that to predict future contraction period of the Azerbaijan non-oil economy using more than 100 publicly available economic and financial data. Our results show plausible and significant performance of composite leading indicator system with average leading time of 7.2 months. We found that between January of 2000 and May of 2014, there were 6 turning points in Azerbaijan non-oil economy, consisting of three peaks and three troughs corresponding three expansion and four contraction periods. It turns out that the average duration of expansion and contraction phases is 43 and 10 month, respectively. Based on selected leading indicators we constructed composite indicator is found to be able to predict all the six turning points. Using dynamic probit model we estimated contraction probability of non-oil output gap for the future period. Out-of sample as well as in-sample forecast performance suggest that the leading indicator systems have significant predictive power and could be used as a useful tool for economic forecasting.

Keywords: Business cycles, Dating, Turning points, Forecasting, Probit Model.

JEL Codes: E32, C22, C25.

Introduction

In last few decades cyclical indicators, composed of a range of statistical indicators sensitive to changes in the business cycles, extensively used for analyzing patterns of economic (short-term) fluctuations, particularly for assessing the current state of economy and for prediction of turning points to provide early warnings of economic downturns/upturns. In that context business cycle indicators particularly became very important and useful empirical tool for policy-making. Objective of this study is to identify cyclical indicators and make a predictions of future state of the Azerbaijani non-oil economy.

Cyclical indicators are classified into three categories—leading, coincident and lagging—based on the timing of their movements. Due to predictive content and policy relevance leading indicators took more attention of economists. The objective of a leading indicator is to predict the peaks and the troughs of the swings in the economy sufficiently far in advance that is possible to react to extreme events they present. The troughs of the cycles represent contraction periods in the economy, and anticipating these downturns in the main focus of most business cycle studies. Such indicators are usually based on empirical observations of relationships between given economic variables and are selected either through the use of economic theory or econometric analyses.

An extensive number of empirical studies have documented comprehensive catalogue of the emprirical features of the business cycles of advanced economies inspired by seminal work of Burns and Mitchel (1946). However, only few research papers can be found for developing country case, such as Zang and Zuang (2002) on Malasia, Salinas and Aguilar (2002) on Peru, Van der Walt (1983) on South Africa, Mongardini and Saadi-Sedik on Jordon. However, only few of the studies devoted to oil exporter countires on this topic. Even, when documenting economic fluctuations in oil rich countries such as Kazakhstan and Russia, the researchers generally focus on the whole economy and ignore the distinct dynamics of the non-oil sector. The rationale behind the focusing on non-oil part of the economy is due to exogenous behaviour of oil sector. The exogenity of the oil sector to respect to monetary policy and excessive weight of oil sector in overall economy poses challenges to monetary authority to absolve a shock and to policy decisions in advance. Contrary, non-oil part of the economy is an endogenous, in a sense that it responds to the decisions of monetary autority, as well as to other market fundamentals.

Azerbaijan is an oil exporting country and regularly exposes to terms-of-trade shocks. Though less than 1% percent of the employed people are working at the oil sector, they produce approximately half of the GDP. Consequenly, shrinkage in the export volumes and earnings on non-oil commodities between 2004 and 2008 (from 52.5 percent to 4.7 in the total export) happened due to dramatic increase of oil sector. İncreasing role of external factors in overall dynamics of the Azerbaijani economy and absence of proper empirical analysis can challenge central banks to observe shocks and to response them adequatly.

To be specific, consider positive terms of trade shock causes to increase oil output, so it does total output to exceed potential output, but not necessarly non-oil output. Hence, the pressure on domestic production capacity inceases. In turn, inflation will be accelerated, current account balance and volume of imported goods will be detorated. Therefore, central bank will increase interest rates to bring down total output to its potential level. However, due to exogeneity of oil sector, central bank policy decision will not effect total output (via oil ouput), rather it will effect non-oil sector. If non-oil output on that time equal or less than potential, then central bank policy action even expected to have adverse effect, i.e., causes to contract even more. Hence, purposed of cyclical barometr of non-oil output of Azerbaijan allows Central Bank of Azerbaijan (hereafter, CBAR) to identify level of capacity utilization, therefore makes possible to predict future state of the economy in order to take a necessary and properpolicy actions.

A practical outcome of this study are twofold. First is that, this study is the first attempt to identify a turning point chronology of Azerbijan non-oil economy. Turning point chronolgy is very useful to cross-country comparisons of economic pefromance and to validate forecasts. The secondly, this study gives a roadmap of the economy over the next periods via cyclical indicators. Clearly, knowing whether or not that map contains the pitfalls of a recession is important. Therefore, measuring cyclical indicators are vital for tracking the future state of general economy and adoption of proactive policy action in advance**.**

The outline of the paper is as follows. Section 2 describes the methodology and data. Our main empriical reults are presented in section 3, and setion 4 summarizes our results and concludes.

Methodology and data

The business cycles literature are very diverse on which cyclical indicator to use. In economic literature classical and growth business cycles are the most discussed concepts. Classical cycles are the fluctuations in the level of the series, whereas growth-cycle is a fluctuations around some trend. There some limitations (or rationales) why we cannot apply classical cycle approach. First, is due to time interval limitation, i.e., classical cycles take around between 7-11 years, however our time interval is very short to empirically observe classical cycles. Instead, duration of cycles in growth cycles sense take time at around 3-5 years that makes empirically possible to investigate this kind of cycles. The second rational, even if classical cycle can be observable, it is less interesting in terms of monetary policy perspective. Because, CBAR doesn't have such a tool to influence 7-10 years business cycle. Moreover, classical cycles tend to vanish over time if the trend growth rises steadily from zero; in the long run the length of the classical contractions become shorter and shorter compared to the expansion so classical turning points will ultimately disappear (Stock and Watson, 1989). However, considering the fact that growth-cycles exibits 3-5 years duration, it is possible to observe enough number of cycles. It allows us to construct turning point chronology of non-oil output of Azerbaijan, which in turn could be used to find out cyclical indicators. Presence of this kind of cycles makes possible to Central Bank to impelement “push and pull” policy when economy is in undesirable state.

In order to estimate growth (business) cycle indicators we employed OECD (2010) methodological framework. For turning points prediction we used probit model suggested by Estrella and Mishkin (1998).

The methodological framework of indicator based prediction of turning points of business cycles involves four major steps. The first step covers identification of reference series and dating of turning points. The second stage comprises selection of proper leading indicators. The third stage is consist of contruction of composite leading indicator. The last, forth stage is a prediction of turning points using composite leading indicator.

Identification of reference series and dates of turning points.

In the economic literature in general cycle considered to be have 4 phases: prosperity, recession, depression and recovery, and two turning points: boom and trough. For the sake of simplicity and practical purposes we will consider prosperity and recovery as a period of expansion, and recession and depression period as a contraction period.

The first step is to select an appropriate indicator as a measure of economic activity, that is also called a reference series, and to identify dates of turning points (peaks and troughs) of the underlying business cycles in that series. The most commonly used measure of economic activity is the monthly index of industrial production (IP) or gross domestic product (GDP). These involve the following steps:

Adjusting for seasonality.

The most of the macroeconomic indicators are often influenced by seasonal fluctuations and other calendar/trading-day effects, which can impede a clear understanding of economic phenomena. Therefore, all other effect other than economic activity should be eliminated from the raw data in order to get consistent results. For this purposes two methods X12-Arima and TRAMO-SEATS is used widely in empirical macroeconomics. [1] We found TRAM-SEATS to be more effective for elimination seasonal patterns more than other methods.

Detrending

Growth cycle approach requires extraction of cycle component from the series. In order to extract cyclical component of the series we employ Hodrick-Prescott (HP, thereafter) filter, which is commonly used in the business cycle literature.

The HP filter is a two-sided optimization procedure and it basically decomposes a time series y_t , into a trend component (τ_t) , as well into a cyclical component (c_t) through the minimization of the following expression:

$$y_t = \tau_t + c_t$$

(1) $$\min_{\tau_t} \sum_t (y_t - \tau_t)^2 + \lambda \sum_t (\tau_{t+1} - 2\tau_t + \tau_{t-1})^2$$

where λ is the smoothing parameter taking value in $[0, \infty)$. Here, the first term, $(y_t - \tau_t)$ corresponds to the cyclical component, while the second term penalizes variations in the growth rate of the trend component, with the penalty increasing with the value of λ. The smoothness of the trend can be determined by choosing the value of the parameter λ. When $\lambda = 0$, minimizing (1) implies first term to be zero making cycle component zero. On the other hand, in the limit when $\lambda = \infty$, second term becomes zero in order to minimize (1) and the trend component becomes linear. So the higher the λ value is, the smoother the trend will be.

[1] More about seasonality methods (Alberto Cabrera, Seasonal Adjustment In Economic Time Serees: 1999)

Main concern over the HP filter application is the choice of λ parameter. Ravn and Uhlig (2002) point out, the choice of λ=1600 for quarterly data actually reflects a specific definition for the duration of business cycles, which may be longer than what is generally observed in emerging market countries. Indeed, Pallage and Robe (1998), Agenor, McDermott, and Prasad (2000), and Rand and tarp (2001) find that business cycles in developing countries (as well as in emerging markets), as opposed to cycles in developed countries, are significantly shorter in duration and the speed from peak to trough and vice versa is faster. Hence setting λ=1600 may be inappropriate for developing countries, as well as for Azerbaijan. Moreover, Aguiar and Gopinath (2007) argue that trend components in emerging market countries are more volatile than the trends observed in developed countries, which serves as another motivation for considering a lower value than 1600 for the smoothing parameter in HP filter. Therefore , using following the formula suggested by OECD we calculate λ parameter for Azerbaijani non-oil economy:

$$\lambda = [4(1 - \cos(\omega_0))^2]^{-1}$$

Whereas ω_0 is the frequency expressed in radians, and ρ denotes the number of periods it takes to complete a full cycle. The two parameters are related through $\omega_0 = 2\pi/\rho$.

Identifying (dating) cyclical turning points

There are several reasons for dating turning points of the non-oil economy of Azerbaijan. Turning point chronology may be helpful to compare the cycles between nations or to point out links between the cycles and diverse economic aggregates. Even more important reason for dating points is to establish a reference cycle dating for a country. In turn, this reference cycle is used in empirical studies either to classify economic series (leading, coincident or lagging) or to validate real-time detection and forecasting methods. This study is the first attempt to identify cycle turning points of the non-oil economy of Azerbaijan.

Economists and statisticians have developed many statistical methods that automate the dating of business cycle peaks and troughs (see Boldin 1994 for a summary). In general, techniques can be classified in two broad categories: parametric (Hamilton (1989) , Artis, Krolzig and Toro, 1999, Krolzig, 2001, 2003, and Anas and Ferrea 2002b) and nonparametric (Conference Board 3d rule, Bry and Boschan 1971, Anas 2000, Lommatzsch and Stephan 2001, Harding and Pagan 2001). Due to necessary calibration of parametric models on dating and to the lack of robustness to the model to sample (Anas and Ferrera 2002b, Anas, Billio, Ferrea and Duca), some authors preferred non-parametric approach. We are not going to dig in all of them to find the their pros and cons. Instead our apporach is to use a methodology which meets *parsimony principle*, stating that a model will be selected which has few assumptions. Following this principle has we think twofold advantages. The first is that selected method will be transparent in a sense that procedure will be very easy reaplicable and policy makers also could participate in estimation period as well. The second is that it will allow us to prepare cycle turning point chronology. It seems Bry and Boschan (1971) algorithm meets this criteria more.

The identification of the first candidates set of turning points on the time series of interest (y_t) is determined by using Bry and Boschan (hereafter, BB) algorithm :

(a) A peak in the cyclical component of real non-oil output of Azerbaijan occurs at time *t* if:

$$(1 - L^K)y_t^c > 0, (1 - L)y_t^c > 0 \ \ and \ \ (1 - L)y_t^c < 0, (1 - L^K)y_t^c < 0$$

(b) A trough in the cyclical component of real non-oil output of Azerbaijan occurs at time *t* if:

$$(1 - L^K)y_t^c > 0, (1 - L)y_t^c < 0 \ \ and \ \ (1 - L)y_t^c > 0, (1 - L^K)y_t^c > 0$$

Here, y_t^c is a cyclical component of non-oil output (i.e., non-oil output gap), L is the lag operator, where $L^K y_t^c = y_{t-k}^c$ and K is a number of month which is chosen to be K=6 for monthly time series. In other words, a contraction occurs if the ecomic activity indicator (non-oil output gap) declines for 6 months and an expansion if it increases for the same interval, turning points shorter than this interval are disregarded. In practise, the BB algorithm also applied some extra cencoring procedures to the dates that emerged from applying the above rule. In particular the contraction and expansion phases must have a minium duration of 6 months and a completed cycle must have a minimum duration of 15 months.

Selection of Leading Indicators

The second step is to select appropriate economic and financial indicators as predictors of the turning points of business cycles. While, OECD listed a number of rationales as criteria for assessing their suitability as leading indicators of business cycles, from practical point of view, we score indicators in terms of five criteria: availability of monthly data, economic rationale, having cyclical movements and leading turning points in the reference series.

Lead times are measured in months, reflecting the time that passes between turning points in the component and reference series. Of course lead times vary from turning point to turning-point but the aim is to construct leading indicators whose lead times are on average between 6 to 9 months and that have relatively small variances. To evaluate the length of leads, both mean and median leads are used, because the mean lead on its own can be strongly affected by outliers. The consistency of leads is measured by the standard deviation from the mean lead. The lead calculations are based on matching turning-points of the reference series and the components or the composite in a 18 to -6 month lead window; matches that have higher leads or lags are discarded and counted as extra or missing turning points. Ideally, potential leading indicators should have a mean lead greater than 2 and a correlation at peak greater than 0.5 (with a peak lead equal or greater than 2). Note that, to obtain a reliable composite indicator, the average lead should not be too different from the peak lead.

As in any multi-criteria problem, there is no ideal solution optimizing all the conditions at the same time and therefore compromises have to be found. However, despite the fact that there is no unique way to build a composite indicator and several criteria can be applied, most of the building procedures usually include a preliminary study of the available series.

Among these variables financial indicators to be proven better predictors (interest rates spread: Esterlla&Mishkin 1998; Esterlla et al. 2003,monetary aggregates: Anderson & Jordan 1986, Cooley and Hanson 1995)). Due to profit expectations, anticipating policy actions of authorities, and interaction with rest of world financial market indicators incorporate all available information. However, it is mostly empirical question whether any specific indicator has very high predictive content or not, due to specific charecteristics of Azerbaijani economy.

Constructing a composite leading index

The third step involves constructing a composite leading index from the selected individual leading indicators. Unlike individual leading indicator, composite index reflect broader spectrum of the country, comprising real, monetary, fiscal and external sector data. In statistical terms, this implies that a composite index reduces the measurement error associated with a given cyclical indicator (Mall, 1999). In some sense reduction of measurement error implies elimination if any false signal appears in any individual series. Moreover, the performance of an individual series may vary over different business cycles, making it a poor indicator in some occasions (Dua and Banerji, 2001).

From the practical point of view, the selection of components series is guided by the following criteria: we drop the series missing more than 30% of reference series turning points; we drop the series having a mean lead less than 2; only those series having a peak lead equal or greater than 2 and with cross-correlation value with the reference higher than 0.5 are considered as components.

Composite indicator is an equally (or not)-weighted liner combination of several series once we control for the fact that they have different variances. Hence, the composite leading indicator uses weights constructed as:

$$CLI_t = \frac{1}{n}\sum_{i=1}^{n} \frac{x_t^i}{\sigma_{x_t^i}},$$

Where $\sigma_{x_t^i}$ is the standard deviation of component variable.

Furthermore, it should bear in mind that a series provides valuable information if it does not flag too many extra cycles and does not miss too many turning points. In choosing between a series having less false signals and one with less missed turning points, researcher should prefer the latter. Indeed, while having extra turning points in some component series might not be a serious concern (since, in principle they should cancel each other out in the aggregate), missing some peaks or some troughs is much more problematic, since signals not captured in the components will not likely be part of the aggregate.

Prediction

After constuction of variables of interest we can use them to predict economic activity. In order to quantify the predictive power of the variables examined with respect to future contractions, we use a probit model. The probit form is dictated by the fact that the variable being predicted takes on only two possible values-whether the economy is or is not in a contraction phase. We focus simply on predicting recessions in discrete dependent variable rather than point estimate of real gdp growth, in order to overcome the problem of spurious accuracy associated point estimate (Estrella and Mishkin, 1998). Then, the probit model is defined with the following form

$$R_{t+k} = \beta' X_t + \varepsilon_t$$

where R_t is an binary variable that determines the occurrence of a contraction at time *t, k* is the length of the forecast horizon, ε_t is a normally distributed error term, β is a coefficients, and X_t is a vector of values of the independent variables, including composite leading indicator and a constant.

The form of estimated equation is

$$P(R_{t+k} = 1 |\ X_t) = F(\beta' X_t)$$

Where F is the cumulative normal distribution function corresponding to $-\varepsilon_t$.

The model is estimated by maximum likelood, with the likelihhod function defined as

$$L = \prod_{\{R_{t+k}=1\}} F(\beta' X_t) \prod_{\{R_{t+k}=0\}} [1 - F(\beta' X_t)]$$

The lag length k can be optimally chosen for each of the single-indicator models by a standard information criterion. In the following application to the Azerbaijani non-oil economy recession forecasting, we employ the Akaike Information Criterion (AIC).

The recession indicator is obtained from the Bry and Boschan algorithm, that is,

$$R_t = \begin{cases} 1, & if\ the\ economy\ is\ in \\ & contraction^{1}\ in\ quarter\ t \\ 0, & otherwise \end{cases}$$

We examine several constructed composite leading indicators with potential predictive power for contractions, and we consider each variable with predictive horizons ranging from one to eight month ahead. Hence we introduce a few summary measures of the predictive power of a given variable with a given horizon.

The principal measure is a *pseudo* R^2 developed in Estrella (1995), that is, a simple measure of goodness of fit that corresponds intuitively to the widely used coefficient of determination in a standard linear regression. Denote the unconstrained maximum value of the likelihood function L as L_u,, and its maximum value under the constraint that all coefficients are zero except for the constant as L_c, The number of observations is n. Then the measure of fit is defined by

$$pseudo\ R^2 = 1 - \left(\frac{LogL_u}{LogL_c}\right)^{-\left(\frac{2}{n}\right)logL_c}$$

The form of this function ensures that the values 0 and 1 correspond to "no fit" and "perfect fit," respectively, and that intermediate values have roughly the same interpretations as their analogues in the linear case. Although the absolute levels of this new measure may differ from measures proposed earlier in the literature, the ordering of alternative models produced by the different likelihood-based measures is the same.

Of particular interest in this paper are the out-of-sample results. We again use the pseudo R^2 measure to assess the out-of-sample accuracy of the forecasts. However, when applied to out-of-sample results, there is no guarantee that the value of the pseudo R^2 will lie between 0 and 1, as is also true in the standard linear regression. Nevertheless, the pseudo R^2 for out-of-sample results is useful as a simple measure of fit and is comparable to the root-mean-square error or R^2 measures in the linear regression case.

[1] Recession phase we estimate from peak (local maxima) to trough (local minima), and for expansion period from trough (local minima) to peak (local maxima).

Data

We use monthly and quarterly aggregate[1] macro data in real as well as nominal terms from 2000 to 2014 on more than 100 different variables from those are available from the databases of State Statistical Committee and Central Bank of Azerbaijan. As it stated before the recession variable is constructed using BB algorithm.

There are several reasons for choosing this particular timespan. Starting from 2000 Azerbaijani economy depicts more oil driven characteristics. Expanding oil extraction and export together with high oil prices in the world markets caused huge inflow of oil revenues into the economy which in its turn led to fiscal expansion. Thus, one can observe high economic growth rates since 2004. Hence, data was choosen in a way that could be possible to cover these important hallmarks of our economy by excluding subtsantially distinguished period.

Results

In this section, we summarize our findings in three subsection. Results found by using λ=1083[2] in the HP Filter for monthly data. First subsection encompasses business cycle chrolongy for Azerbaijani non-oil economy. The second subsection embody regarding the selection of business cycle indicators (leading, coincident) of Azerbaijan non-oil economy. In the last, third subsection prediction results are given.

Turing point chronology

As a reference series we used non-oil real GDP[3] series covering timespan from January of 2000 to March of 2014. Some empirical literature use industrial production index (IIP) as an alternative reference serious for business cycles. However, due to

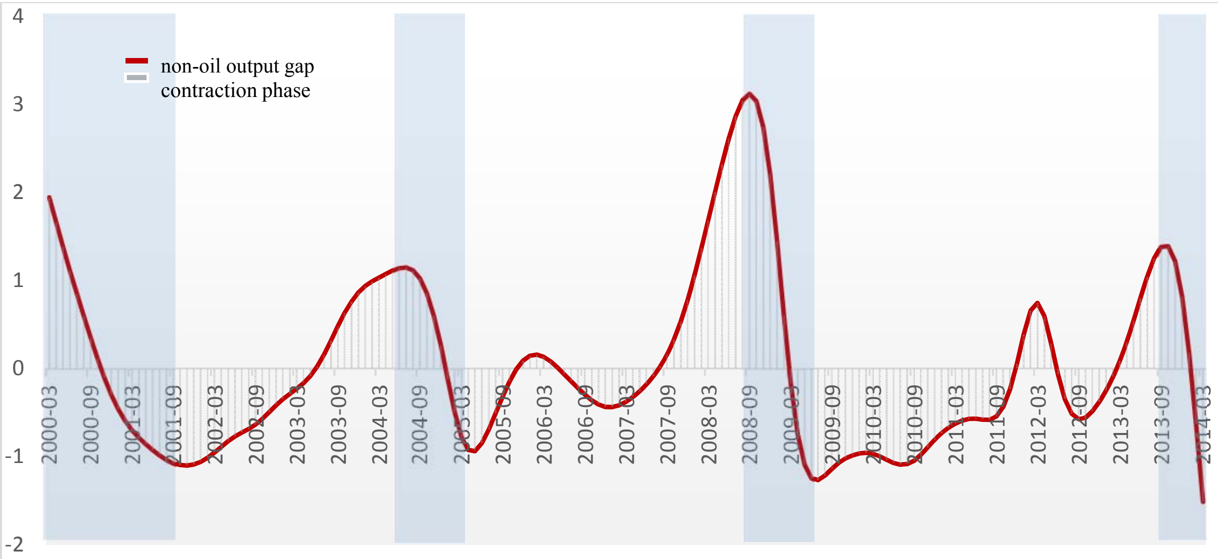
[1] We interpolated quarterly data to mothly data in order to use them in estimation.

[2] ρ is chosen to be 36. It can be justified by other studies, where they found on average full cycle in developing countries 3 years or 36 months.

[3] With 2005 average constant prices.

lack of confidence on quality of IIP, we preferred to use non-oil real GDP. The figure 1 depicts the turning points in Azerbaijan non-oil real GDP series detected by BB algorithm and Table 2A and 2B gives the main statistics about duration of business cycles in Azerbaijan.

Figure 1. Business cycle of non-oil economy of Azerbaijan



The first contraction periods seems to be associated with 1998 Russian financial crisis, known as "Russian Flu". There is no information on starting date of contraction, however it reaches trough point at November of 2001. It seems that up to know more severe recession was the first one due to it is duration. However, consequent contraction periods become shorter in duration. Expansion follows after the first contraction phase up to July of 2004. Expansion had started just after one year when Russia economy started to recover. The second contraction as well as expansion period covering from 2004 to 2007 was the consequences of oil boom period in Azerbaijani non-oil economy. Whereas, world financial crisis is obviously was a cause of third contraction in non-oil economy. It started on October of 2008 and reached its trough point on July of 2009. After that date, non-oil economy of Azerbaijan experienced the longest expansion period in a given timespan, starting from July of 2009 to October of 2013. More detailed information of each phase is given in table 2A and 2B.

Table 2A. Turning point chronology

	Phase	Start	End	Duration	Amplitude
1	Contraction	-	2001M11	-	-
2	Expansion	2001M11	2004M7	32	2.3%
3	Contraction	2004M7	2005M5	10	2.1%
4	Expansion	2005M5	2008M9	40	4.1%
5	Contraction	2008M9	2009M7	10	4.4%
6	Expansion	2009M7	2013M10	57	2.7%

Starting points do not included in the interval, however ending points included.

Table 2A is a statistical summary of each phase of business cycles. Due to lack of information on the starting point of first contraction and ending point of the last contraction we were not able to calculate duration and amplitude[1] of them. We found overall 6 turning points, 3 peak and 3 troughs in real non-oil gdp series over the 14 years. These turning points correspond to 3 expansion periods and 4 contraction periods accordingly. Oil boom period, from 2005 to 2008 seems that associated with the highest output gain (4.1%) in non-oil GDP with quite long 40 month duration. The longest duration of the expansion period of non-oil economy experienced from July of 2009 to October of 2013. However, duration of contraction periods is more subtle, 10 month longevity for each fully observed contraction.

[1] Single amplitude calculated starting from peak point to trough point.

Table 2B. Turning point chronology

	Amplitude	Duration
Exp =]T;P]	3%	42.7
Contr =]P;T]	3.3%	10

Table 2B summarizes average statistics on turning points. It turns out that average amplitude of expansion phase is 3% with average 43 month duration. Contraction however, has shown 3.3% amplitude on average with 10 month average duration. One important fact is obvious that extreme asymmetry exists between the phases, that is, expansion period retained longer time than contraction. Particularly, expansion period took approximately 3.6 years, whilst contraction even didn't persist for a year. This asymmetry also noted in other emerging countries by several authors such as Pallage and Robe (1998), Agenor, McDermott, and Prasad (2000), and Rand and Tarp (2001). All the above said will be very useful to validate chosen cycle indicators and forecasts.

Cyclical Indicators

Once the reference series is identified, we select a set of indicators that could have the same cyclical pattern as the reference series. Below we summarized statistics leading indicators.

Leading indicators

Analysis found 29 possible candidates for leading indicator based obove criteria, summarized in table 7. However, not all of them have good performance matching with turning points. We found several of them, russian real gdp *(rgdp_rus),* Turkey real gdp *(rgdp_turk),* spread between total domestic and foreign currency deposits *(sprdep),* transport turnover *(turn_trans)* (excluding pipelines), non-food retail *(retail_nfood),* long-run deposits in domestic currency *(dep_long_azn),* state budget current expenditures *(budexp_cur),* tax revenues *(tax_rev)* have shown good performance. Carefully looking to them, it will be clear that, they have minimum missed points and gave less extra points (false signals), as well as higher mean lead, peak lead closer to mean lead and higher correlation coefficient.

Table 4 here

Behaviors of deposits are also very interesting. While deposits presented in domestic currency units has found to be procyclical, in foreign currency are countracyclical. Therefore, spread between domectis and foreign deposists shows countercyclical behaviour. In contrast, foreign currency deposits presented in dollar units are countercyclical. Such a difference indicates the possibility that households use AZN denominated deposits and FX denominated deposits for different motives. During a boom, agents may increase their domestic currency assets while decrease FX denominated assets. Holding FX assets might be driven by diversification motives and hedging purposes against FX denominated borrowing and inflation uncertainty. However, the differences in the cyclical behavior might be due to the cyclical behavior of nominal exchange rates as well. Since nominal exchange rates are strongly countercyclical, during a boom domestic currency appreciates and attractiveness of FX denominated assets decrease.

In general out of 100 variables only few variables found to have good predictive power, particularly international variables, some real and financial variables. This conclusion could be explained with the argument that non-oil economy still has some structural problems that couldn’t respond market fundamentals.

Composite Leading Indicators

Summary results of composite leading indactors is given in table 5. Table summarizes statistical proporties of 4 possible candidates.

Table 5. Composite Leading Indicators

Name	Turning points			Mean Lead	Peak Lead (corr. Value)	Std. Lead
	Targeted	Missed	Extra			
CLI 1	6	2	0	4	4 (0.601)	6.04
CLI 2	6	1	1	6.8	5 (0.623)	5.88
CLI 3	6	1	0	4.6	5 (0.571)	5.85
CLI 4	6	1	0	7.2	5 (0.584)	6.11

This first composite indicator (CLI 1) leads the reference series by 4 months and misses 2 turning point, but didn't flag any false signals. Peak lead reach at 4 with 0.601 correlation and 6.04 standard deviation of lead. Whereas, the second composite leading indicator (CLI 2) leads the reference series by 6.8 (or 7) months and misses 1 turning point, but flags 1 false signal. Peak lead reach at 5 with 0.623 correlation and 5.88 standard deviation of lead. When we compare two of these indicators the second one appears better one in terms of higher leading (7.0) and comparatevly lower standartd deviation (5.88), but flags one false signal. While, the first one doesn't flag any false signal, instead has lower mean lead (4) and higher standard deviation (6.04).

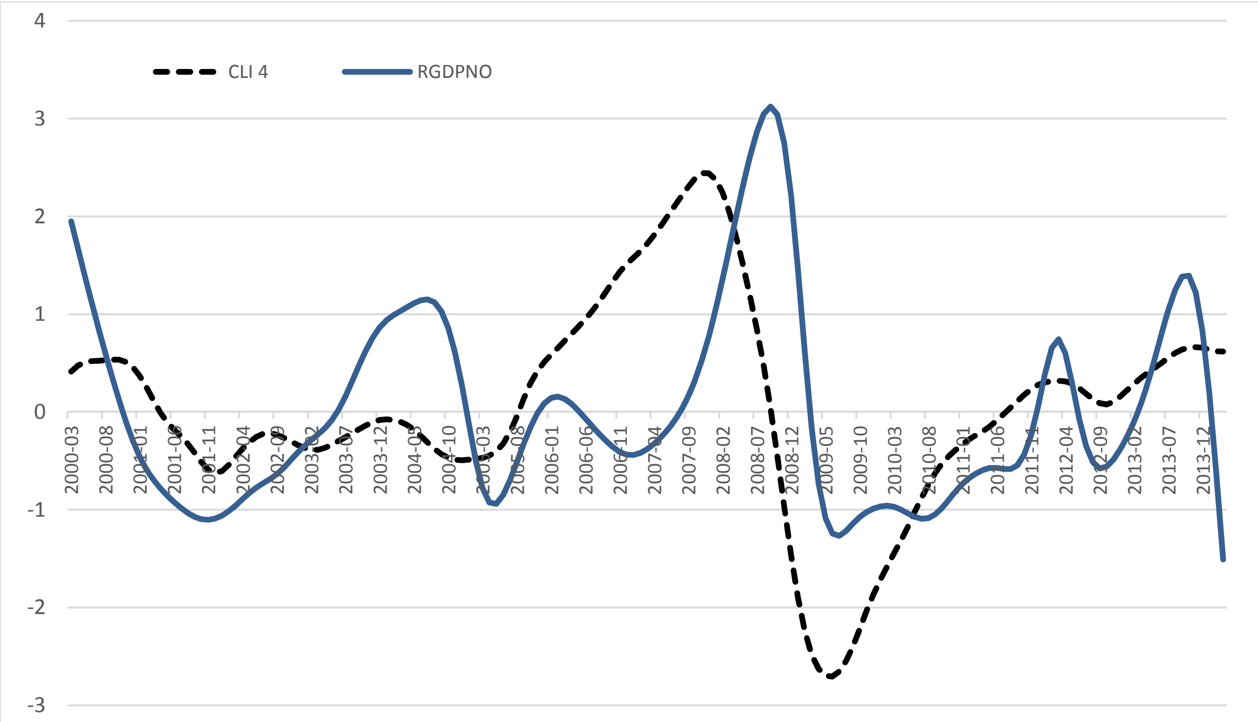
The more interesting fact about composite indicatiors is the components that included in the contruction of them. The first composite indicator composed of domestic variables like spread between volume of domestic and foreign deposits (sprdep), state budget current expenditures (budexp_cur), long deposits in domestic durrency (dep_long_azn), transport turnovers (exluding pipelines (turn_trans), non-food retail (retail_nfood). Whereas the second composite indicator comprised of spread between volume of domestic and foreign deposits (sprdep), state budget current expenditures (budexp_cur) and some foreign demand variables like, Eurpoean Union real GDP, Russian real GDP and Turkey real GDP. Surprisingly inclusion of the foreign demand variables increased statistical performance of the composite indicator.

The third composite indicators (CLI 3) doesn’t flag any false signal as well, but lead time appear to be short, 4.6 month with 5.85 high standard deviation. We included spread between volume of domestic and foreign deposits (sprdep), state budget current expenditures (budexp_cur), long deposits in domestic durrency (dep_long_azn), tranport turnovers (exluding pipelines (turn_trans), non-food retail (retail_nfood), tax revenue (tax_rev) and Russian real gdp (rgdp_rus) and European union real gdp (rgdp_eu). Inclusion of this variable could only eliminate false signal, instead caused to decrease lead time.

In the last, forth composite indicator (CLI4) we left with mostly international variables like, Russian real gdp (rgdp_rus) and European union real gdp (rgdp_eu), Turkey real gdp (rgdp_turk), US Real GDP (rgdp_us) and only two domestic variables spread between volume of domestic and foreign deposits (sprdep) and transport turnovers (exluding pipelines (turn_trans). And it appears that inclusion of all demand factors increased leading performance of the composite indicator. Among the four composite indicator candidates CLI 4 has higher lead time, 7.2, however highest standard deviation of lead time. It can be noticed that spread between volume of domestic and foreign deposits (sprdep) and transport turnovers (exluding pipelines (turn_trans) appears in all composite indicators, exclusion of them reduces predictive power as well as statistical performance of the composite indicator, indicating good leading indicator. Another point is worth to notice that although some series are particularly good according to one criterion but can be disregarded for not meeting the others. Therefore, as a last criteria we will chek their forecasting performance.

The figure 2 plots both composite indicators and the reference series and shows that the second aggregate (dash line) leads more than the first one (blue line). Apparently CLI 4 leads reference series, and easy noticable that leading performance obviously decreased after the 2008 financial crisis.

Figure 2. Composite indicator versus Non-oil output gap.

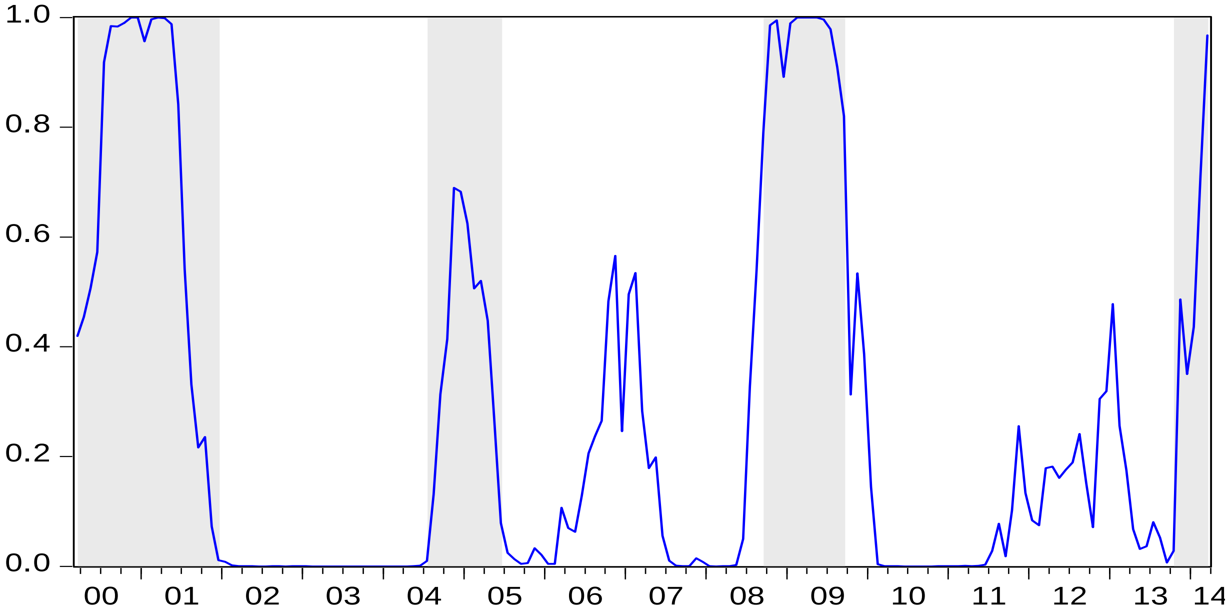


Prediction

In sample performance

In this section we present in-sample forecast performance of the probit model. In sample performance test usually encompasses comparing fitted values with the actual contraction (expansion) dates. Figure 3 depicts prediction performance of selected composite leading indicator CLI 4.

Figure 3. In –sample prediction performance of CLI 4.



In-sample forecast yields quite well fitted results. Someone can argue that the model flags false signal on contractions between 2006-2007 and 2011-201. However, probability to be contraction in these particular periods for each of them in overall does not exceed 0.5. This can be driven due to single reference series bias. Therefore, it can be overcome by using composite coincident indicator.

Table 7 summarizes comparative in-sample forecast performance of the candidate composite leading indicators based on pseudo R^2 , t-statistics and statistical significance.

Table 7. In Sample Measure of Fit and t-statistics for Probit model.

$$P(R_{t+k} = 1) = F(\beta' X_t)$$

k = months ahead

	1	2	3	4	5	6	7	8	9	10
CLI 1										
Pseudo R^2	0.000	0.003	0.010	0.021	0.036	0.055	0.076	0.098	0.117	0.133
t-stat	0.194	0.895	1.603	2.310 [c]	2.986 [b]	3.585 [a]	4.100 [a]	4.521 [a]	4.842 [a]	5.101[a]

CLI 2										
Pseudo R^2	0.022	0.010	0.002	0.000	0.006	0.021	0.042	0.069	0.095	0.116
t-stat	-2.189[c]	-1.484	-0.672	0.233	1.204	2.167[c]	3.051[a]	3.774[a]	4.313[a]	4.695[a]
CLI 3										
Pseudo R^2	0.000	0.001	0.005	0.0118	0.023	0.038	0.057	0.077	0.096	0.113
t-stat	-0.175	0.430	1.060	1.695	2.321[b]	2.904[a]	3.439[a]	3.908[a]	4.308[a]	4.646[a]
CLI 4										
Pseudo R^2	0.006	0.026	0.052	0.077	0.098	0.117	0.136	0.157	0.182	0.213
t-stat	1.006	2.068[b]	2.828[b]	3.343[a]	3.678[a]	3.907[a]	4.130[a]	4.450[a]	4.861[a]	5.152[a]
a Significant at 1% level										
b Significant at 5% level										
c Significant at 10% level										

Results clearly indicate that 4th composite leading indicator has better in-sample predictive performance. Particularly, 4th CLI has a higher value of pseudo R^2, in 10 month ahead it gets 21% fit and significant at 1% level, whilst other composite leading indicators do not exceed 13% level. Moreover, fortifying evidence is that, statistically significance starting from the second month for the 4th CLI, whereas for others the significance starts later.

Out-of sample performance

For the case out-of sample forecast t-statistics is no longer available to calculate. Therefore, we use just use pseudo R^2 to evaluate out-of sample performance of composite indicators. Table 7 summarizes out-of sample performance of various composite leading indicators.

Table 7. Out-of sample Measure of Fit for Probit model.										
$P(R_{t+k}=1)=F(\beta' X_t)$ k = months ahead										
	1	2	3	4	5	6	7	8	9	10
CLI 1										
Pseudo R^2	-0.088	-0.085	-0.070	-0.043	-0.007	0.036	0.087	0.150	0.204	0.251
CLI 2										
Pseudo R^2	-0.072	-0.104	-0.117	-0.108	-0.079	-0.030	0.035	0.112	0.179	0.231
CLI 3										
Pseudo R^2	-0.042	-0.047	-0.041	-0.025	0.001	0.036	0.080	0.130	0.175	0.211
CLI 4										
Pseudo R^2	-0.047	-0.096	-0.072	-0.014	0.055	0.126	0.180	0.218	0.244	0.262

Obviously 4th leading indicator has higher pseudo R^2 implying about higher predictive power. Negative out-of sample R^2 implies a very poor out-of sample fit and therefore, is not very informative. 4th composite leading indicator becomes after the 5th month informative about the future state of the non-oil economy.

Conclusion remarks

This paper has attempted to construct leading indicator systems and based on that to predict behavior of the Azerbaijan non-oil economy using more than 100 publicly available economic and financial data. Our results show plausible and significant performance of composite leading indicator system.

We found that between January of 2000 and May of 2014, there were 6 turning points in Azerbaijan non-oil economy, consisting of three peaks and three troughs corresponding three expansion and four contraction periods. It turns out that average amplitude of expansion phase is 3% with average 43 month duration. Contraction however, has shown 3.3% amplitude on average with 10 month average duration. Another interesting fact is that, cycles exhibits asymmetry that is, expansion period took more long time than contraction. Particularly, the expansion phases exposures approximately 3.6 years, whereas, contraction continues less than a year. These results are consistent with other business cycles research in developing countries such as, Pallage and Robe (1998), Agenor, McDermott, and Prasad (2000), and Rand and Tarp (2001).

Among the number of macro, financial and fiscal variables only 29 have found to be possible candidate to be leading indicator. According to our findings russian real GDP *(rgdp_rus),* spread between total domestic and foreign currency deposits, transport turnover (excluding pipelines), non-food retail, long-run deposits in domestic currency has shown good performance.

In general out of 100 variables only few variables found to have good predictive power, particularly international variables, some real and financial variables. This conclusion could be explained with the argument that non-oil economy still has some structural problems that couldn't respond market fundamentals.

Based on selected leading indicators we constructed composite indicator is found to be able to predict all the six turning points with average leading time of 7.2 months. Constructed composite indicator mostly comprised of international variables like, Russian real gdp and European union real gdp, Turkey real gdp, US Real GDP and only two domestic variables spread between volume of domestic and foreign deposits and transport turnovers (exluding pipelines). And it appears that inclusion of all demand factors increased leading performance of the composite indicator.

Using dynamic probit model we estimated contraction probability of non-oil output gap for the future period. To asses predictive performance of the composite leading indicator we performed in-sample as well as out-of sample performance tests. In-sample forecasting performance gave quite good fitted results. Reasonable value of *pseudo* R^2 in out-of sample forecast performance also suggest that the leading indicator systems have significant predictive power and could be used as a useful tool for economic forecasting.

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Appendix

Table 4. Leading indicator performance

Name	Turning points			Mean Lead	Peak Lead	Peak Lead (corr. Value)	Std. Lead
	targeted	missed	extra				
Monetary variables							
rm3	6	3	3	8	1	0.535	7.48
rem	6	3	3	6	7	0.511	2.16
Financial variables							
sprdep	6	1	1	4.2	10	0.628	6.05
dep_long_azn	4	0	0	5.25	13	0.514	8.87
cred_agr	6	3	3	5.5	-22	0.67	6.5
sprdep_long	5	2	2	3.33	7	0.619	3.3
dep_azn	6	3	1	5	3	0.562	4.08
cred_13_h	5	3	2	6	6	0.552	1
i_cred13	5	4	2	4	-10	0.569	0
r_cred13_h	5	3	2	16	-16	0.524	0
cred_ener	4	3	2	3	-21	0.523	0
cred_hous	5	4	4	5	-4	0.506	0
dep_long_val	5	3	2	17.5	24	0.502	0.5
cred_trans	5	3	3	5.5	-10	0.491	8.5
Fiscal variables							
budexp	6	3	1	5	1	0.565	2.94
tax_rev	6	2	0	6.75	8	0.5	6.14
budexp_cur	6	1	1	9.2	3	0.5	5.1
Real sector							
turn_trans	6	2	0	12.5	24	0.643	2.5
retail_nfood	6	1	1	5.4	1	0.529	5.2
gfsf_noil	6	3	3	3.5	-2	0.656	7.5
rgdp_tr	5	4	3	7	2	0.61	0
rgdp_agr	6	4	4	7.5	-12	0.608	4.5
wage	6	3	3	8.67	-11	0.6	5.44
noilip_q	6	3	1	7.33	-3	0.587	8.65
rgdp_elec	6	3	1	6.67	-1	0.559	4.99
rgdp_fish	6	4	4	7.5	-12	0.635	4.5
noex_q	5	1	1	3.25	1	0.50	7.4
International variables							
rgdp_rus	6	1	0	5.2	3	0.698	6.62
rgdp_eu	6	4	3	3.5	4	0.499	3.5
rgdp_us	6	3	1	3.67	3	0.464	5.19
rgdp_turk	6	3	2	3	5	0.457	3.27