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Dating Turning Points for Austria: A Suggestion

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Abstract

The present paper proposes to use the information contained in a large panel data set, and to group those series together that display similar time series and business cycle properties, whereby the groups are also part of the estimation and not set a priori. Based on a dynamical structure which identifies a group of leading and a group of coincident series, we are able to date historical turning points and to make probabilistic forecasts on future ones. The results are consistent with common expectations, in particular the group of leading series includes Austrian confidence and sentiment indicators, German survey indicators, exports to G7 and to U.S. and interestingly, the Austrian and the German stock market indices.

1. Introduction

In this paper, I suggest to estimate business cycle turning points for Austria by using the information contained in a large set of economic, real and financial, variables. The information about the cyclical stance is extracted by estimating groups of series that display similar dynamics over time. To capture the fact that some groups of series usually lead the cycle, two groups of series are linked by an additional dynamical structure. That is, we explicitly allow for a group that leads another one in the cyclical dynamics. As the leading/coincident properties of series are not known with certainty (except perhaps for GDP and its components), we also estimate which groups may be linked by the dynamical structure. Obviously, not all series can be classified into one of both the coincident and the leading group of variables. Therefore, the remaining group, which collects all the series not following the coincident and the leading group of series, is moving "independently" from the other two groups.

The methodological approach pursued in the paper is based on the idea of model-based clustering of multiple time series (Frühwirth-Schnatter and Kaufmann, 2004a). An extension is introduced here in the sense that an additional dynamical structure links two groups in the panel. How to form the groups and which groups are linked by the dynamic structure is subject to estimation. Moreover, as the series are demeaned before the analysis, the estimation yields an inference on growth cycles. The growth cycle itself is modeled by a process which identifies periods of above-average and below-average growth. As these periods usually cannot a priori be identified with certainty, I will assume that an unobservable first-order Markov process is driving the economy.

Recently, research on the euro area business cycle has intensified. The areas which numerous papers deal with are dating business cycle turning points, assessing the current stance of the business cycle, forecasting the cycle itself as well as the probability of turning points. The model of the present paper is related to Benoechea and Pérez-Quirós (2004) who estimate a bivariate Markov switching model for the industrial production index and the industrial confidence indicator. With the so-called filter probabilities of the state indicator, which reflect the state probability in period t given the information up to period t, they assess the current state of the euro area business cycle and form a forecast on the probability of a turning point. While they apply the Markov switching framework to two aggregate variables, namely industrial production and the industrial confidence indicator, here the cyclical stance is extracted from the information contained in a large cross-section of economic series. Moreover, while they are modeling the state indicators of each series as switching independently or jointly, here, one group is explicitly defined as leading another, the coincident, group.

Forni et al. (2000) suggest using dynamic principal components to extract the coincident and the leading index of economic activity. From a large cross-section, they choose a set of core variables usually considered to be the most relevant to describe the business cycle stance, and include additional variables that are most correlated with this core and have only minor idiosyncratic dynamics. The common component extracted from these series allows to compute a coincident indicator for the euro area as a whole and for each individual country as well. The Austrian series included in the core are GDP, investment, consumption and industrial production. Austrian orders is the only series additionally taken into consideration in the final estimation. Generally, all financial and monetary variables are not sufficiently correlated to the core to be included in the final estimation, and neither are the price series and the share prices. Not surprisingly, orders turn out to be strongly correlated to the common component of the core series. Finally, the country-specific comparison of turning points with the euro area aggregate reveals that Germany, and also Austria, are not leading the euro area coincident indicator.

These results are of interest as the ones reported in the present paper point into the same direction. Financial variables do not pertain to the set of core variables, i.e. they do not fall into the leading group of variables and neither into the coincident group of variables. On the other hand, asset prices (the Austrian ATX and the German DAX stock market indices) fall into the leading group of series. Orders, confidence and economic sentiment indicators as well, fall into the leading group of variables.

Another possibility to predict turning points is suggested in Canova and Ciccarelli (2004). Based on the estimation of a Bayesian panel VAR for the G7 countries, forecasts in the growth rates of GNP are used to predict turning points and the probability of turning points. In principle, one could use the approach for a single country and form several VARs for related series in the panel, like business surveys, labor market series, trade series etc. Nevertheless, panel VARs appear most attractive to capture cross-country or country-specific inter-industry interdependencies. Our data set does not include many foreign variables, nor are the included series very disaggregate. Therefore, I will use the "basic" panel approach described in the following section.

Finally, a very specific approach is described in Bruno and Lupi (2004). Using early released reliable indicators, specifically a business survey series on future production prospects and the quantity of goods transported by railways, the authors specify a parsimonious forecasting model to produce a forecast of actual industrial production which then is used in an unobserved components model to assess the actual stance of the business cycle. In the present paper, however, we want to exploit the information of many series, of which many are also timely released, to form an expectation about turning points. Missing data on actual industrial production or other national account series can be handled as missing values and replaced by an estimate given the information we have on other timely released series (see also Frühwirth-Schnatter and Kaufmann, 2004b).

The paper is organized as follows. Section 2 introduces the model, section 3 outlines the estimation procedure. The data and the results are summarized in section 4.

2. The Econometric Model

Let y_{it} represent the (demeaned) growth rate at date t of a time series i in a large panel of economic variables, all assumed to be important for assessing the business cycle stance. The time series are assumed to follow the process:

$$y_{it} = \mu^i_{I_{it}} + \phi^i_1 y_{i,t-1} + \ldots + \phi^i_p y_{i,t-p} + \varepsilon_{it}, \tag{1}$$

with $\varepsilon_{it} \sim iid\ N(0, \sigma^2 / \lambda_i)$, $t = 1, \ldots, T$. For a single time series, the model comes close to the one estimated in Hamilton (1989) for US GNP. We assume that the growth rate $\mu^i_{I_{it}}$ depends on a latent state variable I_{it}, which takes one of $J = 2$ values, i.e. either 1 or 2:

$$\mu^i_{I_{it}} = \begin{cases} \mu^i_1 & \text{if} \quad I_{it} = 1 \\ \mu^i_2 & \text{if} \quad I_{it} = 2 \end{cases}. \tag{2}$$

The latent specification of I_{it} takes into account the fact that the state prevailing in each period t is usually not observable with certainty. Moreover, as periods of higher growth might have a different duration than periods of lower growth, we specify I_{it} to follow a Markov switching process of order one, $P(I_{it} = l \mid I_{i,t-1} = j) = \xi^i_{jl}$, with the restriction $\sum_{l=1}^{2} \xi^i_{jl} = 1$, $j = 1,2$.

The superscript i is used here to denote that each time series, in principle, can follow an independent process (if the observation period is long enough). However, if time series are evolving similarly over time, efficiency gains might be exploited by pooling the information in the respective series (see e.g. Hoogstrate et al., 2000, and Frühwirth-Schnatter and Kaufmann, 2004a). The difficulty in following this procedure is to form the appropriate grouping of series. If we do not have a priori certain information about it, we might wish to draw an inference on the appropriate grouping characterizing the series included in the panel. To this aim, an additional latent group-indicator S_i, $i = 1,\ldots,N$, is defined that relates to group-specific parameters, whereby S_i can take one out of K different values, $S_i = k$, $k = 1,\ldots,K$, if we assume to have K distinct groups of countries in the panel. Therefore, the model for $\mu^i_{I_{it}}$ given in (2) may be extended to:

$$\mu^{S_i}_{I_{it}} = \begin{cases} \mu^k_1 & \text{if} \quad S_i = k \text{and} I_{kt} = 1 \\ \mu^k_2 & \text{if} \quad S_i = k \text{and} I_{kt} = 2 \end{cases}, \quad k = 1,\ldots,K, \tag{3}$$

whereby the probabilities $P(S_i = k)$ are given by η^k, $k = 1,\ldots,K$ with the restriction $\sum_{k=1}^{K} \eta^k = 1$.

In model (1), the autoregressive parameters are also thought to be group-specific, i.e. $(\phi^{S_i}_1,\ldots,\phi^{S_i}_p) = (\phi^k_1,\ldots,\phi^k_p)$ if $S_i = k$. In principle, these coefficients can also be modeled as state-dependent. This would capture the fact that business cycle downturns are steeper than business cycle upturns, which would be reflected in higher autoregressive coefficients in the latter case. However, a preliminary investigation revealed that the autoregressive parameters are not state-dependent. Therefore, also for expositional convenience, the general specification is dropped.

We further assume group-specific state indicators (see the specification in (3)). This specification is appropriate to early detect or predict turning points. We expect that some series of the panel are leading the cycle, while some other series will be coincident with the cyclical dynamics of GDP. To capture this dynamic stylized fact, we put an additional structure on two of all of the group-specific state indicators.

Assume that the second group of series is the leading group while the coincident series are classified into the first group. We may parameterize this additional structure by designing an encompassing state indicator with restricted transition probability matrix (see also Phillips, 1991).

Note that each state indicator I_{kt} is assumed to have its own transition matrix $\xi^k = (\xi^k_{11}, \xi^k_{12}, \xi^k_{21}, \xi^k_{22})$. Define the encompassing state variable I^*_t which captures all $J^* = 4$ possible constellations of both state indicators 1 and 2 in period t:

$$\begin{aligned} I^*_t &= 1 := (I_{1t} = 1, I_{2t} = 1) \\ I^*_t &= 2 := (I_{1t} = 1, I_{2t} = 2) \\ I^*_t &= 3 := (I_{1t} = 2, I_{2t} = 1) \\ I^*_t &= 4 := (I_{1t} = 2, I_{2t} = 2). \end{aligned}$$

If the state indicator of group 2 is assumed to lead the state indicator of group 1,[1] eight of the 16 elements of the transition distribution of I^*_t will in fact be restricted to zero:

$$\xi^* = \begin{bmatrix} \xi^*_{11} & \xi^*_{12} & 0 & 0 \\ 0 & \xi^*_{22} & 0 & \xi^*_{24} \\ \xi^*_{31} & 0 & \xi^*_{33} & 0 \\ 0 & 0 & \xi^*_{43} & \xi^*_{44} \end{bmatrix} = \begin{bmatrix} \xi^1_{11}\xi^2_{11} & \xi^1_{11}\xi^2_{12} & 0 & 0 \\ 0 & \xi^1_{11}\xi^2_{22} & 0 & \xi^1_{12}\xi^2_{22} \\ \xi^1_{21}\xi^2_{11} & 0 & \xi^1_{22}\xi^2_{11} & 0 \\ 0 & 0 & \xi^1_{22}\xi^2_{21} & \xi^1_{22}\xi^2_{22} \end{bmatrix}, \qquad (4)$$

whereby ξ^*_{12}, ξ^*_{24}, ξ^*_{31}, ξ^*_{43} are equal to $1-\xi^*_{11}$, $1-\xi^*_{22}$, $1-\xi^*_{33}$, $1-\xi^*_{44}$, respectively.

[1]The leading behavior of state 2 is modeled in a strict form in the sense that a switch in the state indicator of group 2 will be followed by a switch in the state indicator of group 1 before the state indicator of group 2 may switch back to the initial state.

Finally, if state 1 is assumed to be the below-average state, $1/(1-\xi_{22}^{*})$ will be the expected lead of the second group out of a trough, and, correspondingly, $1/(1-\xi_{33}^{*})$ the expected lead of the second group in reaching a peak.

For expositional convenience I assumed so far that group 2 is leading group 1, while the remaining $K-2$ groups would behave independently over time. An additional difficulty arises, if there is uncertainty about which group is leading and which group is coincident. Therefore, we define a variable, say ρ^{*}, which characterizes the dynamical structure of the groups by taking one realization ρ_l of the $L=K(K-1)$ possible permutations of $\{1,2,0_{K-2}\}$.[2] The element in ρ^{*} which takes the value 1 refers to the group of coincident series, the element which takes the value 2 refers to the leading group, and all other elements refer to the groups that behave independently. If we have no a priori knowledge on the dynamic structure between groups, each permutation is given a priori equal weight $\eta_{\rho}=1/(K(K-1))$.

3. MCMC Estimation

The following notation is adopted to describe the estimation in a convenient way. While y_{it} denotes observation t for time series i, y_i^t gathers all observations of time series i up to period t, $y_i^t=\{y_{it},y_{i,t-1},\ldots,y_{i1}\}$, $i=1,\ldots,N$. The variables Y_t and Y^t will denote accordingly all time series observations in and up to period t, respectively, $Y_t=\{y_{1t},y_{2,t},\ldots,y_{Nt}\}$ and $Y^t=\{Y_t,Y_{t-1},\ldots,Y_1\}$. Likewise, the vectors $S^N=(S_1,\ldots,S_N)$ and $I^T=(I_1^T,\ldots,I_K^T)$, where $I_k^T=(I_{kT},I_{k,T-1},\ldots,I_{k1})$, $k=1,\ldots,K$, collect the group and the state indicators, respectively. Moreover, θ will denote all model parameters[3] and $\psi=(\theta,S^N,I^T,\lambda^N,\rho^{*})$ will be the augmented parameter vector which includes additionally the two latent indicators, the series-specific weights and the structure variable.

The model is estimated within the Bayesian framework using Markov chain Monte Carlo simulation methods. Starting point is Bayes' theorem

[2]The vector 0_{K-2} denotes a vector of $K-2$ zeros.

[3]That is: $\theta=(\mu_1^1,\mu_2^1,\ldots,\mu_1^K,\mu_2^K,\phi_1^1,\ldots,\phi_p^1,\ldots,\phi_p^K,\sigma^2,\xi^1,\ldots,\xi^K,\eta^1,\ldots,\eta^K)$, where $\xi^k=(\xi_{11}^k,\xi_{12}^k,\xi_{21}^k,\xi_{22}^k)$, $k=1,\ldots,K$.

$$\pi(\psi \mid Y^T) \propto L(Y^T \mid \psi)\pi(\psi), \tag{5}$$

where an inference on the posterior distribution $\pi(\psi \mid Y^T)$ is obtained by updating prior information on the augmented parameter vector characterized by the distribution $\pi(\psi)$ with the information given in the data, which is given by the likelihood $L(Y^T \mid \psi)$.

For known values of S^N, I^T and ρ^*, the likelihood $L(Y^T \mid \psi)$ can be factorized in

$$L(Y^T \mid \psi) = \prod_{t=p+1}^{T} \prod_{i=1}^{N} f(y_{it} \mid y_i^{t-1}, \mu_{I_{S_i t}}^{S_i}, \phi_1^{S_i}, \ldots, \phi_p^{S_i}, \sigma^2, \lambda_i), \tag{6}$$

where $f(y_{it} \mid \cdot)$ denotes the density of the normal distribution:

$$f(y_{it} \mid y_i^{t-1}, \mu_{I_{S_i t}}^{S_i}, \phi_1^{S_i}, \ldots, \phi_p^{S_i}, \sigma^2, \lambda_i) = \frac{1}{\sqrt{2\pi\sigma^2/\lambda_i}} \exp\left\{ -\frac{1}{2\sigma^2/\lambda_i} \left(y_{it} - \mu_{I_{S_i t}}^{S_i} - \sum_{j=1}^{p} \phi_j^{S_i} y_{i,t-j} \right)^2 \right\}. \tag{7}$$

The prior on the augmented parameter vector is specified in a way which assumes that the group-specific state indicators I^T, the group indicator S^N, the weights λ^N, are independent of each other and independent of the model parameters θ:

$$\pi(\psi) = \pi(I^T \mid \rho^*, \xi)\pi(S^N \mid \eta)\pi(\lambda^N)\pi(\rho^*)\pi(\theta), \tag{8}$$

with know densities for $\pi(I^T \mid \rho^*, \xi)$ and $\pi(S^N \mid \eta)$, respectively.

The prior distribution for ρ^* is discrete, and each permutation ρ_l, $l = 1, \ldots, L$, out of the $L = K(K-1)$ possible ones from $\{1, 2, 0_{K-2}\}$ is given a prior probability of $\eta_\rho = 1/(K(K-1))$. The weights λ^N are distributed independently, $\pi(\lambda^N) = \prod_{i=1}^{N} \pi(\lambda_i)$, assuming a Gamma prior distribution for each λ_i, $\pi(\lambda_i) = G(\nu/2, \nu/2)$, with degrees of freedom $\nu = 8$.

The Bayesian model setup is completed with the specification of the prior distribution for the model parameter θ, $\pi(\theta)$, which, for the sake of brevity, is not described in detail here. Basically, the parameter vector is further broken down into appropriate blocks of parameters for which we can specify well-known conjugate prior distributions.

The inference on the joint posterior distribution $\pi(\theta, S^N, I^T, \lambda^N, \rho^* | Y^T)$ is then obtained by successively simulating out of the following conditional posterior distributions:

(i) $\pi(S^N | Y^T, I^T, \lambda^N, \theta)$,

(ii) $\pi(\rho^* | Y^T, S^N, \lambda^N, \theta)$,

(iii) $\pi(I^T | Y^T, S^N, \lambda^N, \rho^*, \theta)$,

(iv) $\pi(\lambda^N | Y^T, S^N, I^T, \theta)$,

(v) $\pi(\theta | Y^T, S^N, I^T, \lambda^N)$.

The Markov chain simulation proves to be handy in the present case as all distributions in (i)-(v) can be derived and sampled from quite easily (see e.g. the appendix in Kaufmann, 2004). For given (sensible) starting values for θ, λ^N and I^T, iterating several thousand times over the sampling steps (i)-(v), thereby replacing at each step the conditioning parameters by their actual simulated values, yields a sample out of the joint posterior distribution $\pi(\theta, S^N, I^T, \lambda^N, \rho^* | Y^T)$. The simulated values may then be post-processed to estimate the properties of the posterior distribution, e.g. the mean and standard error may be inferred by computing the mean and the standard deviation of the simulated values. For practical implementation, step (v) involves a further break-down of the parameter vector θ into appropriate sub-vectors (corresponding to the prior specification) for which the conditional posterior distributions can fully be derived and simulated straightforwardly.

4. Results

4.1. Data

The analysis is done with a large cross-section of Austrian quarterly time series covering the period of the first quarter of 1988 through the fourth quarter of 2003. The data include GDP, its components and industrial production, economic confidence and sentiment indicators for Austria, Germany and the US, the consumer price index, the harmonized consumer price index as well as its components, wholesale prices, wages and labor market series, trade series and exchange rates, and, finally, financial variables also containing besides the ATX, the DAX index the Dow Jones index. The complete set is available in table form from the author upon request. Before the estimation, the data are transformed to stationary series by taking first differences or first differences of the logarithmic level multiplied by 100. All series are additionally demeaned to remove long-run trends.

Some basic data properties are displayed in table 1. To save space, only those series are reported for which the contemporaneous correlation with GDP (YER) is significant. We see that all series have distinct mean above-average and below-average growth rates, which justifies the two-states specification (this is also the case for the series not reported). The contemporaneous correlations of the series with GDP (in the column labeled "GDP") give a first hint about the series that might be moving contemporaneously with the business cycle. Obviously, the components of GDP (PCR, ITR, GCR, MTR, XTR) and industrial production (INDPROD) are correlated with GDP. Some confidence and economic sentiment indicators (QTPR to EBAUSE), in particular the German IFO indices (IFOERW, IFOKL, IFOGL), some trade series (EXPG to IMP-DE) and labor market series (ALQN to STANDR) are also significantly correlated with GDP, whereby the unemployment rates are so negatively. We do not find significant correlation for the price series except for the aggregate wholesale prices (GHPIG) and the wholesale prices without seasonal goods (GHPIOS). Among the financial variables, we find the 3-months interest rate (STI), the government bond yield (SEKMRE) and some credit aggregates (DCR-HH, DEBT, DCR) which are positively correlated with GDP.

4.2. The Classification of Series

To receive an impression of the usefulness of the proposed method, the model is estimated for three groups, $K = 3$, and the lag length is set to $p = 4$. Two groups will be linked by a dynamic structure such that one group will lead the other one in the switching process, while the third will collect all other series. This is a very restrictive, and almost surely a miss-specification, because the third group is a mix of series that differ from the first two in terms of the group-specific parameters or in terms of the switching state indicators. On the other hand, if we focus on finding the "core" series reflecting the stance of the business cycle and the series leading the cycle, then this "minimum" specification may capture the most relevant information contained in the data set.

To estimate the model, we iterate 8,000 times over the sampling steps (i)-(v) described in section 3. The first 2,000 iterations are discarded to remove dependence on starting conditions.

Chart 1 depicts the posterior state probabilities $P(I_k^T = 0 | Y^T)$ of the coincident ($S_i = 2$) and of the leading group ($S_i = 3$) of series. They are obtained by averaging over the M simulated values $I^{T,(m)}$, $m = 1,...,M$. The inference is quite clear as nearly all posterior probabilities are either one or zero. What is also recognizable at first view is that the lead into recession is slightly shorter than the lead into recovery. This is confirmed if we compute the transition matrix of I^{*T}, see equation (10) below. The leading group is usually between two and three quarters in the below-average growth state before the contemporaneous group follows. On the other hand, when the leading group switches back to the above-average growth state, the contemporaneous group follows after slightly more than 3 quarters.

Chart 2 depicts the posterior group probabilities $P(S_i = k \mid Y^N)$ for each series. First of all, most classifications emerge again quite clearly. From the picture, we observe that with some exceptions, variables of the same kind fall into the same group. Table 2 explicitly lists the variables falling into the coincident and the leading group of series. As already mentioned, GDP and its components (YER to XTR), except for government consumption, obviously belong to the coincident group of variables. Trade data (EXP6 to IMP-DE) and industrial production (INDPROD) do so likewise. Some financial variables like terms of trade (TOT), energy (HICP-E) and wholesale prices (GHPIG to GHPIKONG) move also contemporaneously. The retail sales sentiment indicator (EHANSE) falls also into the group of contemporaneously moving time series.

The series which are traditionally relied upon to assess and to forecast the cyclical prospects of the economy fall into the group of leading variables. The actual situation and the expectations in industrial production and the construction sector (QTAUF to QTBAGL) fall into this group, the economic sentiment and the confidence indicators of the industry and the construction sector (KTPROL to EBAUSE) as well. As the Austrian economy heavily relies on exports, it does not surprise that also the German IFO economic indicators (IFOERW, IFOKL, IFOGL), the US purchasing index (PMI), and exports in machinery and automobiles (EXP7) and exports to the US (EXP-US) are leading the GDP cycle. Finally, it is interesting to note that the ATX and the DAX index are classified as leading the business cycle.

Based on figure 1, we may now decide how to date turning points for Austria. With the present model specification, we identify growth cycles, i.e. $I_{kt} = 0$ relates to periods of below-average growth. Therefore, the turning point in the series will effectively have occurred before falling into this state. Hence, I choose to identify turning points on the basis of the posterior state probabilities of the leading group of variables. Period t will be identified as a peak if $P(I_{k,t-2} = 1, I_{k,t-1} = 1, I_{k,t} = 1 \mid Y^T) < 0.5$ and $P(I_{k,t+1} = 1, I_{k,t+2} = 1 \mid Y^T) > 0.5$; likewise, period t will be identified as a trough, if

$P(I_{k,t-2}=1, I_{k,t-1}=1, I_{k,t}=1 \mid Y^T) > 0.5$ and $P(I_{k,t+1}=1, I_{k,t+2}=1 \mid Y^T) < 0.5$, where k refers to the group of the leading variables, in our case group 3.

The turning points identified with this rule are found in table 4, on the line labeled "MS leading group". As no official dates are available for Austria, we compare the dates with those reported by the Economic Cycle Research Institute (ECRI, www.businesscycle.com). The two chronologies are in close accordance to each other. There is only some ambiguity with respect to the two most recent downturns. Using the posterior probabilities of the leading group, we identify a shorter downturn from the second quarter of 2000 through the end of 2001, while ECRI dates the peak nine months earlier. We can also identify a period of below-average growth in the second half year of 2002, which has not been dated by the ECRI.

Finally, it is interesting to note that the turning points identified for the coincident group of series, in particular for GDP, are also in accordance with the major turning points identified with the OeNB's Economic Indicator (OEI), see Fenz et al. (2004).

4.3. The Probability of a Turning Point in 2004

At the end of 2003, it is highly probable that both the leading and the coincident groups are in a state of above-average growth. Given that both groups of series are in state 2, or in other words in state 4 of I_T^*, what is the probability of reaching a turning point in the first half year of 2004? We may compute a forecast:

$$\pi(I_{T+h}^* \mid Y^T) = \xi^{*h} \cdot \pi(I_T^* \mid Y^T), \tag{9}$$

which would yield, if $h=2$, a 46% probability of reaching a turning point ($I_{T+2}^*=3$) and a 13% probability of reaching a below-average state ($I_{T+2}^*=1$) in both groups of series. These forecasts are obtained when we substitute $'\hat{\xi}^*$ for ξ^* in (9), the mean posterior transition distribution for ξ^* obtained from the MCMC output (see also table 3 for each group-specific state persistence):

$$\hat{\xi}^* = \begin{bmatrix} \hat{\xi}_{11}^* & \hat{\xi}_{12}^* & 0 & 0 \\ 0 & \hat{\xi}_{22}^* & 0 & \hat{\xi}_{24}^* \\ \hat{\xi}_{31}^* & 0 & \hat{\xi}_{33}^* & 0 \\ 0 & 0 & \hat{\xi}_{43}^* & \hat{\xi}_{44}^* \end{bmatrix} = \begin{bmatrix} 0.68 & 0.32 & 0 & 0 \\ 0 & 0.67 & 0 & 0.33 \\ 0.35 & 0 & 0.65 & 0 \\ 0 & 0 & 0.36 & 0.64 \end{bmatrix}. \tag{10}$$

Another formulation would be that the expected duration of the above-average state at the end of 2003 is $1/(1-\hat{\xi}^{*}_{44}) = 2.78$ periods, i.e. between half a year and 3 quarters of a year. Comparing with the economic performance during the first half of 2004, we see that indeed, after a subdued first quarter, GDP experienced a pick-up in the second quarter. Chart 3 draws GDP growth along with the posterior below-average state probabilities. We can observe that GDP picks up during the first half year of 2004 (the dark shaded periods in the graph).

5. Conclusion and Further Issues

In the present paper I propose to use the information contained in a large panel of quarterly economic and financial variables to estimate business cycle turning points for Austria. The econometric model is based on the idea of model-based clustering of multiple time series, which suggests pooling those series together which display similar time series and business cycle dynamics, whereby the appropriate classification of series is also part of the estimation method. To account for the fact that some series are leading the business cycle, I explicitly link two groups by a dynamical structure, defining one of them as the group of series which is leading another group of series. We may expect the latter one to be the series moving contemporaneously with the business cycle. As I demean all series prior to estimation, the method identifies growth cycles.

The results for a system assuming three groups are broadly consistent with expectations. GDP and its main components (except for government consumption), industrial production and some trade series, energy and whole sale prices as well, fall into the group of contemporaneous series. The group of leading series consists of Austrian confidence and sentiment indicators in the industrial and the construction sectors, of German survey indicators (IFO-business cycle indicator), exports to G7 and to US in particular, and, interestingly, the Austrian and the German stock market indices.

Because the method identifies growth cycles, the chronology of turning points is constructed based on the results for the leading group of series. The dates closely correspond to those identified by the Economic Cycle Research Institute. The turning points of the group of coincident series, which includes GDP, are also consistent with those identified by the OeNB's Economic Indicator.

The model estimate allows forming a forecast about the probability of a turning point conditional on the economic stance at the end of the sample. Given that at the end of the year 2003, both groups of series were in an above-average growth state, the probability of reaching a turning point in the first half year of 2004 was 46% and the probability of reaching a below-average state for both groups was quite lower (13%). Actually, GDP experienced a pick-up in the first half year of 2004.

Although these results are quite promising, there are some issues which remain to be settled. The present investigation assumes that three groups are present in the panel data set. While two groups are linked by the dynamical structure, the third is behaving independently from the other two. This third group collects all series which do not fit into the other two in terms of the group-specific parameters or in terms of the business cycle dynamics. A further investigation of these series, in particular whether they could further be split up in more than one group, would certainly improve the general fit of the data. Eventually, one might even extend the dynamical structure to specify a group of series which is lagging the business cycle.

Another unresolved question is the handling and the identification of counter-cyclical variables. Some obvious series like unemployment and the unemployment rate are negatively correlated with GDP. Actually, these series fall into the third group of series, presumably because their parameters are of opposite sign in each business cycle state. The model may be extended to explicitly allow for series that are behaving contemporaneously, but counter-cyclically to the business cycle. The sampler needs then to be adjusted to identify counter-cyclically behaving series.

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Appendix A: Tables[4]

Table 1: Data Properties

Series	Mean	Mean above average	Mean below average	Standard deviation	GDP	P-value
YER	0.58	0.48	–0.46	0.58	1.00	1.00
PCR	0.60	0.40	–0.43	0.61	0.44	0.00
ITR	0.64	1.71	–2.06	2.29	0.48	0.00
GCR	0.38	0.42	–0.54	0.73	0.37	0.00
MTR	1.43	1.84	–1.84	2.64	0.30	0.02
XTR	1.46	1.89	–1.78	2.31	0.54	0.00
QTPR	–0.02	3.75	–3.75	4.67	0.30	0.02
QTPRO	0.07	3.27	–3.07	4.20	0.29	0.02
QTBAGL	0.18	4.27	–4.27	5.59	0.28	0.02
INDSEN	–0.03	2.96	–3.57	3.99	0.25	0.04
KTPROL	0.07	5.12	–5.45	6.47	0.25	0.04
KTAUF	–0.15	4.78	–5.09	5.98	0.25	0.05
KTAUSL	–0.13	4.81	–5.12	5.83	0.26	0.04
KTVPN	–0.04	3.44	–4.42	4.81	0.31	0.01
EECOS	–0.07	3.17	–2.80	3.85	0.27	0.03
EINDSE	–0.05	2.95	–3.14	3.74	0.30	0.02
EBAUSE	–0.03	2.93	–2.75	3.66	0.26	0.04
IFOERW	0.16	2.64	–2.48	3.35	0.31	0.01
IFOKL	0.03	2.16	–2.45	2.81	0.38	0.00
IFOGL	–0.11	2.27	–3.12	3.19	0.34	0.01
GHPIG	0.26	0.54	–0.51	0.69	0.28	0.03
GHPIOS	0.26	0.60	–0.60	0.75	0.31	0.01
EXPG	1.49	1.85	–1.97	2.52	0.44	0.00
EXP6	1.07	1.71	–2.20	2.46	0.31	0.01
EXP7	1.55	2.40	–3.09	4.23	0.40	0.00
EXP-EU	1.34	2.12	–2.12	2.79	0.46	0.00
EXP-DE	1.64	1.99	–2.26	2.67	0.45	0.00
IMP-EU	1.56	2.01	–1.77	3.08	0.35	0.00
IMP-DE	1.45	2.20	–2.20	3.09	0.30	0.02
ALQN	0.02	0.14	–0.14	0.17	–0.30	0.02
ALQNSA	0.02	0.16	–0.14	0.18	–0.30	0.02
ALOSM	0.59	3.19	–2.48	3.54	–0.32	0.01
OFST	–0.36	5.77	–5.09	6.41	0.42	0.00
STANDR	0.92	6.66	–7.09	8.08	–0.40	0.00
INDPROD	0.79	1.24	–1.24	1.57	0.58	0.00
STI	–0.04	0.36	–0.30	0.46	0.38	0.00
SEKMRE	–0.04	0.30	–0.24	0.34	0.42	0.00
DCR-HH	1.78	0.75	–0.51	0.71	0.32	0.01
DEBT	1.31	0.53	–0.53	0.66	0.30	0.02
DCR	1.24	0.54	–0.58	0.68	0.31	0.01

[4] Source of all tables and charts: Author’s calculations.

Table 2: Series Classification

Contemporaneous	Leading
YER	QTAUF
PCR	QTEXPA
ITR	QTPR
MTR	QTPRO
XTR	QTBAUF
TOT	QTBPR
EHANSE	QTBBGL
HICP-E	QTBAGL
GHPIG	INDSEN
GHPIOS	KTPROL
GHPIVBG	KTAUF
GHPIKONG	KTAUSL
EXP6	KTPRON
IMPG	KTVPN
IMP6	BAUVPN
IMP7	EECOS
IMP8	EINDSE
EXP-EU	EBAUSE
EXP-DE	IFOERW
IMP-US	IFOKL
IMP-EU	IFOGL
IMP-DE	PMI
INDPROD	EXP7
	EXP-US
	ATX
	DAX

Table 3: Results

coefficient	$I_{S_it}=2$		$I_{S_it}=1$	
	$S_i=2$	$S_i=3$	$S_i=2$	$S_i=3$
$\mu_{I_{S_it}}^{S_i}$	0.48	1.92	–0.41	–2.07
	(0.37 0.60)	(1.65 2.21)	(–0.51 –0.30)	(–2.36 –1.79)
$\phi_1^{S_i}$	–0.02	0.24		
	(–0.08 0.03)	(0.19 0.30)		
$\phi_2^{S_i}$	0.04	0.09		
	(–0.01 0.08)	(0.04 0.14)		
$\phi_3^{S_i}$	–0.01	0.02		
	(–0.06 0.04)	(–0.03 0.07)		
$\phi_4^{S_i}$	–0.02	–0.15		
	(–0.07 0.03)	(–0.19 –0.10)		
unc. mean	0.47	2.42	–0.41	–2.61
	(0.36 0.59)	(2.07 2.80)	(–0.51 –0.30)	(–2.98 –2.25)
number of series	23	26		
$\xi_{11}^{S_i}$	0.83	0.82		
conf. int.	(0.71 0.94)	(0.69 0.93)		
quarters	5.98	5.52		
$\xi_{22}^{S_i}$	0.79	0.81		
conf. int.	(0.64 0.92)	(0.67 0.94)		
quarters	4.72	5.17		

Table 4: Growth Cycle Peak and Trough Dates, 1988Q1–2003Q4.

	P	T	P	T	P	T	P	T	P	T
MS leading group	90:1	93:1	94:4	96:2	97:4	98:4	00:2	01:4	02:2	02:4
ECRI *										
quarterly	90:1	93:1	94:4	96:1	98:2	99:1	99:3	01:3		
monthly	2/90	3/93	11/94	3/96	5/98	2/99	7/99	9/01		

* The ECRI dates growth cycles on a monthly basis. The quarterly dates are derived from the monthly ones.

Appendix B: Charts

Chart 1: Posterior Probabilities, $P(I_{kt}=1|Y^T)$, of the Coincident ($S_i=2$) and the Leading Group ($S_i=3$), 1988Q1–2003Q4, $K=3$, $p=4$. The Series are Standardized by their Specific Variance, σ^2/λ_i.

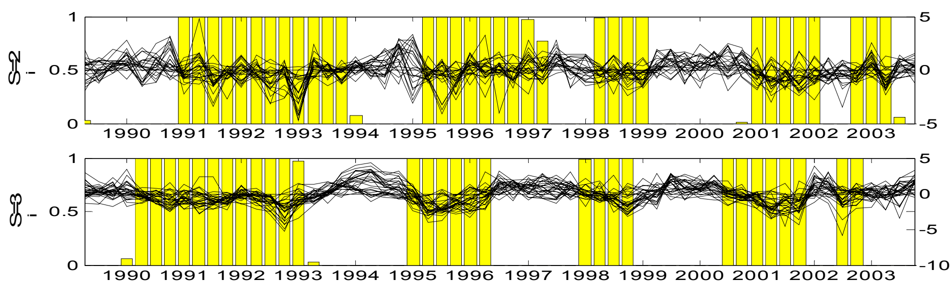
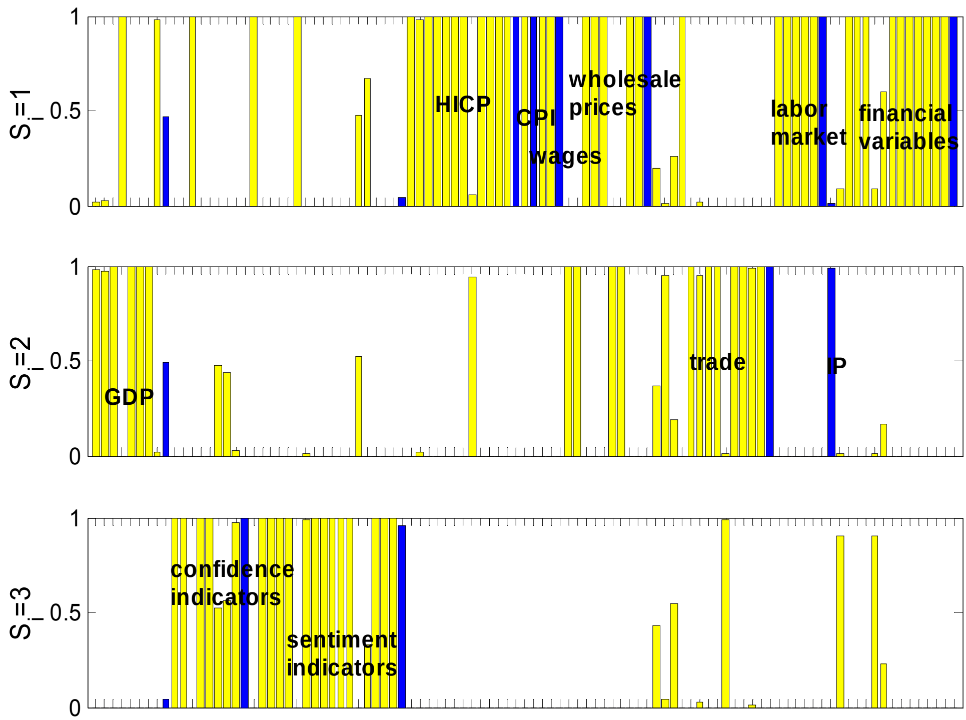


Chart 2: Posterior Group Probabilities of the Coincident ($S_i = 2$) and the Leading Group ($S_i = 3$), 1988Q1–2003Q4, $K = 3$, $p = 4$.



Note: The shaded bars demarcate the last series in a specific class of series.

Chart 3: GDP Growth (Right–Hand Scale) Along with the Posterior Probability of below–average Growth for the Second Group, $P(I_{2t}=1|Y^T)$ *(Left-Hand Scale).*