National Bank of the Republic of Macedonia
Working Paper

Forecasting Macedonian business cycle turning points using Qual VAR model

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Abstract

This paper aims to assess the usefulness of leading indicators in business cycle research and forecast. Initially we test the predictive power of the ESI within a static probit model as a leading indicator, commonly perceived to be able to provide a reliable summary of the current economic conditions. We further proceed by analyzing how well an extended set of indicators performs in forecasting turning points of the Macedonian business cycle by employing the Qual VAR approach of Dueker (2005). In continuation, we evaluate the quality of the selected indicators in pseudo-out-of-sample context. The results show that the use of survey-based indicators as a complement to macroeconomic data work satisfactory well in capturing the business cycle developments in Macedonia.

JEL classifications: F42, C25, C22
Keywords: Forecasting, Business cycle turning points, Qual VAR, MCMC, Latent variable

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1. Introduction

Economic analysts have been making great efforts to derive a mix of macroeconomic indicators that could summarize and predict business cycle patterns. Moreover, the prediction of business cycle phases is very challenging given that fluctuations in macroeconomic conditions are never directly observable. A good comprehension of business cycle facts is essential to macroeconomic decision-making, especially in monetary and fiscal policies. The GDP cycle was extracted using a double Hodrick-Prescott (HP) filter. This particular approach works towards achieving greater turning points signal stability. Furthermore, given that business cycle forecasting is creation of postulates about how the business cycle will evolve in the future, analysts use variety of economic indicators to form the predictions. For instance, the so called leading indicators are variables that have a tendency to change ahead of the economy as whole, so they are frequently used in business cycle forecasting. Following this practice we considered employing the European Commission's Economic sentiment indicator (ESI) for Macedonia in our analysis. Namely, ESI as a single variable reflecting economic agents' sentiment integrates most of the information embedded in multiple indicators. We examined the leading property of the ESI relative to GDP firstly by using a static probit model. With this regard, we find that the cyclical movement of ESI is helpful in monitoring and predicting the turning points of GDP.

Large and growing body of literature (for instance, on the case of U.S. recessions, the work by Kauppi and Saikkonen (2008), Nyberg (2010), and Ng (2012), among others), has found evidence that including dynamic elements (e.g., lags of the binary response variable) in the probit models can yield more accurate forecasts of recessions than standard probit regressions. Consequently, we concentrate upon the Qual VAR method of Dueker (2005). One improvement that Dueker contributes to business cycle turning points forecasting literature is that this author's method includes a latent variable underlying the recession periods along with other indicators in a VAR setting. To this end, good forecasting indicators should closely match the volatile economic development.

Our Qual VAR model showed that both growth rates of real GDP, as most natural choice, and ESI alone are good candidate indicators, but however, do not reflect satisfactory well the recent Macedonian business cycle history. When it comes to ESI for the Macedonian economy, we would like to point out that it is a quite new publicly available indicator, so to this end, we believe that this paper could contribute towards enlightening its forecasting power in business cycle analysis. Therefore, we proceeded with additional experiments that combine different financial and macroeconomic activity variables with the above selection of data. After many such simulations, we concluded that ESI along with the real GDP and the capacity utilization rate in manufacturing (which typically climbs when the economy is vibrant and falls when demand softens), can actually smoothly predict the Macedonian business cycle fluctuations. In addition, in our knowledge this work is among the first papers on this subject for the Macedonian economy (aside from business cycle synchronization analysis).

This paper is organized as follows. The next chapter provides literature overview, while chapter 3 evaluates the usefulness of ESI in assessing the current state of the Macedonian economy. Chapter 4 explains the Qual VAR approach that is used and chapter 5 provides the results, followed by the concluding part.

2. Literature review

The complicated nature of business cycle modeling has caused many difficulties in modern macroeconomics. During the last decades, researchers have kept on searching for the most accurate and reliable economic models to reflect in a best way the future economic behaviors. Most recession forecasting models use mathematical techniques originating from the vector autoregression method. However, a number of recent studies combine traditional probit models and vector autoregression models to develop more comprehensive dynamic probit VAR approaches.

Dueker (2005) presented a new Qual VAR model by incorporating information from qualitative and/or discrete variables in vector autoregressions. With a Qual VAR, it is possible to create dynamic forecasts of the qualitative variable using standard VAR forecasts. Previous forecasting methods for qualitative variables, in contrast, only produce static forecasts. Dueker applied the Qual VAR to forecasting the 2001 US business recession. Out of sample, the model predicted the timing of the 2001 recession quite well relative to the recession probabilities put forth at the time by professional forecasters. Most importantly, unlike traditional approaches in recession modeling, Dueker included a binary indicator for each recession as a dynamic component in the Qual VAR model. As an augmented VAR, the Qual VAR, which includes information about the qualitative variable in the form of a truncated normal latent variable, can also enhance the quality of density forecasts of other variables in the system, such as output growth, relative to the VAR without the qualitative variable.

Similarly to Dueker (2005), most of the other papers that used Qual VAR approach were also focused on business cycle analysis. Chen (2014) applied the Qual VAR method developed by Dueker (2005) to search for the macroeconomic indicators that fully fit the in-sample movements of business cycle fluctuations and accurately predict the out-of-sample recession probability in Canada. This study examined the performance of several leading indicators in predicting future Canadian recessions using the sample from 1959 to 2012. Consistent with the findings from Estrella and Mishkin (1998), this paper finds that the slope of the yield curve provides the most reliable in-sample fitness of economic turning points in recent Canadian history. Besides, the US-Canada noon-spotted exchange rate also presents some in-sample forecasting power. However, none of the single variables included in this study provided significant out-of-sample forecasting power. Combining the exchange rate and the term spread provided the most accurate short-term signal of upcoming recessions in Canada. The addition of the growth rate of real chain-weighted GDP to the exchange rate and the term spread produced the most trustable forecasting model in the long run. Besides

the advantages, one cannot ignore the fact that Qual VAR model may still suffer from the potential overfitting problem, thus careful choice of the appropriate forecasting indicators is crucial.

Moon and Lee (2012) evaluated the forecasting performance of the Korean Economic sentiment indicator (ESI) with respect to GDP growth and cycle. They found out that constructed ESI (based on business survey index and consumer survey index) had a good tracking performance as a leading indicator of GDP. Using the Granger causality tests they showed that the ESI precedes GDP growth, implying the former contains useful information in predicting GDP growth. Also, using a probit model, the authors confirmed that the ESI is helpful in monitoring and predicting the turning points of GDP.

In the recent years, there are empirical papers that used Qual VAR approach for oil and stock prices analysis in the framework of the business cycle, as well as for analyzing the effects of the unconventional monetary measures, obviously pointing to the opportunities for wider usage of this approach. Gupta and Wohar (2015), considering that oil prices, stock prices and economic activity are in non-linear relationship, applied a Qual VAR approach. They found as important modelling nonlinearity through the use of the latent business cycle indicator, in their case for the oil and stock prices forecasting, being valid for a different time horizon (medium to long run for the oil prices and short to medium run for the stock prices). Meinush and Tillmann (2014) used Qual VAR model developed by Dueker (2005) for analyzing the impact of the Quantitative easing by FED over the real sector in the American economy. In their model, they incorporated a binary index of Quantitative easing announcements, industrial output, long term real interest rate and stock market index. Their findings pointed to the impact of these unconventional measures on the interest rates and financial conditions, while having a smaller impact on the economic activity.

3. Tracking the leading features of ESI with respect to GDP cycle

This Chapter aims to assess the extent to which the Macedonian cyclical development is affected by changes in consumer and producer business cycle evaluations, as summarized by the Economic sentiment indicator of the European Commission. Sentiment survey data are usually assumed to be leading variables relative to business cycles. The span of lead time however, is less certain and subject to empirical verification. The amount of lead time may change over time as well. In this section, patterns of both the Macedonian business cycle and the economic sentiment cycle are analyzed.

We initiated the procedure of mapping the peaks and troughs in the Macedonian economic downturns by first adopting a multivariate case of Chow and Lin (1971) as a temporal disaggregation method to estimate monthly from quarterly figures of the official GDP. For the economic cycle indicator, the industrial production and retail trade were embedded as high frequency external information that is believed to satisfactory represent

the dynamics of the target variable[2]. The GDP cycle was extracted by applying a double Hodrick-Prescott (HP) filter to the previously obtained monthly figures. The HP filter is run twice to achieve a smoothed de-trended cycle (removing a long-term trend from the seasonally adjusted GDP and then smoothing this de-trended series). Namely, setting λ = 133,107.94 in the first step and then imposing λ = 13.93 in the second step of the filtering procedure allows us to remove the cyclical components that have a cycle length longer than 120 months and those that have a cycle length shorter than 12 months[3].

The ESI is composed of the industrial, services, consumer, construction and retail trade confidence indicators. The economic sentiment indicator is compiled as an index with zero mean (i.e. mean value of 100 at an index number) and standard deviation of ten over a fixed sample period[4]. Values of the economic sentiment indicator above (below) 100 indicate above-average (below-average) economic sentiment. For the purposes of the econometric analysis we generated a smoothed-curve representation of ESI. The adjustment of the sensitivity of the trend to short-term fluctuations is achieved by setting the value of the multiplier λ of the HP filter to 13.93.

European Commission publishes ESI for Macedonian economy (and several other candidate countries) on monthly basis, seasonally adjusted[5]. The surveys used to construct this indicator for Macedonia were launched for the first time in May 2008[6]. The data set managed in this paper spans over the period from May 2008 to December 2014, reflecting this particular limitation.

Figure 1 displays the trajectory of both ESI cycle and GDP cycle, with monthly frequency. ESI cycle serves as a proxy of consumers' and producers' set of opinions about the general state of the economy. On the other hand, GDP cycle describes the economic conditions from the perspective of production and supply, as well from consumption and demand standing point.

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[2] We also considered the monthly data for the construction works, but due to the high volatility they were not included into the interpolation procedure.

[3] Going from frequencies to λ parameter is achieved by substituting into the formula: $\lambda = [4(1 = \cos n(\omega_0))^2)]^{-1}$ whereas ω_0 is the frequency expressed in radians, and τ denotes the number of periods it takes to complete a full cycle. The two parameters are related through $\omega_0 = 2\pi/\tau$. So the λ values above correspond to τ =120 months and τ =12 months (http://www.oecd.org/std/compositeleadingindicatorsclifrequentlyaskedquestionsfaqs.htm#12).

[4] Source: http://ec.europa.eu/eurostat/web/products-datasets/-/teibs010

[5] Source: http://ec.europa.eu/economy_finance/db_indicators/surveys/time_series/index_en.htm

[6] However, the data on confidence indicator for consumers are published since May 2012. According to the User guide by EC, (March 2014), the ESI summarizes the confidence indicators in five areas of the economy, according to the following weights: industry (40%), services (30%), consumers (20%), construction (5%) and retail trade (5%).

Figure 1
Cyclical components of ESI and GDP
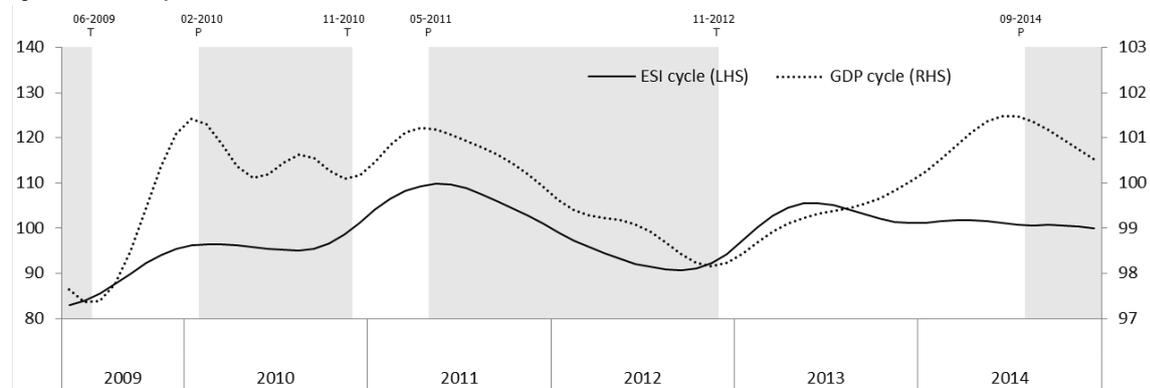
The leading feature of the cyclical movement of ESI with respect to that of GDP, observed in Figure 1, is also fully-confirmed by the cross-correlation analysis of the cycles. To this end, Table 1 suggests patterns of small leads and lags between these variables, a factuality which will be picked up later by the Qual VAR model, given its dynamic structure. The maximum cross-correlation is 0.71 and 0.68, when the cyclical component of ESI is 0 and 1 month ahead of GDP, respectively, as shown in Table 1.

Table 1
Cross-correlation of the cycles of the ESI and GDP

Leading (-1) or Lagging (+1) months												
-6	-5	-4	-3	-2	**-1**	**0**	1	2	3	4	5	6
0.06	0.22	0.38	0.51	0.61	**0.68**	**0. 71**	0.61	0.48	0.34	0.21	0.08	-0.02

The detected relation between the cross-tabulated variables leads us to a static probit model aiming to further examine the leading property of the cyclical component of ESI with respect to that of GDP. To this end, our approach is exactly analogous to that of Moon and Lee (2012). Additionally, in continuation in this Chapter we provide an evaluation of the forecast performance of the ESI cycle in identifying the business cycle turning points in both in-sample and pseudo out-of-sample context.

Following Moon and Lee (2012), we define a binary dependent variable, Y_t which takes on only values of one and zero as follows:

$$Y_t = \begin{cases} 1, \text{ if the economy is in deceleration period} \\ 0, \text{ otherwise} \end{cases}$$

Then the estimated probability of being in the deceleration period is of the form

$$P(Y_t = 1|x, \beta) = F(\beta_0 + \beta_1 x_1 + \cdots \beta_k x_k)$$

where $x_1 \ldots, x_k$ are k explanatory variables, $\beta_1 \ldots, \beta_k$, are the corresponding regression coefficients and F is the cumulative distribution function (cdf) of a standard normal distribution, i.e.,

$$F(a) = \Phi(a) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{a} e^{-t^2/2} dt$$

Here the deceleration period is defined based on the peak and trough points of the GDP cycle. The contemporaneous and lagged values of the cyclical component of ESI are introduced as explanatory variables in the probit model from above. Moreover, Table 2 shows that both of them are statistically significant. Note that the sign of estimated coefficient of ESI_CYC(-1) is positive, implying that ESI_CYC(-1) and the contemporaneous GDP cycle tend to co-move.

We also carried out the LM test for heteroskedasticity using the artificial regression method described by Davidson and MacKinnon (1993, section 15.4). We tested the null hypothesis of homoskedasticity against the alternative of heteroscedasticity. So to this end, the null was accepted. We also performed the Hosmer–Lemeshow goodness-of-fit test. The test results confirmed that the model is correctly specified.

Table 2
Probit model estimation

| Variable	Coefficient	Std. Error	z-Statistic	Probability
C	9.1340	3.0781	2.9674	0.0030
ESI_CYC	-0.8864	0.1829	-4.8453	0.0000
ESI_CYC(-1)	0.7965	0.1650	4.8263	0.0000
McFaddenR-squared	0.3953			

Hosmer-Lemeshow chi2(8) = 3.5217
Prob > chi2 = 0.8975
Heteroskedasticity L-M test = 2.8737
Probability = 0.2377

From the estimated probit regression, the probability of being in the deceleration period can be computed for each data point, which is called in-sample forecast. The probabilities from the in-sample forecast are graphed together with the GDP cycle in Figure 2.

Figure 2

Estimated probabilities and the GDP cycle
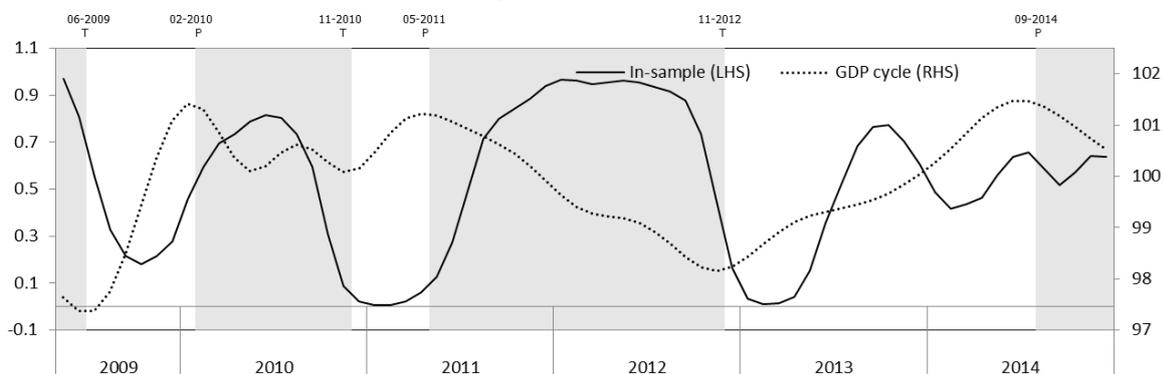
Note: P-peak, T-trough.

The estimated probabilities are shown to be high in the shaded areas which represent Macedonian business cycle recessions. In particular, they are close to 1 during the deceleration phase spanning from mid-2008 to mid-2009 reflecting the new global reality i.e. the global downturn and mid-2011 to end-2012 reflecting the second wave of the crisis (Greek debt crisis).

In addition, recursive 1-step ahead out-of-sample forecasts were run over the period from May 2011 to December 2014. The predictive accuracy of these forecasts is evaluated by comparing the percentage of correct classification based on the pre-specified cutoff value, which is a procedure analogous to that described in Moon and Lee (2012). So, there are two types of correct classifications. One is that the predicted probability is greater than the cutoff and the observed $Y_t = 1$, and another is that the predicted probability is less than or equal to the cutoff and the observed $Y_t = 0$.[7] The portion of $Y_t = 1$ observations that are correctly predicted is called sensitivity, while the fraction of $Y_t = 0$ observations that are correctly classified is called specificity. In this particular empirical implementation, the sensitivity is calculated for the deceleration phase and the specificity for the acceleration phase. Moreover, a percentage of correct classification among total observations is calculated.

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[7] Recessions / expansions are defined by the binary code 1 / 0. For example, with cutoff value of 0.6, all results of the probit model for recession with probability equal or higher than 0.6 will be plausible.

Table 3
Percent of correct classification 1-step ahead

Cutoff value	Phase	Percent of correct classification 1-step ahead
0.4	Deceleration	100
	Acceleration	75
	Total	66
0.5	Deceleration	96
	Acceleration	60
	Total	70
0.6	Deceleration	83
	Acceleration	50
	Total	68

Table 3 summarizes the reliability of the recursive 1-step ahead out-of-sample forecasts based on three cutoff values of 0.4, 0.5, and 0.6. Percentage of correct classification depends on the choice of the cutoff. In the deceleration period it is highest when the cutoff value is 0.4 since the smaller cutoff value implies declaring deceleration more easily. Evidently the total forecast power tends to decrease as the cutoff value gets bigger. When it comes to correct classification of the acceleration periods, Table 3 highlights that the model's forecasting performance weakens to some extent. Still, our estimated probit model seems to identify the business cycle turning points satisfactory well.

4. Predicting business cycle turning points using Qual VAR approach

4.1. A brief note on the usefulness of the Qual VAR

Large and growing body of literature (for instance, on the case of U.S. recessions, the work by Kauppi and Saikkonen (2008), Nyberg (2010), and Ng (2012), among others), has found evidence that including dynamic elements (e.g., lags of the binary response variable) in the probit models can yield more accurate forecasts of recessions than standard probit regressions. Therefore, this Chapter adapts the Qual VAR model from Dueker (2005). Intuitively speaking, Qual VAR is a combination of standard VAR and a probit-type approach to predict business cycle turning points, which per se is our key interest. So, one distinctive actuality about the Qual VAR of Dueker (2005) is that it adds to the information set a so called latent index of nearness to a turning point. An increase in this index indicates that the business cycle conditions are improving — either moving closer to an exiting recession or to

stronger expansion. On the other hand, a decline in the index suggests that business cycle conditions are worsening — either moving closer to entering a recession or to a deeper recession. Moreover, for the in-sample period, the index is by construction negative during recessions and positive during expansions.

Our Qual VAR model had been inferred based on its historical efficiency in recognizing the most recent business cycle trends. In line with this actuality, a lag length of 1 month was selected. This also corroborates with Chauvet and Hamilton (2005) who recommend simpler specifications that perform well historically in the dating of the future business cycle turning points of an unknown character.

4.2. Estimation of a Qual VAR

This section discusses the formal algorithm that we exploited to forecast future business cycle fluctuations using Dueker's (2005) multivariate dynamic probit model, also referred to as a Qual VAR. An intuitive derivation along with a detailed description of this algorithm is provided by Meinusch and Tillmann (2014). This section is practically an adaptation of these authors' work.

So, intuitively, the Qual VAR model augments a standard VAR with a probit-equation for the probability of a recession. Due to this non-linear equation, estimating the model involves evaluating an integral numerically, which is implemented by Markov Chain Monte Carlo (MCMC) techniques. As in simple probit models, one can assume that a continuous latent variable, y_t^*, lies behind the binary dependent variable, i.e. a 0/1 variable that denotes expansions and recessions, with switches at business cycle turning points.

The factuality that the latent variable, y_t^*, is an autoregressive process makes the dynamic probit a proper equation for a VAR system. The law of motion of the latent variable y_t^* is shown in equation (1). In the application to forecasting of the business cycle developments, the latent variable y_t^* can be called an index of nearness to a turning point, because its distance from zero indicates how many standard deviations is the economy from a business cycle turning point. It is defined as an autoregressive process of order ρ depending on a constant δ, its own lagged values and a set of lagged explanatory variables X_{t-p}; $\emptyset$ and β are vectors of the coefficients; ε_t is a random error term following standard normal distribution and $t = 1, \dots, T$ is the time index.

$$y_t^* = \delta + \sum_{l=1}^{\rho} \phi_l y_{t-l}^* + \sum_{l=1}^{\rho} \beta_l X_{t-l} + \epsilon_t, \qquad \epsilon_t \sim \mathcal{N}(0,1). \qquad (1)$$

We associate the value of one to a binary variable y_t if business cycle downturn occurs in period t and zero otherwise. The value of the binary variable y_t takes the form

$$y_t = \begin{cases} 0 & \text{if } y_t^* > 0 \\ 1 & \text{if } y_t^* \leq 0 \end{cases} \qquad (2)$$

The VAR(ρ) process for the dynamics of k regressors is given by

$$Y_t = \mu + \sum_{l=1}^{\rho} \phi^{(l)} Y_{t-l} + v_t,$$

$$v_t \sim \mathcal{N}(0, \Sigma) \qquad (3)$$

with a $k \times 1$ vector $Y_t = (X_t, y_t^*)'$ where X_t incorporates $k-1$ time series of observed macroeconomic data and y_t^* constitutes a vector of the latent variable. The set of VAR coefficients is described by

$$\Phi^{(l)} = \begin{bmatrix} \Phi_{XX}^{(l)} & \Phi_{Xy^*}^{(l)} \\ \Phi_{y^*X}^{(l)} & \Phi_{y^*y^*}^{(l)} \end{bmatrix}, \qquad (4)$$

μ is a $k \times 1$ vector of constants and v_t constitutes the $k \times 1$ error vector. The covariance matrix of the errors is Σ.

Dueker (2005) shows that the model (3) can be estimated by MCMC class of algorithms for sampling from a probability distribution, in particular via Gibbs Sampler. A Gibbs Sampling strategy allows joint estimation of the VAR coefficients $\emptyset$, the covariance matrix of the VAR residuals Σ and the latent variable y_t^*.

With a sufficient number of iterations i, the obtained draws make up the true joint posterior distribution. Thus, Gibbs Sampling only requires knowledge of the full conditional posterior distribution of the VAR coefficients $\emptyset$, the covariance matrix Σ and the latent variable y_t^* [8].

With each iteration we generate a draw for the latent variable by first establishing a state space model. The state equation is defined as

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[8] The conditional posterior for the VAR coefficients under the Jeffrey's prior is multivariate Normal and the conditional posterior of the variance is Wishart distributed. In each period a single observation of the latent variable is truncated Normal with truncation limits imposed by the observable binary variable y_t.

$$\begin{bmatrix} y_t^* \\ y_{t-1}^* \\ y_{t-2}^* \\ \vdots \\ y_{t-\rho+1}^* \end{bmatrix} = \begin{bmatrix} c_{y^*} \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \begin{bmatrix} \Phi_{y^*y^*}^{(1)} & \Phi_{y^*y^*}^{(2)} & \Phi_{y^*y^*}^{(3)} & \cdots & \Phi_{y^*y^*}^{(\rho)} \\ 1 & 0 & 0 & \cdots & 0 \\ 0 & 1 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & & 0 \\ 0 & 0 & \cdots & 1 & 0 \end{bmatrix} \begin{bmatrix} y_{t-1}^* \\ y_{t-2}^* \\ y_{t-3}^* \\ \vdots \\ y_{t-\rho}^* \end{bmatrix} + \begin{bmatrix} \Phi_{y^*X}^{(1)} & \cdots & \Phi_{y^*X}^{(\rho)} \\ 0 & \cdots & 0 \\ 0 & \cdots & 0 \\ \vdots & \vdots & \vdots \\ 0 & \cdots & 0 \end{bmatrix} \begin{bmatrix} X_{t-1} \\ X_{t-2} \\ X_{t-3} \\ \vdots \\ X_{t-\rho} \end{bmatrix}$$

$$+ \begin{bmatrix} \epsilon_{y^*,t} \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \tag{5}$$

With the following measurement equation

$$y_t^* = \begin{bmatrix} 1 & 0 & 0 & \cdots & 0 \end{bmatrix} \begin{bmatrix} y_t^* \\ y_{t-1}^* \\ y_{t-2}^* \\ \vdots \\ y_{t-\rho}^* \end{bmatrix} \tag{6}$$

So, we set up a state-space model, and smooth the data with a measurement equation that leaves out only one data point. The Kalman smoother[9] gives the mean and variance of the state variable, i.e. y_t^* given all the other y_t^* plus the rest of the model. Suitable initial values for the Smoother can be obtained from the binary data for the latent variable and from OLS estimates for the coefficients given the binary data. Contingent on the first two moments we then sample from the truncated Normal for y_t^*. We start the Kalman Smoother in period $\rho - 1$, and generate conditional draws for the VAR coefficients from a multivariate Normal.

For the VAR, everything except the lag coefficients on the y_t^* end up in the "X" component of the state space model, the state equation only needs the dynamics involving the y_t^*. The MCMC sampler was set up to do 30,000 iterations. The first 5,000 iterations were discarded not only to allow the sampling process to converge to the posterior distribution but also to be less dependent on the initial values. Draws of the VAR coefficients from the OLS distribution that were not stationary were rejected and re-sampled. From the resulting sample, we calculate the mean of the latent variable, the VAR coefficients and the variance.

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[9] The Kalman filter uses past and current observations to predict the current state, (i.e., $\{S_t|Y_t\}$ for each , t where S_t is state variable, i.e. unobserved variable, and Y_t is observed variable). While this is sufficient for computing the likelihood of the system, this is suboptimal for estimating the sequence of states. The econometrician should use all available data to estimate the sequence of states $\{S_t|Y_T\}$ (for each t), which is the advantage when using Kalman smoother which uses current, past and the future available observations.

4.3. The data set

The first part of this section provides a basic argument for each variable selected in the model building process, while the second part elaborates upon the data transformation techniques.

As a first step, as we already mentioned, the business cycle is extracted from the monthly real GDP data series using a double Hodrick-Prescott (HP) filter. Furthermore, a binary dependent variable, which takes value of 1 if the economy is in deceleration period and 0 otherwise, is created. The finally selected indicators beyond this dummy variable can be classified as survey data and macroeconomic data. A joint feature that lies behind these variables is their strong link with the GDP cycle.

Our Qual VAR model put together the following indicators: real GDP (interpolated GDP, with monthly frequency), as the most comprehensive measure of the state of the economy, ESI, as well as the capacity utilization rate in one of the main productive sectors, i.e. manufacturing.

ESI as a survey-based indicator aims to get insight into the mindsets of economic agents, both from the supply and the demand side of the economy. If consumers and manufacturers are optimistic about the current and future economic situation, they might increase their consumption and production respectively.

The capacity utilization rate in manufacturing is also a well-recognized indicator of economic slack at a point in the business cycle. The information it provides is about the extent of spare or used production capacity, so it therefore measures the "output gap", whether positive or negative. Intuitively, if growth was gaining momentum, capacity utilization ought to be increasing. The opposite is true if utilization levels are decreasing, signaling a deceleration in the economy.

Restricted by a non-availability of longer series for ESI, the data set managed in this section covers the period starting from May 2008 and ending on December 2014. Regarding the final data transformations, we would like to stress that our Qual VAR employs the annualized monthly percentage change in real GDP (log approximation based on seasonally adjusted data); the year on year change in the level of ESI as well as the year on year percentage points change in the capacity utilization rate in manufacturing. All of them come along with the binary variable illustrated earlier in this paper. ESI and capacity utilization level in manufacturing enter the model in year on year changes since their 12-month differences exhibit high correlation with their reference series (i.e. GDP cycle). Moreover, the usage of the 12-month change is a parsimonious way of allowing longer lags to enter the model (i.e. 1 parameter summarizes 12 lags). Another potential benefit in enabling longer lags to play a role lies in the fact that it permits smoother trajectory of the latent business cycle turning point index[10]. Additionally, this type of data formulation proved to deliver

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[10] In the Qual VAR, the latent index (unobservable variable), driving an observable binary variable, and a number of other observables (jointly) follow a VAR process. Estimating a VAR process instead of a single state space specification using solely

significant prediction accuracy gain around business cycle turning points (Section 5 addresses this turning point signal stability issue in greater detail).

When it comes to data selection process, we would like to acknowledge that a variety of VAR-specifications covering different real and financial variables were tested. To this end, we found that the monthly growth rates of both the real GDP and ESI alone serve as poor forecast indicators. The model extension with the inclusion of the monthly annualized inflation rate along with the monthly change in both, CB bill rate (main policy rate) and money supply M2 did not help as well in improving the model's predictive power.

5. Empirical results

The Qual VAR model that we propose tries to improve upon the early detection of the business cycle turning points. With this regard, we argue that an adequate forecasting model should provide a reasonably good record of business cycles in pseudo out-of-sample context. Following this evaluation criteria, we found that our Qual VAR is satisfactory successful in the accurate and timely assessment of near-term business cycle developments. The next section is an overview of the ability of our model to capture the most recent cyclical facts.

5.1. Pseudo out-of-sample simulation

At this point, we would like to accentuate that, the analysis of the model's forecasting performance is labeled as "pseudo" because the vintages are not obtained in pure real time but from the latest available data set – a practice perceived as a natural framework to evaluate the value added in forecasting.

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the Kalman smoother procedure, thereby exploiting more information, leads to efficiency gains in the identification of the latent variable.

Figure 3

Posterior mean of latent variable and its 12-months-ahead forecast (shaded areas indicate recession dates)
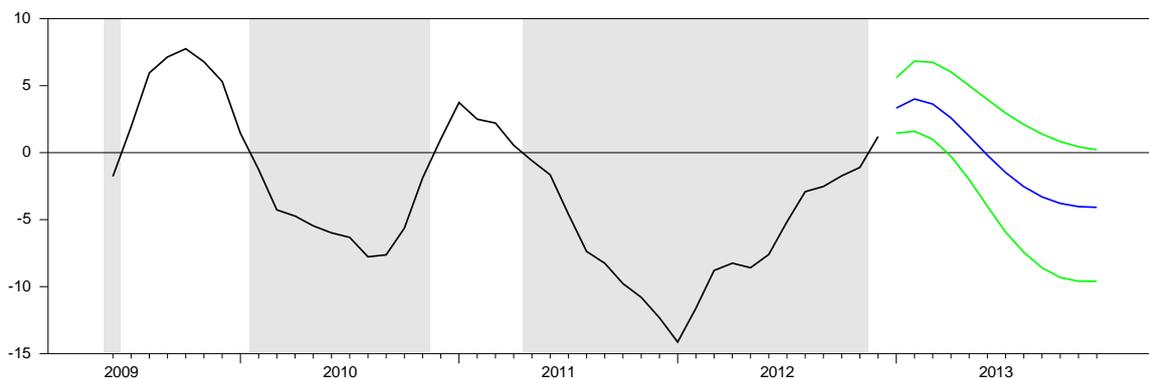
The Figure 3 plots the pseudo real-time prediction of the direction of the business cycle in 2013 from information set ending in December 2012. The ex post knowledge on the real direction of the GDP cycle in the corresponding period points out that the accuracy of the index is limited to only near-term business cycle developments (the first few months).

In order to achieve greater quality assurance, we performed an additional robustness check by repeating the above procedure on a data set ending in December 2010. This time, results comply with the subsequent knowledge on the cyclical facts for the entire 2011. However, like in the previous case, the empirical findings are statistically significant only on a very short horizon.

5.2. Pure out-of-sample results

Figure 4 displays the model simulated trajectory for the business cycle direction in 2015 from an information set ending in December 2014. For the sake of further clarification, in-sample, the business cycle index crosses zero by construction at turning points. So its distance from zero actually indicates how many standard deviations the economy is from a business cycle turning point. In other words, in-sample, every point of the index shows the magnitude of shock in standard deviations that could change the business cycle direction. Just for an illustration, in mid-2010, a shock of around three standard deviations was necessary to cause an altering in opposite direction of the cycle's trajectory.

Figure 4

Posterior mean of latent variable and its 12-months-ahead forecast (shaded areas indicate recession dates)
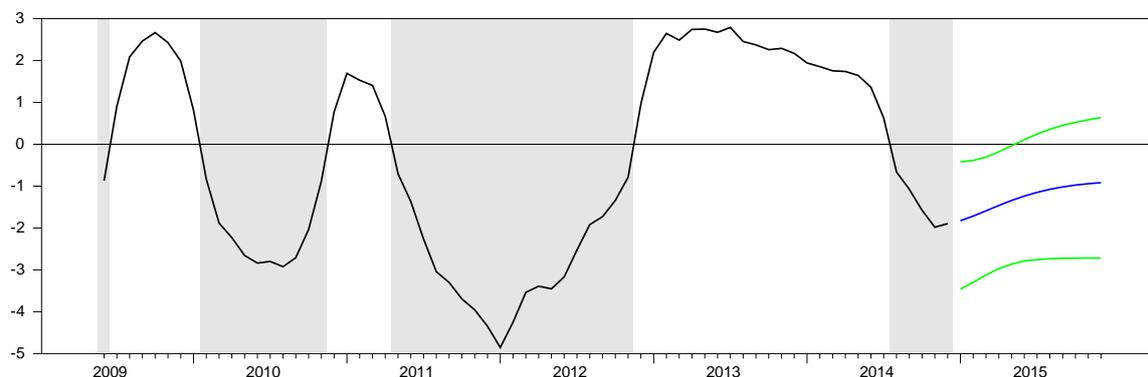
In addition, the purely out-of-sample predicted raise in the index indicates that the business cycle conditions are expected to improve in 2015, i.e. a recession is not foreseen that far ahead. But again, the statistically significant period spans only over the first few months of 2015.

Altogether, the results suggest that our Qual VAR predicts the business cycle developments reasonably well on near-term horizon, so that forecasts of it are perceived to be a useful addition to NBRM's existing framework aimed at GDP nowcasting.

6. Conclusion

The derivation of a mix of macroeconomic indicators that could summarize and predict business cycle patterns usually is a challenging task, given the fluctuations in macroeconomic conditions. A good understanding of business cycle facts is crucial to macroeconomic decision-making, especially in monetary and fiscal policies. This paper describes the procedure of mapping the peaks and troughs in the Macedonian economic cycle. A number of recent studies in this area combine traditional probit models and vector autoregression models to develop more comprehensive dynamic probit VAR approaches that is also done in this work, on the case of Macedonian economy.

Sentiment survey data are commonly assumed to be leading variables relative to business cycles, therefore we use the Economic sentiment indicator – ESI for Macedonian economy, published by the European Commission. The detected relation between these two variables directs us to a static probit model aiming at further examining the leading property of the ESI with respect to GDP. Additionally, we provide an evaluation of the forecast performance of the ESI cycle in identifying the business cycle turning points in both in-sample and pseudo out-of-sample context. The estimated probabilities within in-sample forecast are shown to be high during the deceleration phase of Macedonian business cycle spanning from mid-2008 to mid-2009 reflecting the global economic downturn and from

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mid-2011 to end-2012 reflecting the second wave of the crisis (Greek debt crisis). The predictive accuracy of out-of-sample forecasts is evaluated by comparing a percentage of correct classification based on the pre-specified cutoff value, which is procedure analogous to that described in Moon and Lee (2012). The estimated probit model seems to identify the business cycle turning points satisfactory well.

According to large and growing body of literature, the inclusion of dynamic elements in the probit models can yield more accurate forecasts of recessions than standard probit regressions. Therefore, we adapt the Qual VAR model from Dueker (2005). Our Qual VAR model put together the following indicators: real GDP (interpolated GDP, with monthly frequency), ESI and the capacity utilization rate in manufacturing. Considering its reasonably good track record in approximating the business cycle facts in pseudo out-of-sample context, we found that our Qual VAR is satisfactory successful in the accurate and timely assessment of near-term business cycle developments. To this end, the forecasts of it are perceived to be a useful addition to NBRM's existing framework aimed at GDP nowcasting.

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