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Business Consumer Surveys: Do They Help in Predicting the GDP Turning Points? The Case of Cyprus

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BUSINESS CONSUMER SURVEYS: DO THEY HELP IN PREDICTING THE GDP TURNING POINTS? THE CASE OF CYPRUS

Christos S. Savva

Abstract

The aim of this study is to find a useful tool for analyzing current business conditions and constructing real time predictions for Cyprus's business cycles. The model is based on Markov Switching (MS) specifications. We first present GDP growth forecasts using Hamilton's univariate MS. Even though the univariate model is able to almost successfully describe the majority of past business cycles, it is unable to provide reliable real time predictions, due to the lack of information for the current level of the GDP. We then show how the combination of the GDP and the Economic Sentiment Indicator (ESI) series – which is available for the current period t - in a multivariate MS model, offers accurate forecasts for the state of the economy.

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ΣΤΟΙΧΕΙΑ ΕΡΕΥΝΩΝ ΟΙΚΟΝΟΜΙΚΗΣ ΣΥΓΚΥΡΙΑΣ: ΠΟΣΟ ΒΟΗΘΟΥΝ ΣΤΗΝ ΠΡΟΒΛΕΨΗ ΤΟΥ ΡΥΘΜΟΥ ΑΝΑΠΤΥΞΗΣ ΤΟΥ ΑΕΠ? Η ΠΕΡΙΠΤΩΣΗ ΤΗΣ ΚΥΠΡΟΥ

ΠΕΡΙΛΗΨΗ

Σκοπός της μελέτης είναι να βρεθεί ένα χρήσιμο εργαλείο για την ανάλυση των τρεχουσών συνθηκών των επιχειρήσεων και την κατασκευή έγκαιρων προβλέψεων για τις κυκλικές οικονομικές διακυμάνσεις της Κύπρου. Το μοντέλο είναι βασισμένο στα μοντέλα Markov Switching (MS). Αρχικά, παρουσιάζουμε τις προβλέψεις που προκύπτουν από το μονοδιάστατο (univariate) μοντέλο του ΑΕΠ. Παρόλο που το μοντέλο αυτό μπορεί να περιγράψει την πλειοψηφία των προηγούμενων οικονομικών κύκλων, δεν μπορεί να παρέχει έγκαιρες προβλέψεις. Στην συνέχεια, δείχνουμε πως ο συνδυασμός του ΑΕΠ μαζί με το Δείκτη Οικονομικής Συγκυρίας (ΔΟΣ) σε ένα πολυμετάβλητο (multivariate) αλγόριθμο, βελτιώνουν τις προβλέψεις σχετικά με την κατάσταση της οικονομίας. Αυτό το (multivariate) Markov Switching μοντέλο φαίνεται να είναι επαρκές για την σωστή και έγκαιρη πρόβλεψη της πιθανότητας της κατάστασης που βρίσκεται η οικονομία.

1. INTRODUCTION

Modern economies are characterized by the continuous phases of economic growth and contraction. Understanding these phases, or business cycles as they are called, has been the main focus of many years of research and, as it most often happens, researches have divided into two main camps. Some examine the real variables that they believe are the actual driving force behind an economy while others take a look at growth cycles, translating the phases of expansion and recession into periods of increasing and decreasing growth. Both approaches are important to economic agents who strive to understand the economy in order to make their decisions.

The introduction of the euro and the ascension of Cyprus into the euro area have increased the interest in, and the need for a business cycle analysis for the newly introduced member state. Although this business cycle model is in no way representative of the entire euro area, its usefulness lies in the interest of local economic agents.

Therefore, the purpose of this paper is to find a useful tool (model) for identifying and forecasting Cyprus's business cycles. Using minimal information, the model is able to identify the current state of the cycle and provide a forecast about subsequent periods. The model is based on Markov Switching (MS) models as proposed by Hamilton (1989) and developed by Bengoechea, Camacho and Perez-Quiros (2006). Recent related literature on MS models and euro area business cycles includes the work of Krolzig (2001), Massman and Mitchell (2003), Artis, Marcellino and Proietti (2003), Artis, Krolzig and Toro (2004), Harding (2004), Krolzig (2004), Mitchell and Mouratidis (2004), and Krolzig and Toro (2005). However, these researchers focus only on the euro area, thus the need for a country specific model remains unsatisfied, and this paper presents several contributions that overcome some shortcomings of the aforementioned literature.

Following most of the aforementioned papers we use the Gross Domestic Product (GDP) as the main variable to gauge the state of the economy and make inferences as of the phase of the cycle.[1]

Additionally, we enhance the ability of the MS model to correctly identify and predict the business cycle through the use of closely related, to the GDP, series. The published GDP has a

[1] Many authors characterized GDP as problematic series (since the published statistics are too short and are subject to standardization and aggregation that introduce a lot of noise into the series) and instead they used Industrial Production Index (IPI) which is one of the most important indices used in the construction of the GDP for industrialized countries. Since the Cypriot economy is mostly based on services and tourism, the IPI has low correlation with GDP. Therefore, we opt to use GDP as the best measure to identify the different phases of the economy.

one or two quarters delay until it is released by the reporting agency and thus econometricians find it difficult to accurately generate real time predictions. Following Oller and Tallbom (1996), Kauppi, Lassila and Terasvirta (1996), and Garcıa-Ferrer and Bujosa-Brun (2000) and Bengoechea et. al. (2006), we gather the necessary information, about the economy, through indicator based on survey data. Specifically, we consider the Economic Sentiment Indicator (ESI), an indicator closely related to the performance of the economy. Those papers concentrate on dating the cycle and on how the survey data precede the turning points of the series of interest with some lead. This paper integrates the GDP and ESI series in a multivariate algorithm that generates forecasts of the Cypriot business cycle in real time.

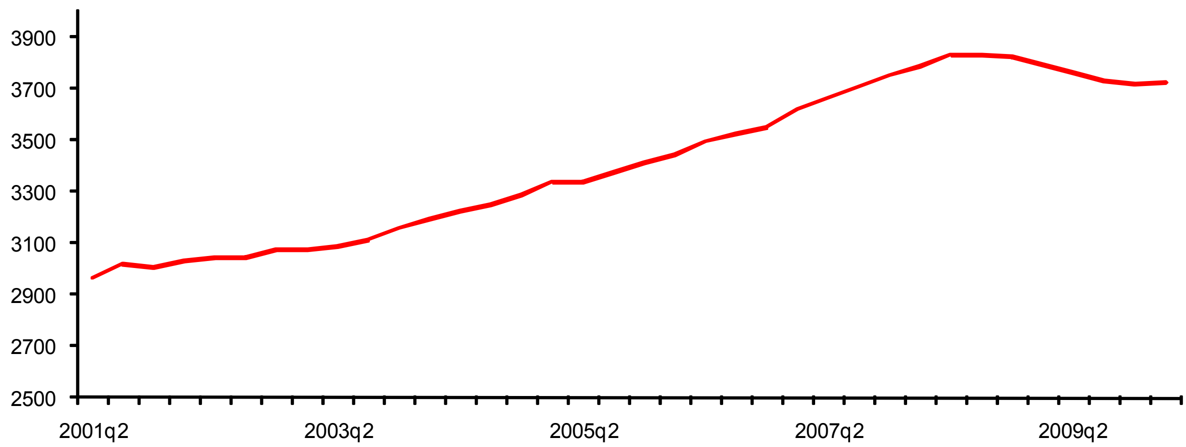
The rest of the paper is organized as follows. Section 2 describes the data. Section 3 presents the forecasts developed with univariate models of GDP. Section 4 shows how to use the ESI information to update the forecasts about the state of the economy by using an extension of the existing bivariate Markov-switching model. Section 5 concludes.

2. PRELIMINARY DATA ANALYSIS

2.1 Cyprus and the Gross Domestic Product

In this paper we use the natural logarithm of the seasonally adjusted GDP (depicted in Figure 1) which is collected and published by the Statistical Service of Cyprus. The series is quarterly and the sample period is between 2001.Q2 and 2010.Q1. As already mentioned, a crucial shortcoming of this series is its two quarters delay from the time collected and the time published by the Statistical Service. This translates into a loss of information about the real time level of GDP. In contrast, ESI is a very good measure that describes the current performance of the economy and it is available in real time.

Figure 1: Cyprus Gross Domestic Product (GDP), 2001.Q2-2010.Q1



2.2 The Economic Sentiment Indicator

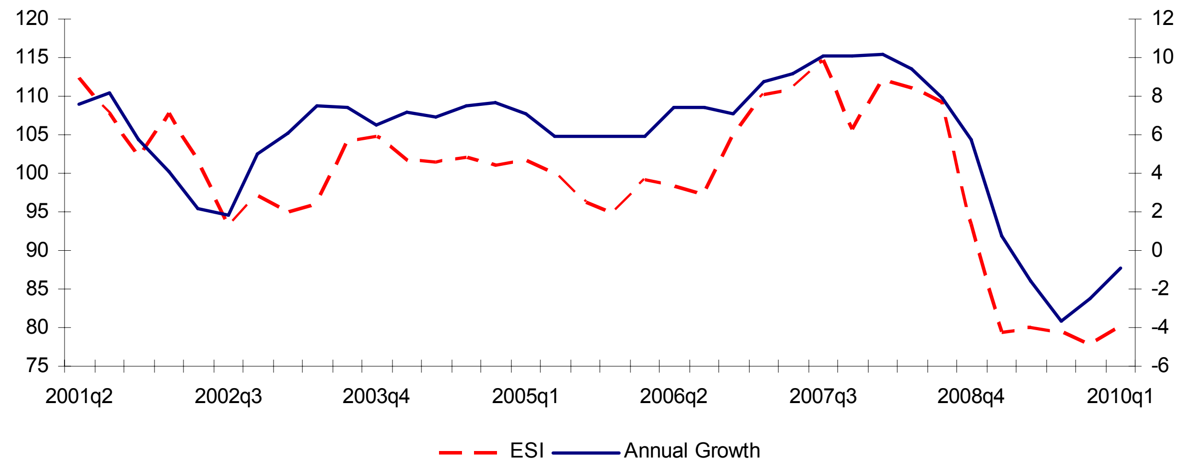
The European Commission carries out harmonised surveys in EU member states and a number of candidate countries. Business and Consumer Surveys (BCS) cover various sectors of the economy, such as services, retail trade, construction and manufacturing, as well as consumers. Individual answers obtained from the surveys are presented as the net balances of positive and negative replies for each question covering all sectors and consumers. In order to be able to capture the overall economic climate in each country, the Commission constructs the ESI which summarises the developments in all four sectors and among consumers. More precisely, fifteen questions, (four from the consumer survey, three from industry, two from construction, three from retail trade and three from services survey) are used to calculate the ESI. The questions from each sector and consumers included in the ESI are weighted using the same weights for all countries, namely 40% for industry, 30% for services, 20% for consumers, 5% for construction and 5% for retail trade. A detailed description of the construction of the ESI can be found in the User Guide for The Joint Harmonised EU Programme of Business and Consumer Surveys, published by the European Commission.[2]

The first use of the ESI can be traced back to the U.S. in 1953 and numerous studies have been undertaken to gauge its usefulness as a forecasting tool. The National Association of Purchasing Managers (NAPM) survey of manufacturers goes back to 1931. In Europe, the first business survey dates back to the late 1940s (IFO in Germany in 1949) and early 1950s (INSEE in France and ISCO in Italy, 1951).

Due to the European effort for harmonized consumer and business surveys, data series have been available since 1980. Unfortunately, in Cyprus the series starts from 2001. Generally, consumer and business surveys have gained popularity in the assessment of business cycles since the highly correlated co-movement of the index with the Euro recession of the early 90's. This coincidence was considered as strong evidence for the importance of the index as a predictor of the movement of the business cycle. In addition, as is seen in Figure 2, unlike the systematic delay of 1 or 2 quarters with which the GDP series is published, the ESI series does not exhibit any delay.

[2] Web address: http://ec.europa.eu/economy_finance/indicators/business_consumer_surveys/userguide_en.pdf

Figure 2: Levels of ESI (red dotted line) and annual growth rates of GDP (blue line), 2001.Q2-2010.Q1



2.3 Co-movements between GDP and ESI [3]

The suitability of the ESI has been evaluated by its ability to track the evolution of the annual growth rates of the domestic industrial production. By examining the time cross correlation coefficients between the GDP and ESI we were able to obtain this information. The cross correlation can be seen in Table 1, which shows a strong concordance correlation coefficient between the two variables. Furthermore, it is revealed that the ESI series is a coincident indicator of the annual growth rate of the GDP of Cyprus (see Figure 2).

The power of the indicator, as a predictor of GDP growth, originates from the habitual benchmarking of one's inventory level to the one of the previous year. Generally, the respondents tend to compare each quarter's inventory the same month of the previous year thus formulating the ESI index as a backwards looking indicator. These high correlations suggest that we may have reliable information about the GDP two quarters in advance, which coincides with the difference in publication time between the GDP and ESI series.

Table 1: Cross correlation in annual growth rates of GDP and ESI

	GDP leads-lags						
	-3	-2	-1	0	1	2	3
ESI	0.526	0.584	0.604	0.591	0.403	0.168	0.0313

[3] The following model and analysis are based on the work of Bengoechea et. al. (2006).

3. FORECASTING WITH UNIVARIATE MODELS

3.1 The model

The proposed, by Hamilton (1989) algorithm, allows for the inference and forecasting of the state of the business cycle from an economic time series. His argument is that the expected value of the series of interest is different during each phase of the cycle. However, his filter is only defined for stationary series. The Augmented Dickey Fuller (ADF) and Philips – Peron (PP) unit root tests reveal a unit root for the log of the GDP while we reject the null for non stationarity. Letting Y_t be the GDP and defining $y_t = 100ln(Y_t/Y_{t-1})$ we consider the conditional expectation to be:

$$E(y_t) = \mu_1 \text{, if the economy is in expansion}$$
$$E(y_t) = \mu_2 \text{, if the economy is in recession} \tag{1}$$

with $\mu_1 > \mu_2$. These expectations can be recast as:

$$y_t = \mu_{st} + u_t , \tag{2}$$

where s_t is an unobservable latent variable that takes values of 1 and 2. Since the dynamics of the series are more complex than the two expectations we also provide for an autoregressive error term u_t:

$$u_t = \sum_{i=1} \varphi_i u_{t-i} + \varepsilon_t, \tag{3}$$

with $\varepsilon_t\ i.i.d \sim N(0, \sigma^2)$.

Plugging (3) in (2) we construct:

$$y_t = \mu_{s_t} + \sum_{i=1} \phi_i u_{t-i} + \varepsilon_t, \tag{4}$$

and substituting u_{t-i} with its value defined in (1), we obtain

$$y_t = \mu_{s_t} + \sum_{i=1} \phi_i (y_{t-i} - \mu_{s_{t-i}}) + \varepsilon_t, \tag{5}$$

Eq. (5) is called an observation equation. It allows for the casting of series y_t as a function of the unobservable variable s_t, which represents the phase of the business cycle. Following Hamilton's (1994) suggestion it is assumed that the important states of the economy, for the purpose of the autoregression, are equal to $k = 2^{p+1}$. These states are collected in a new variable s_t^*. This variable is a summary of all the different states of the economy.

Furthermore, the estimation of this model requires the calculation of the motion of the unobservable variable. Following Hamilton (1984), s_t evolves as a Markov chain of order one.

Therefore, the transition probabilities are:

$$\Pr\,[s_t = j|s_{t-1} = i, |\Omega_{t-1}] = \Pr[s_t = j|s_{t-1} = i] = p_{ij}, \tag{6}$$

where Ω_{t-1} represents all the available information in the period *t – 1,* and *i,j = 1,2.*[4]

Another difficulty we address is the fact that in the standard Markov switching literature the researchers estimate what is called a Markov switching process in the intercept. The implied specification is then:

$$y_t = \mu_{s_t} + \sum_{i=1} \phi_i y_{t_i} + \varepsilon_t. \tag{7}$$

Even though, this specification leads to a significant reduction in the number of parameters that need to be estimated it can also lead to potential misspecification errors therefore we will use Eq. (5) in the estimation process.

To obtain estimates for the unknown parameters we need to maximize log likelihood function:

$$L = \sum_{t=1} lnf(y_t|\Omega_{t-1}), \tag{8}$$

where $f(y_t|\Omega_{t-1})$ is the conditional density of y_t given the information available at *t – 1.*

Applying the total probability theorem and knowing the states of the economy cannot coincide, the conditional density becomes:

$$f(y_t|\Omega_{t-1}) = \sum_{i=1}^{k} f(y_t|s_t^* = i, \Omega_{t-1}) P(s_t^* = i|\Omega_{t-1}), \tag{9}$$

with *k* being the 2^{p+1} different states of the economy. Further decomposition of Eq. (9) gives us:

$$\begin{aligned} P(s_t^* = i|\Omega_{t-1}) &= \sum_{j=1}^{k} P(s_t^* = i|s_{t-1}^* = j, \Omega_{t-1}) \times P(s_{t-1}^* = j|\Omega_{t-1}), \\ &= \sum_{j=1}^{k} p_{ij}^* P(s_{t-1}^* = j|\Omega_{t-1}), \end{aligned} \tag{10}$$

[4] Hamilton (1994) shows that s_t^* also presents the properties of a Markov chain with transition probabilities p^*_{lm}, with l, m=1, 2, . . .k, which may be derived from pij. These probabilities are usually collected in transition matrices P and P*, whose columns sum to unity.

These probabilities are collected into a *(k* x *1)* vector $\xi^*_{t|t-1}$ and the Bayes' theorem is applied:

$$P(s^*_{t-1} = j|\Omega_{t-1}) = P(s^*_{t-1} = j|y_{t-1}, \Omega_{t-2}),$$

$$= \frac{f(y_{t-1}|s^*_{t-1} = j, \Omega_{t-2}P(s^*_{t-1} = j|\Omega_{t-2})}{\sum_{i=1}^{k} f(y_{t-1}|s^*_{t-1} = i, \Omega_{t-2})P(s^*_{t-1} = i|\Omega_{t-2})} \tag{11}$$

Eq. (11) is a function of $P(s^*_{t-1} = i|\Omega_{t-2})$, which is lagged for one period in Eq. (10). Therefore, eq. (10) and (11) are iterated to obtain the log likelihood function as a function of the parameters and the initial conditions on the state of the economy.

Finally, the optimal *m – period* ahead forecast of the regime conditional on the information available at time *t*, is:

$$\xi^*_{(t+m|t)} = P^* \xi^*_{(t|t)} \tag{12}$$

3.2 Empirical results

We estimate model (5) with a one period lag (as indicated by the Schwarz Information Criterion). Table 2 sums the maximum likelihood estimates of the parameters. For $s_t=1$, the average growth rate is 0.9331 and it is in line with the expansion part of the cycle. By contrast, when $s_t=2$ we get a negative estimate ($\mu_2=-0.3869$) which is indicative of a recession period. The estimated probabilities, $p_{11} and\ p_{22}$, respectively, indicate a persistence in the cycles, with the probability of each regime continuing in the following period very high.

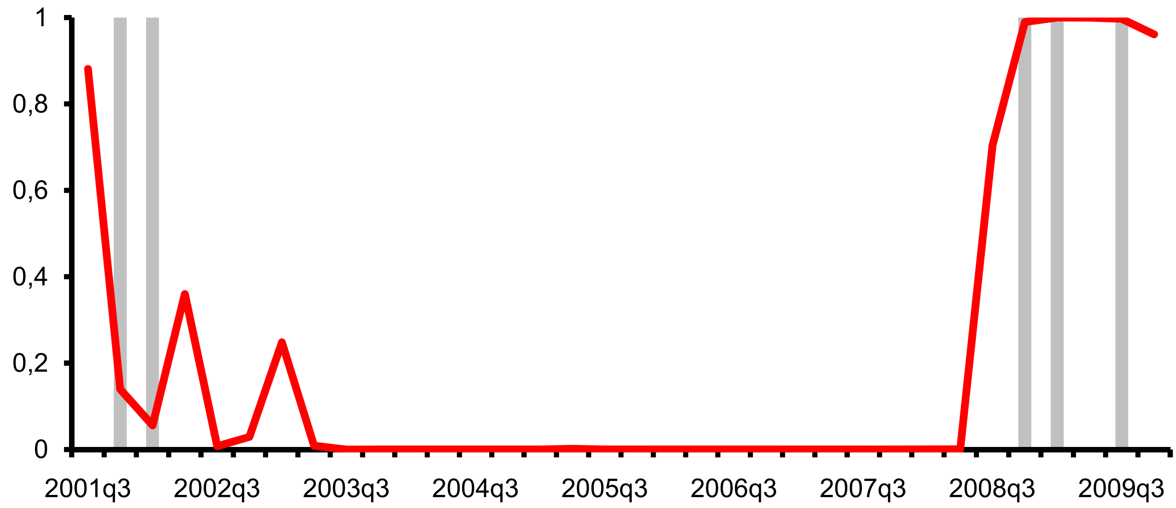
Table 2: Univariate Markov-Switching model

Parameters	Estimates	Std. Errors
μ_1	0.9331	0.1058
μ_2	-0.3869	0.2105
φ_1	0.0736	0.1411
σ	0.1943	0.0627
p_{11}	0.9313	1.7034
p_{22}	0.8973	2.2094

Fig. 3 is the plot of the filtered probabilities of being in a recession. It shows the probability of being in a recession at each period conditional on the available information. It is obvious that a simple Markov switching regime is able to differentiate between the different phases of the business cycle where the probability of being into a recession is equal to one.

In order to validate our results we compare the filtered probabilities with the Bry–Boschan business cycle dating procedure, a method for identifying classical turning points from the levels of GDP.[5] The Bry–Boschan methodology is widely used in the identification of the business cycle turns.[6] Fig. 3 shows, in grey bars, the Bry–Boschan business cycles recessions. They are in agreement (although for some of them in a lesser degree) with the probability predictions, of the univariate model, for states of negative GDP growth. Accordingly, we can view states one and two as a recession and expansion, respectively. Hence, even though the univariate model is able to almost successfully describe the majority of past business cycles it is unable to provide real time predictions.

Figure 3: Filtered probabilities of recessions from univariate Markov Switching model applied to GDP. Shaded areas represent classical recessions obtained by applying Bry-Boschan to GDP, 2001.Q2-2010.Q1



The major flaw of this model lays in the GDP series. The GDP becomes available with a two quarters lag, therefore the information contained in the GDP for time *t* will only be known two quarters later. We demonstrate the extent of the problem with the following out of sample exercise. Assume that we need to accurately provide the forecasts, at quarter *t*, for the probability of a recession at time *t+1*, with *t* going between 2006.Q1 and 2010.Q1. In order to make the first forecast, the portion of the GDP series that the forecaster would know goes from the beginning of the sample until 2005.Q4. Due to the 2 quarters delay the forecaster does not know this series until 2006.Q2. The forecaster would use Eq. (12) to provide the three periods ahead forecast for 2006.Q3, which is the first out of sample prediction. With the addition of new

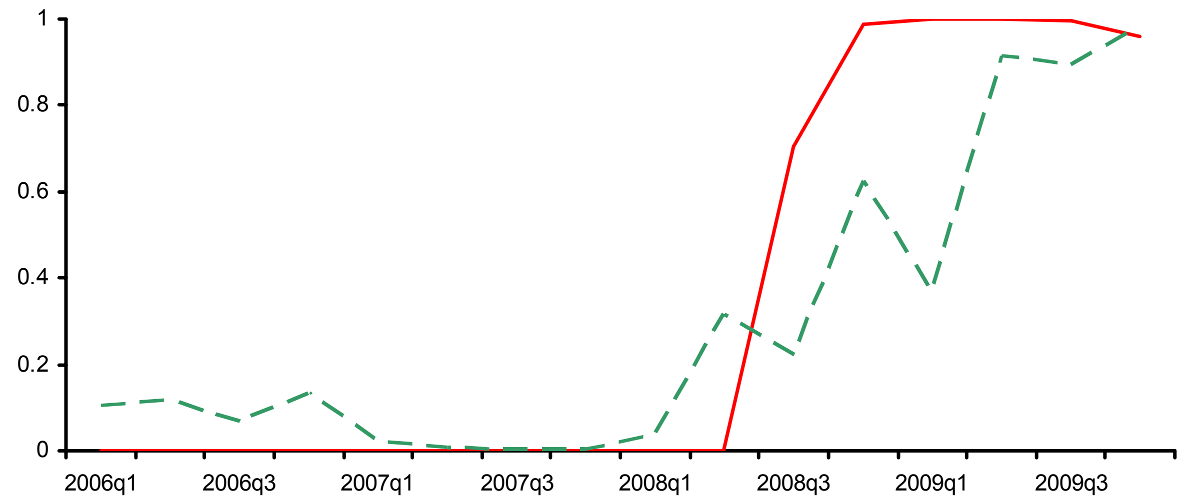
[5] While for the US the official business cycle chronology is provided by the National Bureau of Economic Research (NBER), for the case of other countries this approach is not applicable since there is no widely accepted business cycle chronology. The method of Bry-Boschan offers a good alternative for identifying classical turning points from the levels of GDP (or IPI where applicable).

[6] For details on the Bry-Boschan procedure we refer to Artis, Kontolemis and Osborn (1997).

observations to the GDP a re-estimation of the model is necessary for the computation of the next prediction, 2006.Q4. This process is iterated recursively until the last out of sample prediction, 2010.Q2.

The three period ahead forecasts represent the forecasted probability of being in a recession in period *t+1* with the information available at time *t*, which is dated at *t-2*. In Fig. 4, the out of sample probabilities are plotted against the in sample probabilities. The model systematically predicts late. In concluding this exercise, it is obvious that the model describes the historical dates of the economy very well, however it fails to forecast the future states, because it predicts late. Therefore, the statistical delay is of utmost importance to the correct prediction of the recession and the need for an alternative method is apparent.

Figure 4: In sample (red line) and out-of-sample forecasts (blue dotted line) filtered probabilities of recessions from univariate Markov Switching model applied to GDP. In sample probabilities from 2006.Q1-2010.Q1



4. FORECASTING WITH BIVARIATE MODELS

4.1. The model

As it is evident that the univariate model is inadequate in estimating the correct real time probability of being in a recession we consider adding the information contained in ESI series to the process. Therefore we employ a bivariate Markov switching model for the GDP growth and the ESI first differences. More specifically, we estimate the model developed by Bengoechea et. al. (2006). We let s_t be a latent variable of the unobserved GDP that takes the values 1 if y_t is in an expansion and 2 if y_t is in a recession. The transitional probabilities are p_{ij}. Similarly, v_t

denotes the latent variable of ESI with x_t taking the value 1 if we observe an expansion and 2 a recession. Its transition probabilities are q_{ij}. Finally, the specification is:

$$\begin{pmatrix} y_t \\ x_t \end{pmatrix} = \begin{pmatrix} \mu_{s_t} + \sum_{i=1}^{p_1} \phi_i \left(y_{t-i} - \mu_{s_{t-i}} \right) \\ \gamma_{v_t} + \sum_{i=1}^{p_2} \theta_i \left(x_{t-i} - \gamma_{v_{t-i}} \right) \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}, \tag{13}$$

where $(\varepsilon_{1t}, \varepsilon_{2t})'$ follows the Gaussian bivariate process

$$\begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix} \sim N \left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{pmatrix} \right] \tag{14}$$

We enhance this baseline model with two important additions. Firstly, we examine the degree of the synchronization of the business cycle movements between the GDP and ESI. There are two extreme cases in the literature; of no interdependence and of perfect synchronization. This specification proposes that the real synchronization falls somewhere in between these two cases, therefore it can capture this through a linear combination that can be estimated from the data. In addition, it allows us to examine the degree of interdependence between the individual series. Since the original assumption assumes independence of the two Markov switching processes we will end up with four basic states with the conditional probability of being in each state being equal to the product of the probabilities of being in each of the individual states. That is, the conditional probabilities are:

$$\begin{aligned} \xi_{(t|t-1)}^{I} &= \begin{pmatrix} P(s_t = 1, v_t = 1|\Omega_{t-1} \\ P(s_t = 2, v_t = 1|\Omega_{t-1} \\ P(s_t = 1, v_t = 2|\Omega_{t-1} \\ P(s_t = 2, v_t = 2|\Omega_{t-1} \end{pmatrix} \\ &= \begin{pmatrix} P(s_t = 1|\Omega_{t-1})P(v_t = 1|\Omega_{t-1}) \\ P(s_t = 2|\Omega_{t-1})P(v_t = 1|\Omega_{t-1}) \\ P(s_t = 1|\Omega_{t-1})P(v_t = 2|\Omega_{t-1}) \\ P(s_t = 2|\Omega_{t-1})P(v_t = 2|\Omega_{t-1}) \end{pmatrix} \end{aligned} \tag{15}$$

where the superscript *I* refers to the case of the independent cycles. On the other hand, under the assumption that both series share the state of the economy the conditional probabilities of each basic state could be rewritten as:

$$\begin{aligned} \xi_{(t|t-1)}^{D} &= \begin{pmatrix} P(s_t = 1, v_t = 1|\Omega_{t-1} \\ P(s_t = 2, v_t = 1|\Omega_{t-1} \\ P(s_t = 1, v_t = 2|\Omega_{t-1} \\ P(s_t = 2, v_t = 2|\Omega_{t-1} \end{pmatrix} \\ &= \begin{pmatrix} P(s_t = 1|\Omega_{t-1}) \\ 0 \\ 0 \\ P(s_t = 2|\Omega_{t-1} \end{pmatrix} \end{aligned} \tag{16}$$

where the superscript *D* refers to the case of fully dependent cycles.

From the definition above we can see that only the difference between sharing and not sharing the state of the economy is the form of the transitional probabilities. In order to uncover an intermediate point between the extreme cases of sharing and not sharing, the actual business cycle synchronization is δ times the case of independence and $(1\text{-}\delta)$ times the case of perfect dependence, where 0 ≤ δ ≥ 1. The weight δ can be viewed as a measure of business cycle desynchronization since δ evaluates the proximity of the cycle to the case of independence. Therefore, the transition process becomes:

$$\xi_{(t|t-1)} = (1-\delta)\xi^{D}_{(t|t-1)} + \delta\xi^{I}_{(t|t-1)} \qquad (17)$$

The second extension, Bengoechea et. al. (2006) offer to the existing literature, deals with the reduction in the systematic delay in the prediction of business cycle probabilities. The multivariate approach will give us the joint probabilities of recession for the series GDP and ESI. The multivariate approach has a distinct advantage over the univariate case. Although the univariate approach is able to provide statistical inference about the in sample probabilities of the occurrence of each state of the cycle, the bivariate specification has an important advantage over it.

In the case with the single predictor, at any period *t* we had to make inference about period *t+1* with information available only at *t-2*. This is because of the two month delay in the publication of the GDP series. In the case with the two predictors, we make use of the timely issue of the ESI series to update the forecasts about the business cycle probabilities in *t-1* and *t.* For the prediction of the probability of a recession we follow the following scheme:

1. Calculate the filtered probabilities $P(s_{t-2} = i, v_{t-2} = j|\Omega_{t-2})$. We then estimate the bivariate model from the sample available from both series at time *t*. This implies estimation for both variables up to time *t-2*.

2. Forecast the probabilities $P(s_{t-1} = i, v_{t-1} = j|\Omega_{t-2})$. Use Eq. (10) and the probabilities for each state at time *t-2* as well as the transition probabilities stated above to predict the probability of being in recessions and expansions in *t-1*.

3. Use the ESI data for *t-1* to update the filtered probabilities $P(s_{t-1} = i, v_{t-1} = j|\Omega_{t-1})$.

4. Forecast the probabilities $P(s_t = i, v_t = j|\Omega_{t-1})$. Using the transition probabilities of Eq. (10) and the filtered probabilities we find the probabilities of recessions and expansions at *t*.

5. Apply the ESI data to update the filtered probabilities $P(s_t = i, v_t = j|\Omega_t)$ in period t.

6. Compute predictions $P(s_{t+1} = i, v_{t+1} = j|\Omega_t)$. We use Eq. (10) to obtain updated forecasts of the business cycles probabilities for the next month.

4.2. Empirical results

We estimate the maximum likelihood parameters of the model stated in Eq. (13). These are displayed in Table 3 in the first column, labeled as Model 1. Our first interest is to examine the comovements among the respective business cycle dynamics of the series. We, therefore, test the null that the series have the same inertia in terms of probabilities of staying in a recession or expansion. To apply the test, we estimate Eq. (13) under the assumption that the two variables share the probability of staying in expansions or recessions. The estimates are given in the second column of Table 3, labeled Model 2. With a *p*-value of 1% we fail to reject the null that these series have the same probabilities of staying in each of the business cycles phases.

We have shown above that the two series share the same transitional probabilities. In order to test for that, we need a more restrictive question. Do these series share the state of the economy in each period of time? In terms of our notation, this becomes, is $s_t = v_t, \forall t$? If this is the case then the addition of a second model becomes null since both series move with the same unobserved variable. The estimated model is displayed in the third column of Table 3, labeled Model 3. The problem with this test is that, given that the two models are not nested, there is no standard formal way in the literature to test this hypothesis.

We base our test on the assumption that the business cycle synchronization is an average between the case of perfect synchronization and the case of complete independence. Parameter *d* determines the proximity to the case of independent cycles. Maximum likelihood estimates for this specification are displayed in the fourth column of Table 3, labeled Model 4. The estimated δ is 0.22, which is close to zero. Hence, the assumption that they share the business cycle is more viable than the assumption of independence. However, the data generating process falls closer to Models 2 and 3.

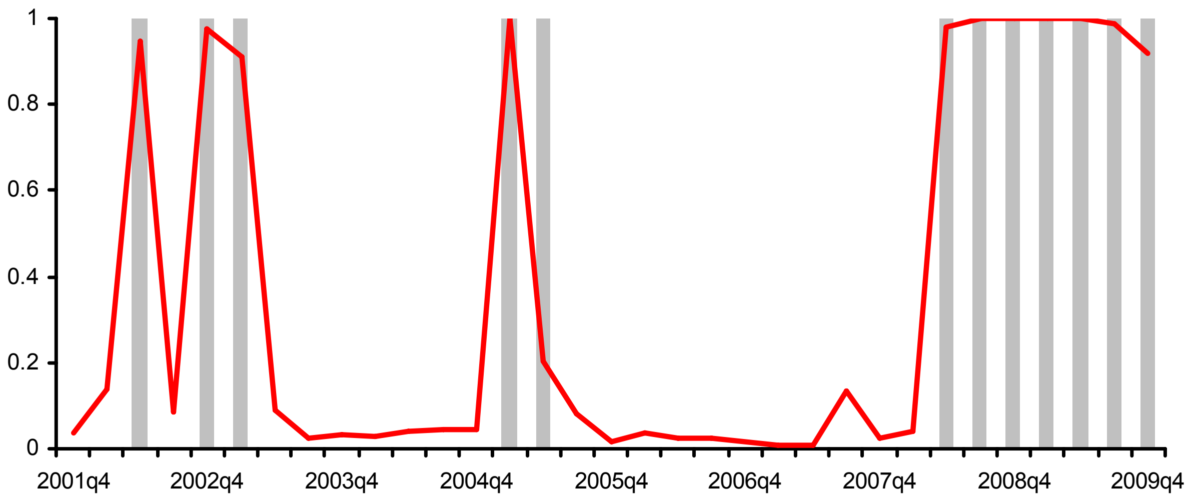
Examining the estimates of Model 4, the first regime is characterized by a positive GDP growth rate ($\hat{\mu}_1 = 1.08$) and positive differences of the ESI ($\hat{\gamma}_1 = 0.64$), so we can interpret this regime as the expansion period. However, in the second regime the average GDP growth rate and the average ESI differences are negative ($\hat{\mu}_2 = -0.13, \hat{\gamma}_2 = -3.83$), an indication of a recession. Furthermore, each regime is highly persistent, with shared estimated probabilities of one regime being followed by the same regime of 0.86 and 0.75 respectively.

Table 3: Bivariate Markov-Switching Model

	Model 1	Model 2	Model 3	Model 4
Parameters	Estimates	Estimates	Estimates	Estimates
μ_1	0.888 (0.127)	0.888 (0.127)	0.948 (0.124)	1.085 (0.122)
μ_2	-0.165 (0.253)	-0.165 (0.253)	-0.333 (0.222)	-0.134 (0.163)
φ_1	0.261 (0.168)	0.261 (0.168)	0.247 (0.199)	0.392 (0.183)
p_{11}	0.967 (0.041)	0.967 (0.041)	0.965 (0.054)	0.869 (0.074)
p_{22}	0.921 (0.118)	0.926 (0.118)	0.921 (0.156)	0.754 (0.153)
γ_1	-0.702 (1.063)	-0.702 (1.063)	0.204 (0.746)	0.646 (0.761)
γ_2	-0.702 (1.729)	-0.702 (1.729)	-4.362 (1.477)	-3.840 (1.583)
θ_1	0.010 (0.173)	0.010 (0.173)	-0.146 (0.172)	-0.239 (0.230)
θ_2	-0.139 (0.163)	-0.139 (0.163)	-0.205 (0.163)	-0.220 (0.180)
q_{11}	0.965 (0.031)	0.965 (0.031)		
q_{22}	0.919 (0.132)			
σ_{11}	0.203 (0.059)		0.187 (0.056)	0.099 (0.037)
σ_{22}	28.349 (7.154)	28.349 (7.154)	24.548 (6.187)	23.267 (6.671)
σ_{12}	1.042 (0.556)	1.042 (0.556)	0.915 (0.435)	0.657 (0.403)
δ				0.229 (0.260)
L	-63.003	-63.003	-60.219	-59.736

We continue by examining the dynamics of the unobserved state variables against the business cycles of Cyprus. Fig. 5 reports the filtered probabilities estimated by Model 4 for both series in state two. Clearly, they do not match the classical business cycles outlined in Fig. 3. Relating these probabilities to the GDP series shown in Fig. 1, there exist episodes with a high probability of state two that are characterized by low but not negative growth rates of the GDP series.

Figure 5: In sample filtered probabilities of recessions from bivariate Markov Switching model applied to GDP and ESI. Shaded areas represent classical recessions obtained by applying Bry-Boschan to the Hodrick-Prescott cycle of GDP, 2001.Q2-2010.Q1



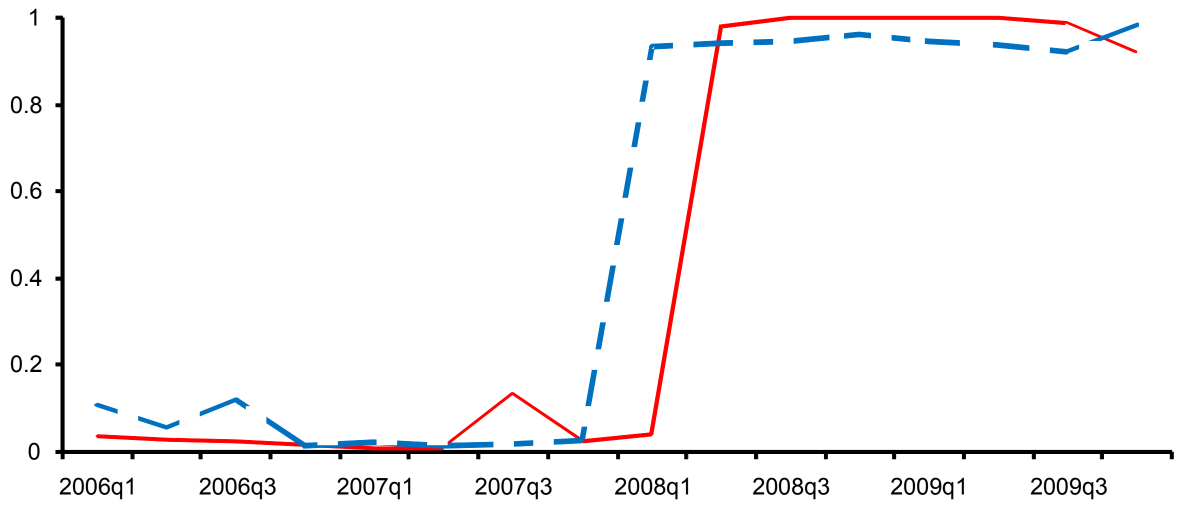
Comparing these probabilities to those in Fig. 1 we can see an instance of high probability for state two that is characterized by low but not negative GDP growth rates. An example for such states would be the middle of the period from 2004.Q4 to 2005.Q3. The fact that our model is predicting more recessions than the classical dating model is an indication that the unobserved state variables of the bivariate model may refer to growth rate cycles instead of classical cycles.

In examining this fact, we apply the Bry – Boschan procedure to the GDP gap, which is the difference between the GDP and its standard Hodrick – Prescott trend. We are thus able to compute the dating of the growth rate cycles. Fig. 5 indicates a strong concordance between the growth rate recessions of GDP and the periods of high filtered probabilities of both GDP and ESI being in state two. In this case, the bivariate model is able to generate true growth rate cycles.

Although Fig.5 shows that the Markov switching filter is able to generate cycle probabilities that correspond closely to the historical sequence of GDP growth rate cycles, this is not enough to validate the utility of ESI for the forecasts of business cycles in real time. We, therefore, examine whether the ESI issues help the forecasters circumvent the systematic delay in the forecasts of the univariate model.

In order to address the out of sample performance of the bivariate model we apply the following procedure. We estimate the model recursively and compute out of the sample forecasts using the proposed filter for the period 2006.Q1 – 2010.Q1. Fig. 6 is a plot of the results along with the in sample filtered probabilities plotted on Fig. 5. Both series are much closer to each other than the ones presented in Fig. 4. Therefore, the systematic delay in the prediction of the future state of the business cycle has been corrected. These results may be interpreted as an empirical support in favour of our proposed filter for forecasting probabilities of recessions of Cyprus in real time.

Figure 6: In sample (red line) and out-of-sample forecasts (blue dotted line) filtered probabilities of recessions from bivariate Markov Switching model applied to GDP and ESI. In sample probabilities from 2006.Q1-2010.Q1



5. CONCLUSIONS

The literature on business cycles has revealed many difficulties in identifying and forecasting business cycles phases in real time. This is mainly because the series related to the business cycle (such as GDP) are published with a systematic delay of one or two quarters.

In this paper we employed a bivariate Markov Switching model (developed by Bengoechea et.al. 2006) to analyze the current business conditions of Cyprus and construct real time predictions for its business cycle. This specification overcomes the problem of delay, since it allows to use both GDP series and ESI (which are available in real time). Furthermore, it allows us to examine the likelihood of the state of the economy in period t and make reliable forecasts for the subsequent periods.

Our results indicate that the bivariate Markov Switching model is adequate in estimating the correct real time probability of being in a recession. Furthermore, it suggests that ESI is closely related to GDP growth and is very useful for identifying and forecasting the state of the growth rate cycles of the Cypriot economy.

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