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New Composite Leading Indicators for Hungary and Poland

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Abstract

This paper presents new composite leading indicators for the two largest of the EU accession countries, Poland and Hungary. Using linear and non-linear dynamic factor models we find for both countries that a parsimonious specification, which combines national business cycle indicators, series reflecting trade volumes and supranational business expectations makes for the most reliable business cycle leaders. The composite leading indicators significantly Granger-cause GDP growth rates, while the estimated Markov-switching probabilities of being in a recessionary state agree well with a priori determined cycle chronologies.

JEL Code: C32, C53, E32.
Keywords: Business Cycles; Composite Leading Indicators; EU Enlargement; Markov-switching, Turning Points.

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1 Introduction

With the enlargement of the European Union by 10 Central and Eastern European Countries in May 2004, the Union did not only become larger but also more heterogeneous, especially seen from the economic angle. While the joint economic output of all new member countries only amounts to 5% of the EU-15 GDP, distinctly higher growth rates during the past years already reduced the gap, and for the near future it is likely that the accession to the EU will further boost the convergence process. This impressive growth performance of the new member states combined with already very pronounced trade integration with the EU-15, especially with Germany, makes forecasting their real economy an exercise of great interest and high importance. One common tool for predicting short-run fluctuations of the business cycle are the so-called leading indicators.

This paper develops composite leading indicators for the two largest of the new member countries, Poland and Hungary. Along the lines of Bandholz and Funke (2003b), we employ dynamic factor models with and without regime switching to estimate the indicators. To the best of our knowledge, this is the first attempt to construct business cycle leading indicators for transition countries using dynamic factor models and even using sophisticated econometric optimization tools at all. While there is an increasing literature on descriptive statistics, the poor data availability for the post transition period has so far impeded the usage of econometric tools. However, for the two considered countries we have gathered promising data sets, each consisting mainly of surveys, that enable us to run the model recursions. The approaches employed here integrate the idea of (i) comovement among macroeconomic variables and (ii) asymmetries of business cycle expansions and contractions, the two key features of Burns and Mitchell's (1946) definition of business cycles. Originally, models that incorporate these features were developed in isolation of each other. Stock and Watson (1989, 1991, 1992) used a dynamic factor model to capture comovement and Hamilton (1989, 1990) extended the Markov-switching approach of Goldfeld and Quandt (1973) in order to picture regime-shifts. More recently, Chauvet (1998), Diebold and Rudebusch (1996), Kim (1994) or Kim and Nelson (1998) proposed a combination of both aspects by an empirical synthesis of factor and regime-switching models. Roughly speaking, the dynamic factor model extracts the leading indicator as the common component out of a group of exogenous variables that contain information on the future course of the economy, while the Markov-switching approach translates the cyclical movements of this indicator into probabilities of being in a period with high or with low economic growth, i.e. in an expansion or a cyclical downswing. Thus, arbitrary meth-

ods used to determine turning points were redundant.
The remainder of the paper is organized as follows. In the next section, the basic econometrics behind the dynamic factor models without and with Markov-switching are explained. Section 3 describes the data used in the empirical work. Besides the selection of the leading variables, we also discuss the choice of a reference series, i.e. the series that reflects contemporaneous economic activity. Section 4 summarizes the estimation results with regard to parameter estimates, leading indicators and recession probabilities. Conclusions and suggestions for further research are given in section 5.

2 The Models

The Linear Dynamic Factor Model

Within the dynamic factor model, a vector of cyclical macroeconomic variables is modeled as composed of two autoregressive processes: a single unobserved component, which corresponds to the common factor among the variables, and an idiosyncratic component. Borrowing from Stock and Watson (1989, 1991, 1992) we consider the following model

$$y_{it} = \gamma(L) i_t + e_{it} \tag{1}$$

$$\phi(L) i_t = \omega_t \qquad \omega_t \sim i.i.d.\ N(0,1) \tag{2}$$

$$\psi(L) e_{it} = \epsilon_{it} \qquad \epsilon_{it} \sim i.i.d.\ N(0,\sigma_i^2) \tag{3}$$

where y_{it} is the $n \times 1$ vector of stationary endogenous observable time-series that were supposed to lead overall economic conditions. i_t is the common factor (the leading indicator) and e_{it} the $n \times 1$ vector of idiosyncratic components.[1] The lag-polynomial $\gamma(L)$ indicates that i_t is allowed to enter equation (1) with different weights and different lags. The latter is useful in the case of phase shifts between the y_{it}, which means that the endogenous variables exhibit different leads against the business cycle. The dynamics of the unobserved components i_t and e_{it} were captured by equations (2) and (3). Again, the lag-polynomials $\phi(L)$ and $\psi(L)$ allow for a flexible treatment of the dynamics. The main identifying assumption in the model is the orthogonality of $\{e_{1t},\ ...,\ e_{nt},\ i_t\}$ at all leads and lags. This is achieved by making $\psi(L)$ diagonal and $\{\epsilon_{1t}, ...,\ \epsilon_{nt},\ \omega_t\}$ orthogonal. Additionally, $Var(\omega_t)$ is normalized to unity.

[1]The model is estimated in deviations from means, i.e. $y_{it} = Y_{it} - \bar{Y}_i$ and $i_t = I_t - \bar{I}$. Stock and Watson (1991) have shown that otherwise some of the absolute terms of the equations were not separately identified.

As the dynamic factor model (1) to (3) is linear in the unobservable component, the Kalman filter (Kalman, 1960) can be employed to estimate the unknown parameters and to uncover the latent components. To use the filter, the model is expressed in its state-space form. The latter is comprised of two parts. While the *measurement equation* relates the observed variables to the elements of the unobserved state vector, the *transition (state) equation* describes the dynamics of this state vector. A general state-space representation of the models that were estimated in the course of this paper is given by

$$j_t = H\beta_t \tag{4}$$

$$\beta_t = F\beta_{t-1} + \nu_t \tag{5}$$

with $j_t = (y_{1t}, ..., y_{nt})'$, $\beta_t = (i_t, e_{1t}, ..., e_{nt})'$ and $\nu_t = (\omega_t, \epsilon_{1t}, ..., \epsilon_{nt})'$ respectively. To allow for the postulated orthogonality between the ϵ_{it} and ω_t, the covariance matrix of ν_t is assumed to be diagonal. The parameters and the variances of the state-pace model are estimated using the MLE method. Given the parameters, the Kalman filter recursions can be employed to obtain the time-varying state vectors $\beta_{t|t}$.[2]

In the next section, the linear factor model is augmented with a bivariate Markov-switching model in the tradition of Chauvet (1998), Diebold and Rudebusch (1996), Kim (1994) or Kim and Nelson (1998). This extension allows us to translate movements in the leading indicator into a signal about future turning points in economic activity.

The Markov-Switching Dynamic Factor Model

In the following, we consider again the model in deviation from mean form. Equations (1) and (3) remain unchanged, whereas regime shifts were introduced into equation (2). Formally, the linear model is altered as follows:

$$y_{it} = \gamma(L)i_t + e_{it} \tag{6}$$

$$\phi(L)(i_t - \mu_{S_t}) = \omega_t \qquad \omega_t \sim i.i.d.\ N(0,1) \tag{7}$$

$$\psi(L)e_{it} = \epsilon_{it} \qquad \epsilon_{it} \sim i.i.d.\ N(0,\sigma_i^2) \tag{8}$$

The mean growth rate of the leading index in equation (7), μ_{S_t}, depends upon an unobserved dichotomous latent state variable S_t

$$\mu_{S_t} = \mu_0(1 - S_t) + \mu_1 S_t \tag{9}$$

[2]Kim and Nelson (1999) or Harvey (1989, 1993) provide further details on additional identifying restrictions and estimation of the system using the Kalman filter.

where S_t switches between state 0 (recession) and state 1 (expansion) with transition probabilities governed by the first-order two-state Markov process

$$Pr[S_t = 1|S_{t-1} = 1] = p$$
$$Pr[S_t = 0|S_{t-1} = 0] = q$$

A general state-space representation of the model (6) to (8) is given by

$$j_t = H\beta_t \tag{10}$$
$$\beta_t = R_{S_t} + F\beta_{t-1} + \nu_t \tag{11}$$

where R_{S_t} contains the state dependent mean. To estimate the model, it is necessary to make inferences about both the unobserved common factor and the latent Markov state. Hamilton's (1989, 1990) papers popularize the use of bivariate Markov regime switches, but the methodology precludes the estimation of multivariate unobservable dynamic models. On the other hand, the dynamic factor model proposed by Stock and Watson is governed by a linear stochastic process and can therefore be estimated using the Kalman filter. However, the non-linearity in the transition equation of the model implies that the usual Kalman filter cannot be applied directly. Therefore, Kim (1994) proposed a combination of Hamilton's non-linear algorithm and the linear Kalman filter, which permits estimation of the unobserved factor as well as the probabilities associated with the latent Markov-state. Moreover, Kim (1994) provides a fast approximation algorithm for the full sample smoother which substantially reduces computational time.[3]
The empirical results of the model's estimates are given in section 4. Before, we turn to the description and selection of the data.

3 The Data

Our empirical investigation will be conducted for two of the most important new member states, Poland and Hungary. Primary data sources were the OECD Main Economic Indicators, the OECD Quarterly National Accounts, the IMF International Financial Statistics, National Central Banks, National Statistical Offices as well as the business and consumer surveys of the DG ECFIN and the Ifo Institute. We use quarterly data because there are only

[3]An intuitive explanation of the computational burden is the following: Each iteration of the Kalman filter produces a twofold increase in the number of cases to be considered. Since S_t takes on two possible values in each time period, there would be 2^T possible paths to consider in evaluating the conditional log likelihood (see Kim and Nelson, 1999).

a few macroeconomic time series available at a monthly frequency. Although for both countries some series exist even before 1990, the estimation sample is set to 1994:1 to 2004:2. Therefor two aspects were decisive. First, by the evasion of pre-transition data, we minimize the risk of structural breaks in the series that could arise between the pre- and post-transition periods. Second, the GDP and its components were not collected until 1995. However, for 1993-1994 Várpalotai (2003) and Darvas and Szapáry (2004) calculated quarterly national accounts data for Hungary and Poland respectively, and thus enabled us to compute annual growth rates for these aggregates back to 1994.

The Reference Series

Before selecting the leading indicators, we next determine the reference series, i.e. the series whose cyclical behavior is intended to predict. Ideally, a quarterly analysis would use national GDP as reference cycle.[4] In this regard, the EU Commission attested to Hungary and especially Poland that they produce their quarterly and annual national accounts on the basis of the European System of Accounts (ESA 95) methodology at a very high level of compliance.[5] However, Artis et al. (2004) prefer to base their business cycle dating for several Accession countries on the index of industrial production (IIP) rather than on GDP. In their opinion, GDP shows too little cyclical variation and is thus not the appropriate measure for monitoring business cycle fluctuations. Figure 1 depicts the annual growth rates of GDP and IIP for both countries.[6]

The main impression from figure 1 is that for Hungary and Poland, both series exhibit very pronounced cyclical comovement, so that the concern of Artis et al. (2004) cannot be shared. In Poland, GDP and IIP decline significantly after the export crisis in 1998 and the stabilization period in 2000/2001. Merely during the first half of the decade, some swings in GDP were not accompanied by similar movements in industrial production. For Hungary,

[4] There is a long debate on the appropriate measure of economic activity. While e.g. Zarnowitz (1963a,b) recommended the examination of several macroeconomic time series, Cloos (1963a,b) argued for a single series, the GDP. However, latest findings of the NBER (2003) or Boldin (1994) suggest that both approaches lead to similar results.
For Poland, composite coincident indicators were provided by Matkowski (2004b) and Stolorz (2004).

[5] See the "Regular Reports" on the countries' progress towards accession, published by the DG Enlargement of the European Commission.

[6] We use annual growth rates rather than deviations from a Hodrick Prescott- or band-pass filter, because of short sample data availability in connection with data irregularities during the first post-transition years.

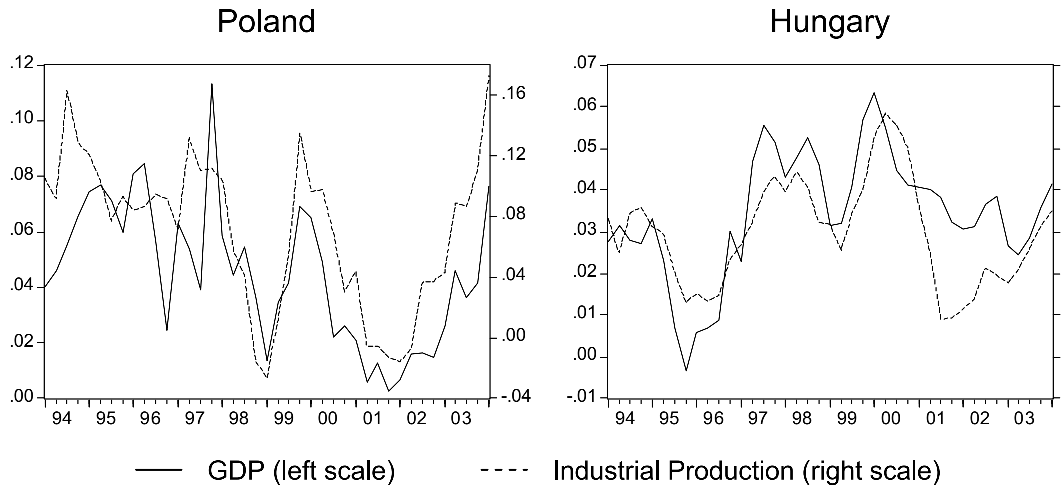

Figure 1: A Comparison of Growth Rates: GDP versus IIP

the picture is qualitatively very similar. GDP and IIP describe three cycles with troughs in 1995, 1999 and 2001 respectively, almost concurrently. According to the high graphical concordance, the contemporaneous correlation between the growth rates of GDP and IIP amounts to 0.72 in Poland and 0.74 in Hungary.

The turning points of GDP were derived with the method of Artis et al. (1997), which is a modification of the Bry and Boschan (1971) procedure.[7] To account for possible data irregularities, we match our results with the business cycle dates of Artis et al. (2004), who identified turning points on the industrial production. Finally, only those turning points were established that were found in both series, GDP and industrial production. Figure 2 depicts the resulting cycle chronologies. The grey shaded areas represent the corresponding recession periods (from peak to trough).[8] For Poland, we identified the two periods with decelerating growth rates already mentioned above: the export crisis (1998), caused by slackening foreign demand and the stabilization period (2000/2001). The latter was characterized by decreasing budget deficits and increasing interest rates. For Hungary, three recessionary phases were identified. In 1995, GDP decelerated as a result of fiscal stabilization, designed by the former minister of finance, Lajos Bokros. As in Poland, the decline of growth rates in 1998/1999 was caused by lower

[7]Originally, the procedure was developed for monthly data. See Bandholz and Funke (2003a) or Bandholz (2004) for a description of the adjustments to quarterly data.

[8]Following common practice, periods with decelerating growth rates were called "recessions". However, against the background of growth rates that were partly still above two percent during these slow-downs, one should apply this expression very carefully.

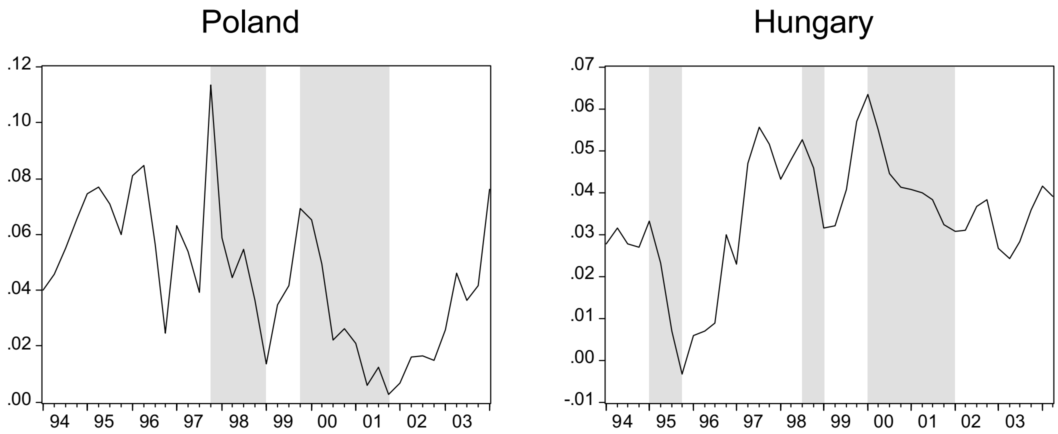

Figure 2: Recession Periods

foreign demand, due to the Asian and the Russian crises. GDP growth in Hungary reached its latest peak in 1999:4. In the subsequent 3 1/2 years it declined from above 6% to less than 3%. Again, the most recent drop in 2002 was a result of sluggish foreign demand, caused by a deceleration of business activity in Western Europe and a rapid appreciation of the forint. The latter additionally led to a weakening of the tourism sector.
Because of their size, their location and their progress towards a market economy in a globalized Europe, the economic developments in Poland and Hungary heavily depend on the course of the economy in adjacent countries. It is likely that this economic integration will be further deepened with the accession into the European Union. Accordingly, in the next step, the selection of the leading variables that might explain future economic developments within Poland and Hungary is not restricted to national variables, but explicitly allows for supranational indicators that might exhibit direct or indirect effects of economic developments in Western Europe on the economy in Poland and Hungary respectively.

The Selection of the Leading Variables

Ever since the seminal work of Mitchell and Burns (1938), the use of business cycle indicators in economic forecasting has been criticized. Despite reasonable forecasting records, it was especially Koopmans (1947) who claimed the indicator-based forecasts as being *measurement without theory*. However, de Leeuw (1991) or the European Central Bank (2001) argue, that there are indeed several theoretical reasons for the lead of indicators against the business cycle. Series like stock prices or interest rate spreads reflect expectations of firms and private households on future developments in economic activity. Other series like new orders were located at an early stage of the production process and thus were succeeded by a pursuant adjustment of production. Regrettably, for the considered countries, respective series were hardly available or at least insufficiently continuous. In contrast, reliable monetary and financial statistics were provided by the National Central Banks and the IMF's International Financial Statistics. Narrow monetary aggregates, interest and exchange rates were commonly used as leading indicators for several countries.[9] During the 1990s, the reliable lead of narrow money M1 and interest rates against GDP growth is confirmed by cross-correlation analysis. Unfortunately, in Poland and Hungary, the relationships between interest rates and M1 on the one hand and GDP growth on the other hand exhibit serious structural breaks at the turn of the millennium, so that correlation coefficients become insignificant or even negative. In contrast, exchange rates were not affected by this changing behavior.

Beyond monetary and financial variables, institutions or supranational organizations like the Ifo Institute, the OECD or the DG ECFIN of the EU Commission offer a large amount of business and consumer surveys. Altogether we have collected a panel with 57 series for Hungary and 47 for Poland. The data sets broadly contain labor market variables (unemployment, wages), financial aggregates (narrow money, interest rates, exchange rates, share prices), trade series (imports, exports, net trade) and survey data (construction, consumer, manufacturing, retail, national economy, supranational surveys). A complete list of the variables with detailed data description and data sources is reported in Appendix A.

Each of the finally estimated composite leading indicators for Poland and Hungary consist of three variables. The primary selection criteria were cross-correlations between the variables and GDP growth.[10] Only those indicators were kept that exhibit a statistical lead against the reference cycle over the whole sample period. Next, using rolling correlations, the stability of the identified leads were examined. The main finding here was the already mentioned instable relationship between GDP and interest rates or narrow money respectively. Besides, in Hungary some other series also exhibit structural breaks in their lead against the reference cycle. Around 1997/1998, the leads of these variables drop significantly, so that the overall correlation coefficients were reduced. The major Hungarian share price index (BUX) for instance leads the reference cycle before 1998 by three quarters and afterwards by

[9]See The Conference Board or several OECD composite leading indicators.

[10]Accordingly, we concentrate on variables that statistically lead the business cycle. Other factors that might influence the effective lead, like early and timely publication dates or lack of revisions, are neglected.

merely one quarter. Despite very high correlation coefficients of 0.78 (before 1998) and 0.53 (afterwards) respectively, the overall correlation coefficient is only up to 0.27. However, graphical inspection suggests that, despite this low value of overall correlation, the index is a very reliable indicator that especially succeeds in predicting turning points. After pre-selecting a group of leading variables by cross-correlation analysis and "eyeball econometrics", we tried a number of alternative specifications. In particular, we have considered 46 different specifications and combinations of 7 candidate variables for Poland and 102 specifications with 17 variables to the empirical analysis for Hungary. Because of the large number of possible specifications, we have applied various testing procedures to help with model selection. The specifications were evaluated based on their within-sample performance. It generally turned out that the indicator's leading properties and the turning point predictions were considerably less satisfactory for alternative models than those reported in the text. Moreover, the chosen specification leads to the most plausible and most robust parameter estimates.

Screening the selected variables for Poland and Hungary, it is apposite to classify them into three groups: variables reflecting (i) national business expectations, (ii) direct trade effects and (iii) indirect trade effects and international economic spill-over. Accordingly, the variables in the latter two groups give empirical evidence on our preliminary suggestion that supranational indicators might influence economic development in Poland as well as in Hungary. Group (i) comprises the demand tendency in manufacturing for Poland and the above mentioned BUX share price index for Hungary. Direct trade effects (ii) were represented by a nominal effective exchange rate for Poland and real imports for Hungary.[11] Finally, group (iii) consists of business expectations for Western Europe (Poland) and of business expectations for Germany (Hungary) respectively. The latter reflects the already extremely pronounced economic integration between Germany and Hungary. Figure 3 depicts the selected variables for Poland and Hungary. The distinct comovement of the series shown there reconfirms the appropriateness of the chosen modeling framework. Unit root test for every respective variable suggest that we can reject the hypothesis of being integrated.

[11] The nominal effective exchange rate (NEER) leads to better empirical results than the theoretically preferred real effective exchange rate (REER). We do not worry about using the NEER instead of the REER, as it is a stylized fact that those for the business cycle analysis relevant short- and medium-term fluctuations of the REER were mainly caused by the NEER and not by relative price levels.

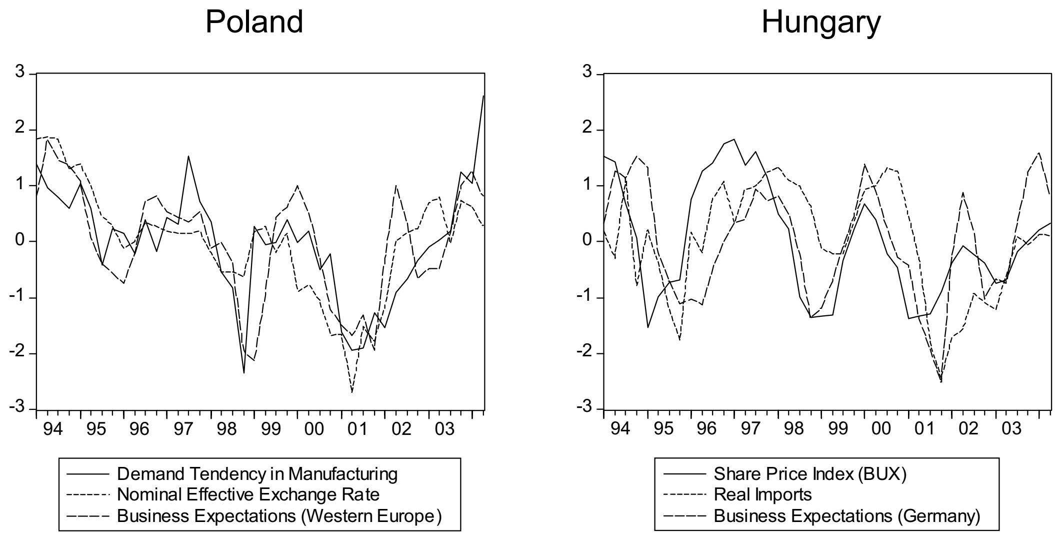

Figure 3: The Selected Exogenous Variables

4 Empirical Results

Results for Poland

Parameter Estimates. Table 1 presents parameter estimates of the linear (1)-(3) and of the non-linear Markov-switching model (6)-(8) for Poland.[12] Using quarterly data, the estimation period is 1994:1 to 2004:2. The endogenous variables y_{it} were ordered pursuant to the above classification, i.e. y_{1t} describes demand tendency in manufacturing, y_{2t} the nominal effective exchange rate and y_{3t} the business expectations for Western Europe. For both, the linear and the non-linear model, the factor loadings γ_{ij} are consistent with that predicted by theory and are significant at the 5% level.[13] Highly significant are also ϕ_1 and ϕ_2, the autoregressive parameters that govern the dynamics of the common factor. The large sum of the coefficients (≥ 0.8) displays a great deal of persistence in business cycle fluctuations. The autoregressive parameters ψ_{ij} capture remaining autocorrelation within the idiosyncratic components e_{it}. Table 2 shows that the inclusion of ψ_{i1} and

[12]A detailed description of the finally specified state-space models is given in Appendix B. The GAUSS codes to perform the maximum likelihood estimates for the linear and the non-linear model are those used in Bandholz and Funke (2003b). Originally, they were kindly made available by Chang-Jin Kim (see Kim (1994) and Kim and Nelson (1998, 1999) for details).

[13]While γ_{31} is not significant, it is needed for the stability of the model.

Table 1: Parameter Estimates Poland

	linear model		non-linear model	
Parameters	estimate	t-value	estimate	t-value
i_t				
ϕ_1	1.21	5.7	1.10	2.8
ϕ_2	-0.37	-2.8	-0.30	-1.4
μ_0			-1.62	-1.8
μ_1			0.61	1.5
p			0.90	9.9
q			0.68	2.6
y_{1t}				
γ_{10}	0.42	3.9	0.27	1.7
ψ_{11}	-0.44	-1.8	-0.34	-1.0
ψ_{14}	0.14	0.8	1.13	0.6
σ_1^2	0.11	1.9	0.14	1.5
y_{2t}				
γ_{20}	-0.30	-2.8	-0.23	-2.4
ψ_{21}	0.92	8.1	0.87	5.4
ψ_{24}	-0.26	-2.2	-0.29	-2.1
σ_2^2	0.13	2.5	0.13	2.6
y_{3t}				
γ_{30}	0.15	1.8	0.13	1.8
γ_{31}	0.16	1.2	0.07	0.5
ψ_{31}	0.46	3.4	0.44	3.2
ψ_{34}	-0.29	-2.1	-0.29	-2.0
σ_3^2	0.27	4.3	0.25	4.0
Log likelihood		16.622		17.786

ψ_{i4} helps to control for serial correlation in quarterly data. The Ljung-Box test for the residuals ϵ_{it} provides evidence that the null hypothesis of 'no correlation' cannot be rejected. Since also the null hypothesis of Doornik and Hansen's (1994) normality test cannot be rejected, the model meets the main assumptions from equation (2) and (3) and therefore seems to fit the data quite well. However, the Brock et al. (1996) BDS test used to check whether the ϵ_i are independent and identically distributed *i.i.d.* suggests the existence of some linear or non-linear dependencies (for ϵ_2 and ϵ_3). As linear dependency was rejected by the Ljung-Box test, the BDS test might point to remaining non-linearity which was not considered within the linear dynamic factor model and thus corroborates the appropriateness of the non-linear fac-

Table 2: Diagnostic Tests Poland

Diagnostics	Test statistics	P-values
$LB(\epsilon_1)$	1.16	0.89
$LB(\epsilon_2)$	4.99	0.29
$LB(\epsilon_3)$	3.80	0.43
DH	10.51	0.10
$BDS(4)-(\epsilon_1)$	-0.02	0.52
$BDS(4)-(\epsilon_2)$	0.06	0.05
$BDS(4)-(\epsilon_3)$	0.05	0.04

Note: Diagnostics are those for the linear model. $LB(\epsilon_i)$: Ljung-Box Q test measuring general AR(4) residual autocorrelation; DH: Doornik and Hansen's (1994) multivariate omnibus normality test; $BDS(m)-(\epsilon_i)$: portmanteau test for time-based independence in a series where m is the so-called embedding dimension (see Brock et al., 1996 for details).

tor model with Markov-switching. The adequacy of the non-linear model is further confirmed by the estimates of the Markov-switching parameters μ_0, μ_1, p and q respectively. All of them are significantly different from zero and exhibit the expected signs. During cyclical downswings, the mean growth rate of the leading index, μ_0, is significantly below zero and *vice versa* in expansions. With regard to the estimated transition probabilities, the probability of staying in an expansion, p, is higher than the probability of staying in a recession, q. This confirms previous findings that the average duration of expansions is larger than the duration of recessions. The expected durations for an expansion $[1/(1-\hat{p})]$ and a recession $[1/(1-\hat{q})]$ are 10.3 and 3.1 quarters respectively.

Performance of the Leading Indicators. The left graph of figure 4 depicts the composite leading indicators estimated by the linear dynamic factor model (I_t) and the non-linear dynamic factor model with Markov-switching ($I-MS_t$) respectively. Both indices show an extremely congruent pattern regarding amplitude, timing, and duration of fluctuations. Accordingly, the correlation between both series amounts to 0.99. The right picture of figure 4 plots the estimated leading indicator I_t against GDP growth.[14] Visual inspection suggests that our new composite indicator exhibits a reliable lead against the reference series. All major expansions and recessions (downswings) have been correctly preceded by a rise or fall of our leading indicator. Maximum cross correlation between the new composite index and GDP growth is

[14]Because of the similarity between I_t and $I-MS_t$ only one leading indicator was plotted in order to ensure an undisturbed comparison with the reference series.

reached at a lead of one quarter. The maximum coefficient amounts to 0.75, which confirms that our indicator exhibits a cyclical pattern very similar to that of the reference cycle at a statistical lead of one quarter.

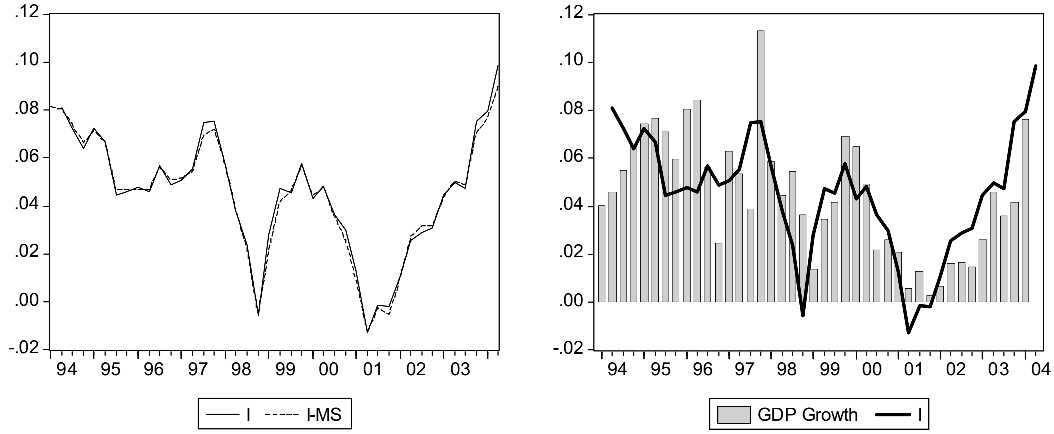

Figure 4: Performance of the Leading Indicators in Poland

A more formal way to evaluate predictive power of the indicator is to check whether its inclusion enhances GDP forecasts that stem from simple autoregressive models. However, the implementation of this procedure in our context suffers from two problems. First, a comparison of our indexes with the predictive accuracy of other representative indicators is hardly possible, as commonly accepted leading indicators like the German Ifo Business Climate Index or the Conference Board indicator for the U.S. exist neither for Poland nor for Hungary.[15] Second, a decent calculation of out-of-sample forecast quality measures such as the Diebold and Mariano (1995) statistic or the *root mean square error (RMSE)* would require a recursive estimation of the dynamic factor model.[16] The latter reproduces the realistic situation that forecasters have data, e.g. the leading indicator, only up to the starting point of their out-of-sample forecast. However, the limited data availability bars us from renouncing too many observations for an appropriate recursive estimation, so that the number of out-of-sample forecasts would be too low for meaningful forecasting quality measures. Consequently, we restrict our evaluation of predictive power to the simple test for Granger causality (Granger,

[15]Composite leading indicators in the tradition of the OECD and the Conference Board were calculated by Drozdowicz-Bieć (2004), Matkowski (2004a) or Stolorz (2004). Matkowski (2004a) additionally provides a summarizing review.

[16]See Banerjee et al. (2004) for a RMSE-based comparison of forecasting variables for numerous acceding countries.

1969), i.e. we test whether past values of the reference series along with our leading indicator better explain the cyclical movement of GDP growth than past values of GDP growth alone.
The naïve benchmark model is a simple first order autoregressive process with constant term: $y_t = \mu + \alpha y_{t-1} + u_t$. We choose the lag length according to the Schwarz information criterion. The benchmark is then augmented with our composite index. The resulting OLS results were reported in table 3. The main finding from these estimates is that the hypothesis of 'no Granger

Table 3: Test for Granger Causality Poland

	Constant	y_{t-1}	I_{t-1}	$\bar{R}^2$
y_t	0.02 (2.6)	0.64 (4.9)	-	0.38
y_t	0.03 (5.1)	0.20 (1.5)	0.01 (4.6)	0.60

Note: The dependent variable is GDP growth (y_t), t-values in parenthesis. Diagnostic tests, not reported here, like the *Jarque-Bera* normality test and the *Lagrange-Multiplier* test for nth order serial correlation suggesting a reasonable model specification.

causality' can significantly be rejected. With a t-value of 4.6, our leading indicator is significantly different from zero on the 1% level. Furthermore, the adjusted R^2 nearly doubles with the inclusion of the composite index, thus providing further support for a distinctly high predictive power.

Probabilities of Turning Points. While the above analysis with Granger causality test, cross correlations and "eyeball econometrics" treated the indicator's leading properties during the whole inspection period, i.e. its average predictive power, policy makers are especially interested in the detection of cyclical turning points. Common rules of thumb state that such a change in economic tendency is confirmed by a change in the directory of the indicator for two or three consecutive quarters. However, the non-linear dynamic factor model with Markov-switching allows us to estimate turning points endogenously, thus preventing us from resorting to arbitrary rules of thumb. Figure 5 plots the estimated probabilities for the Polish economy being in a recession. The grey shaded areas depict the 'true' recession periods, derived in section 3. We can state that the estimated probabilities clearly pick out and date correctly the two recessions that the Polish economy has experienced during the last ten years.
This again positive result confirms, on the one hand, the appropriateness of the selected model and, on the other, the distinct predictive power of our

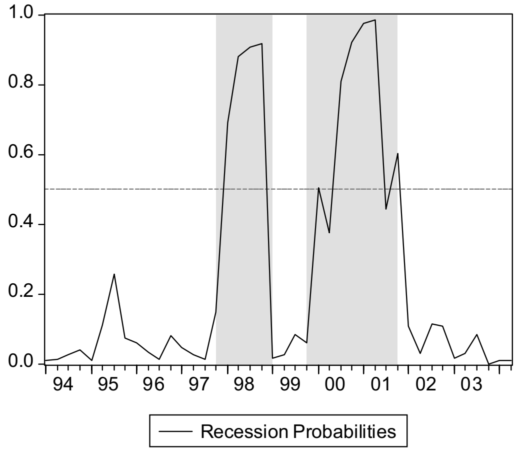

Figure 5: Recession Probabilities Poland

indicator with respect to the overall growth cycle and to the cyclical turning points in particular. Encouraged by these findings for Poland, we next present the results for Hungary in the same manner.

Results for Hungary

Parameter Estimates. Parameter estimates of the linear and the non-linear model for Hungary are presented in table 4. The exogenous variables were ordered as follows: y_{1t} denotes the share price index (BUX), y_{2t} real imports and y_{3t} the Ifo business expectations for Germany. Estimation period covers 42 quarters and ranges from 1994:1 to 2004:2. The factor loadings γ_{ij} that link the exogenous variables y_i to the common factor i_t indicate that all exogenous series influence the course of the indicator significantly. While γ_{10} is insignificant, it is needed for the stability of the estimate. The significant connection between the share price index and the common factor is instead given via γ_{11}. Different from Poland, where the dynamics of the common factor were driven by a second order autoregressive process, we find for Hungary that i_t is best governed by a first order process. However, the parameter estimate for ϕ_1 of nearly 0.8 indicates for Hungary almost the same high persistence in economic fluctuations as for Poland. The dynamics of the idiosyncratic components e_{it} were modeled again using ψ_{i1} and ψ_{i4} terms, which were mainly significant. Remaining second order autocorrelation within ϵ_3 required the additional inclusion of the ψ_{32} term. The results of the Ljung-Box tests presented in table 5 confirm that this specification helps to control for autocorrelation within the idiosyncratic terms of the

Table 4: Parameter Estimates Hungary

Parameters	linear model		non-linear model	
	estimate	t-value	estimate	t-value
i_t				
ϕ_1	0.77	7.3	0.78	9.9
μ_0			-3.00	-2.1
μ_1			0.58	1.6
p			0.92	15.9
q			0.61	2.9
y_{1t}				
γ_{10}	0.10	1.3	0.05	0.8
γ_{11}	0.24	2.9	0.15	1.9
ψ_{11}	0.84	10.0	0.84	8.9
ψ_{14}	-0.30	-3.2	-0.33	-3.5
σ_1^2	0.16	4.3	0.14	3.5
y_{2t}				
γ_{23}	0.62	6.1	0.28	2.6
ψ_{21}	-0.62	-1.1	-0.17	-0.5
ψ_{24}	0.06	0.2	-0.14	-0.5
σ_2^2	0.03	0.5	0.14	1.9
y_{3t}				
γ_{32}	0.23	2.1	0.14	1.8
ψ_{31}	0.83	5.5	0.84	5.1
ψ_{32}	-0.17	-2.7	-0.18	-2.6
ψ_{34}	-0.23	-1.9	-0.21	-1.7
σ_3^2	0.31	4.4	0.30	4.2
Log likelihood		12.491		15.161

three exogenous variables. Additionally, the Doornik and Hansen (1994) test suggests joint normal distribution of the ϵ_i's so that the major assumptions concerning the error terms are fulfilled. Just as for Poland, the BDS test to check the *i.i.d.* assumption indicates that a linear specification disregards eventual non-linearities within the model. For two of the three errors (ϵ_2 and ϵ_3), the null hypothesis of 'no time-based interdependence' can be significantly rejected. Thus, the BDS test confirms the adequacy of the non-linear model also for Hungary. The estimates of the Markov-switching parameters give further support to this notion. We find again that mean growth in state 0, μ_0, is significantly negative, while μ_1 is significantly positive. The corresponding transition probabilities are 0.9 and 0.6, so that an average recession

Table 5: Diagnostic Tests Hungary

Diagnostics	Test statistics	P-values
$LB(\epsilon_1)$	4.66	0.33
$LB(\epsilon_2)$	0.30	0.99
$LB(\epsilon_3)$	7.44	0.12
DH	10.31	0.11
$BDS(4) - (\epsilon_1)$	0.04	0.19
$BDS(4) - (\epsilon_2)$	0.05	0.03
$BDS(4) - (\epsilon_3)$	0.06	0.01

Note: Diagnostics are those for the linear model. $LB(\epsilon_i)$: Ljung-Box Q test measuring general AR(4) residual autocorrelation; DH: Doornik and Hansen's (1994) multivariate omnibus normality test; $BDS(m) - (\epsilon_i)$: portmanteau test for time-based independence in a series where m is the so-called embedding dimension (see Brock et al., 1996 for details).

lasts for 2.6 quarters and an average expansion 12.8 quarters. Accordingly, recessions are, on average, shorter but steeper than expansions, a result that we already obtained for Poland and that is consistent with overall findings in the literature.

Performance of the Leading Indicators. The estimated leading indicators implied by the dynamic factor model without (I_t) and with Markov-switching ($I - MS_t$) are shown in the left picture of figure 6. Again, both indicators exhibit an extreme cyclical concordance, which is underlined by a contemporaneous correlation of 0.95. The general impression from the right-hand graph of figure 6 is that our new composite indicator reliably leads the reference series. All cyclical movements in GDP growth have been correctly announced by previous movements of our indicator. However, closer inspection uncovers a structural break in the lead of the indicator. Despite a diligent examination of the data, it was not possible to avoid this unfavorable property, as in fact most of the observed series exhibit also at least one structural break in their timely relation to the reference series. Using the *CUSUM-Q* test of Brown et al. (1975), the breakpoint was dated to 1997:2. Before, the lead of the indicator against GDP growth amounts to three quarters, while reducing to one quarter afterwards. During the two subperiods, cross-correlations of our indicator with the reference series are quiet high. They amount to 0.69 and 0.71 respectively, whereas overall cross-correlation for the entire sample is only 0.31. While statistical breaks in economic relationships during the early post-transition years were not uncommon, they were primarily not expected for Hungary. Because of the early transition

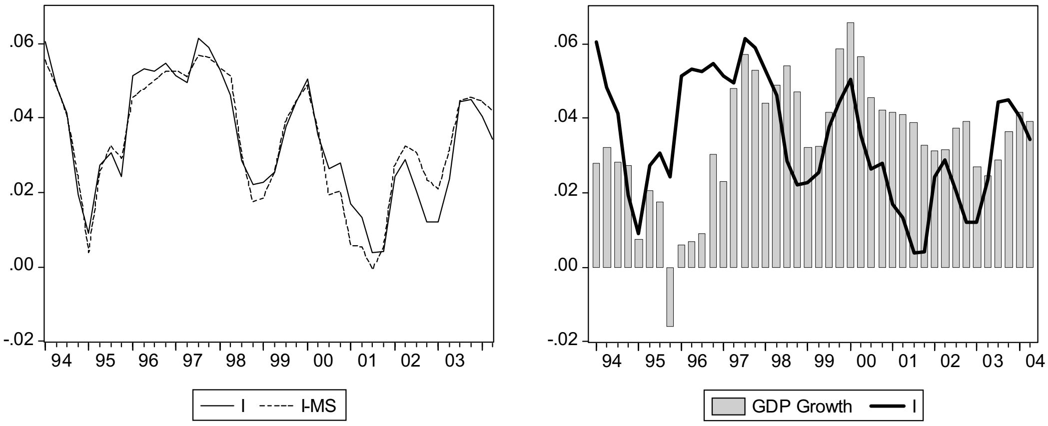

Figure 6: Performance of the Leading Indicators in Hungary

date and recent advantages in social and economic transformation, we are very confident that the relationship between our leading indicator and the reference cycle has stabilized during the last eight years. This perception is explicitly confirmed by figure 6, so that future movements of the indicator should reliably predict direction of GDP growth in the subsequent quarter. Important to reemphasize is that the structural break has no negative impact on the estimation of the dynamic factor models, since GDP growth does not enter these models. It is only relevant for the ex post evaluation of the indicator's predictive power by cross-correlation or Granger causality. To ensure an unbiased test for Granger causality, we exclude the structural breakpoint from the estimation sample by starting in 1997:2. The design of the test is the same as for Poland. In the first step, a naïve autoregressive benchmark equation is estimated before it is augmented with our composite indicator in the second step. The indicator 'causes' GDP growth in the sense of Granger if it significantly enhances the benchmark equation. The results of the test are given in table 6. We find that the inclusion of I_{t-1} is highly significant and that it furthermore increases adjusted R^2 heavily from 0.42 to 0.64. These findings explicitly support a higher forecasting accuracy for the augmented equation so that the null hypotheses of 'no Granger causality' can definitely be rejected.

Probabilities of Turning Points. Information on the turning points of our composite indicator are given in figure 7. Again, the grey shaded areas indicate the 'true' recession periods for Hungary, while the solid line depicts recession probabilities, estimated by the non-linear factor model. It is strik-

Table 6: Test for Granger Causality Hungary

	$Constant$	y_{t-1}	I_{t-1}	$\bar{R}^2$
y_t	0.02 (2.7)	0.63 (4.6)	-	0.42
y_t	0.01 (3.1)	0.41 (3.4)	0.33 (4.2)	0.64

Note: The dependent variable is GDP growth (y_t), t-values in parenthesis. Diagnostic tests, not reported here, like the *Jarque-Bera* normality test and the *Lagrange-Multiplier* test for nth order serial correlation suggesting a reasonable model specification.

ing that the amplitude of the estimated recession probabilities for Hungary is much lower than those for Poland. Probability values of about 0.9 or even 1.0 were never reached. As on the other hand, the probabilities during ex-

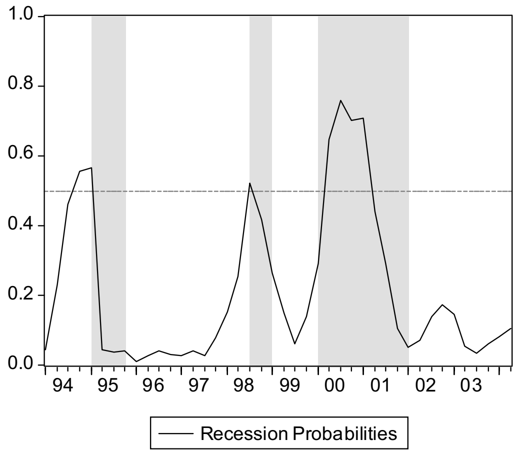

Figure 7: Recession Probabilities Hungary

pansionary phases do also not exhibit any irregular spikes, but rather crawl closely to the zero line, the threshold to distinguish early recession warnings from silent periods might be lower than the commonly used 50% without increasing the risk of getting false signals. But even if we maintain the 50% threshold, the estimated recession probabilities give significant signals for all of the three recessionary phases that the Hungarian economy underwent during the last decade. It is noteworthy that the structural break between leading indicator and GDP growth is also reflected in figure 7. Since the lead of the indicator before 1997:2 amounts to three quarters, the corresponding recession probabilities announce the first recession within the sample (1995) with a likewise pronounced lead. In contrast, the signals after 1997:2 are sent

closer towards the start of the recession.
The evidence presented above proves that the linear and the non-linear factor models sensibly represent business cycle fluctuations in Hungary. Granger tests underline the distinct predictive power of our new leading indicator, while the estimated turning points agree fairly well with independently determined chronologies.

5 Conclusion

An enduring convergence process in combination with deepening trade integration with Western Europe makes forecasting of real activity within the new EU member countries an exercise of high and growing importance. This paper therefore proposes new composite leading indicators for the two largest of the accession countries, Poland and Hungary. Using linear and non-linear dynamic factor modeling approaches, we find for both countries that a parsimonious specification which combines national business cycle indicators, series reflecting trade volumes and supranational business expectations makes for the most reliable business cycle leaders. Our historical results suggest that the two features depicted by our models, comovement and asymmetric regime shifts, are important characteristics of business cycles in Hungary and Poland, so that the parsimoniously specified models produce reasonable forecasting tools. The composite leading indicators significantly Granger-cause GDP growth rates, while the estimated Markov-switching probabilities of being in a recessionary state agree well with a priori determined cycle chronologies.
Because of the limitation of our data sample to the post-transition period, the model evaluation regarding stability and predictive accuracy is confined to the in-sample-fit of the models. While it would be worthwhile to examine the out-of-sample abilities, we refrained from performing the necessary recursive estimation because of the sample size. Left for further research is also the treatment of other new member countries. Encouraged by the very promising results of this paper, we shall next consider the evaluation of composite leading indicators and recession indexes for the more developed countries, e.g. the Baltic countries, the Czech Republic, Slovakia or Slovenia.

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A The Data

Poland

Table 7: Data Set Poland

Series Name	Data Source	Transformation	Available Since
	Labor Market		
Unemployment Rate	MEI	Annual Growth Rate	√
Unemployment Level	MEI	Annual Growth Rate	√
Vacancies	MEI	Annual Growth Rate	√
	Money and Finance		
Exchange Rates			
Nominal Effective Exch. Rate	MEI	Annual Growth Rate	√
Nominal Exch. Rate (USD)	MEI	Annual Growth Rate	√
Real Effective Exch. Rate	MEI	Annual Growth Rate	√
Interest Rates			
Deposit Rate	IFS	Annual Growth Rate	√
Discount Rate	MEI	Annual Growth Rate	√
Lending Rate	IFS	Annual Growth Rate	√
Short term Rate	MEI	Annual Growth Rate	√
Treasury Bill Rate (3m)	MEI	Annual Growth Rate	√
Monetary Aggregates			
M1	MEI	Annual Growth Rate	√
M2	MEI	Annual Growth Rate	√
Real M1	MEI	Annual Growth Rate	√
Real M2	MEI	Annual Growth Rate	√
Velocity M1	MEI	Annual Growth Rate	√
Share Prices			
WIG	MEI	Annual Growth Rate	√
	Business Surveys		
Construction			
Business Climate	MEI	Level	√
Business Situation	CSO	Level	√
Employment (future tendency)	CSO	Level	√
Selling prices (future tendency)	CSO	Level	√
Manufacturing			
Business Climate	MEI	Level	√
Business Expectations	MEI	Level	√
Business Situation	MEI	Level	√
Demand (future tendency)	MEI	Level	√
Demand (tendency)	MEI	Level	√
Employment (future tendency)	MEI	Level	√
Export Order Books (tend.)	MEI	Level	√
Exp. Order Books (future tend.)	MEI	Level	√

Table 7: Data Set Poland (Cont.)

Series Name	Data Source	Transformation	Available Since
Manufacturing (Cont.)			
Production (future tendency)	MEI	Level	$\surd$
Production (tendency)	MEI	Level	$\surd$
Selling Prices (future tend.)	MEI	Level	$\surd$
Stock of Finished Goods	MEI	Level	$\surd$
National Economy			
Business Climate	WES	Level	$\surd$
Business Expectations	WES	Level	$\surd$
Business Situation	WES	Level	$\surd$
Supranational Surveys			
Bus. Climate Eastern Europe	WES	Level	$\surd$
Bus. Climate Europe	IFO	Level	$\surd$
Bus. Climate Germany	IFO	Level	$\surd$
Bus. Climate Trade Sector (East. Germany)	WES	Level	$\surd$
Bus. Climate Western Europe	WES	Level	$\surd$
Bus. Expct. Eastern Europe	WES	Level	$\surd$
Bus. Expct. Germany	IFO	Level	$\surd$
Bus. Expct. Western Europe	WES	Level	$\surd$
Bus. Situation Eastern Europe	WES	Level	$\surd$
Bus. Situation Western Europe	WES	Level	$\surd$
Ec. Sentiment Western Europe	DG ECFIN	Level	$\surd$

$\surd$: the series is available at least since 1994
CSO : Central Statistical Office
DG ECFIN : Business and Consumer Surveys of the Directorate General for Economic and Financial Affairs (EU Commission)
IFO : Ifo Business Survey
IFS : International Financial Statistics (IMF)
MEI : Main Economic Indicators (OECD)
WES : World Economic Survey (IFO)

Hungary

Table 8: Data Set Hungary

Series Name	Data Source	Transformation	Available Since
	Labor Market		
Real Wages	IFS	Annual Growth Rate	$\surd$
Unemployment Rate	MEI	Annual Growth Rate	$\surd$
Unemployment Level	MEI	Annual Growth Rate	$\surd$
Vacancies	MEI	Annual Growth Rate	$\surd$

Table 8: Data Set Hungary (Cont.)

Series Name	Data Source	Transformation	Available Since
	Money and Finance		
Exchange Rates			
Nominal Effective Exch. Rate	EO	Annual Growth Rate	$\surd$
Nominal Exch. Rate (USD)	EO/MEI	Annual Growth Rate	$\surd$
Real Effective Exch. Rate	MEI	Annual Growth Rate	$\surd$
Interest Rates			
Discount Rate	MEI	Annual Growth Rate	$\surd$
Interbank Rate	MEI	Annual Growth Rate	$\surd$
Long term Rate	EO	Annual Growth Rate	$\surd$
Short term Rate	EO	Annual Growth Rate	$\surd$
Treasury Bill Rate (3m)	MEI	Annual Growth Rate	$\surd$
Monetary Aggregates			
M1	MEI	Annual Growth Rate	$\surd$
M3	MEI	Annual Growth Rate	$\surd$
Real M1	MEI	Annual Growth Rate	$\surd$
Real M3	MEI	Annual Growth Rate	$\surd$
Share Prices			
BUX	MEI	Annual Growth Rate	$\surd$
	Trade Sector		
Real Imports	IFS	Annual Growth Rate	$\surd$
	Business Surveys		
Construction			
Business Situation	MEI	Level	1996
Confidence Indicator	DG ECFIN	Level	1996
Employment (future tendency)	MEI	Level	1996
Order Books	MEI	Level	1996
Consumer			
Confidence Indicator	DG ECFIN	Level	$\surd$
Manufacturing			
Business Climate	MEI	Level	$\surd$
Business Expectations	MEI	Level	$\surd$
Business Situation	MEI	Level	$\surd$
Capacity Utilization	MEI	Level	$\surd$
Confidence Indicator	DG ECFIN	Level	1996
Exp. Order Books (future tend.)	MEI	Level	1996
Order Books	EO/MEI	Level	$\surd$
Production (future tendency)	EO/MEI	Level	$\surd$
Production (tendency)	MEI	Level	$\surd$
Stock of Finished Goods	EO/MEI	Level	$\surd$

Table 8: Data Set Hungary (Cont.)

Series Name	Data Source	Transformation	Available Since
National Economy			
Business Climate	KOPDAT	Level	$\surd$
Business Climate	WES	Level	$\surd$
Business Expectations	KOPDAT	Level	$\surd$
Business Expectations	WES	Level	$\surd$
Business Situation	KOPDAT	Level	$\surd$
Business Situation	WES	Level	$\surd$
Economic Sentiment	DG ECFIN	Level	1996
Retail			
Business Climate	MEI	Level	1996
Business Expectations	MEI	Level	1996
Business Situation	MEI	Level	1996
Confidence Indicator	DG ECFIN	Level	1996
Demand (future tendency)	MEI	Level	1996
Employment (future tendency)	MEI	Level	1996
Stock of Finished Goods	MEI	Level	1996
Supranational Surveys			
Bus. Climate Eastern Europe	WES	Level	$\surd$
Bus. Climate Europe	IFO	Level	$\surd$
Bus. Climate Germany	IFO	Level	$\surd$
Bus. Climate Trade Sector (East. Germany)	WES	Level	$\surd$
Bus. Climate Western Europe	WES	Level	$\surd$
Bus. Expct. Eastern Europe	WES	Level	$\surd$
Bus. Expct. Germany	IFO	Level	$\surd$
Bus. Expct. Western Europe	WES	Level	$\surd$
Bus. Situation Eastern Europe	WES	Level	$\surd$
Bus. Situation Western Europe	WES	Level	$\surd$
Ec. Sentiment Western Europe	DG ECFIN	Level	$\surd$

$\surd$: the series is available at least since 1994
DG ECFIN : Business and Consumer Surveys of the Directorate General for Economic and Financial Affairs (EU Commission)
EO : Economic Outlook (OECD)
IFO : Ifo Business Survey
IFS : International Financial Statistics (IMF)
KOPDAT : Kopint-Datorg Business Survey
MEI : Main Economic Indicators (OECD)
WES : World Economic Survey (IFO)

B State-Space Representations of the Empirical Models

General state-space representations of the estimated models were described by equations (4) to (5) for the linear model and equations (10) to (11) for the non-linear model respectively. In the following, the detailed model specifications were given.

B.1 Poland

The Linear Dynamic Factor Model

(1) Measurement equation: $j_t = H\beta_t$:

$$\begin{pmatrix} y_{1t} \\ y_{2t} \\ y_{3t} \end{pmatrix} = \begin{pmatrix} \gamma_{10} & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \gamma_{20} & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \gamma_{30} & \gamma_{31} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \end{pmatrix} \times \begin{pmatrix} i_t \\ i_{t-1} \\ e_{1t} \\ e_{1t-1} \\ e_{1t-2} \\ e_{1t-3} \\ e_{2t} \\ e_{2t-1} \\ e_{2t-2} \\ e_{2t-3} \\ e_{3t} \\ e_{3t-1} \\ e_{3t-2} \\ e_{3t-3} \end{pmatrix} \tag{12}$$

(2) Transition equation: $\beta_t = F\beta_{t-1} + \nu_t$:

$$\begin{pmatrix} i_t \\ i_{t-1} \\ e_{1t} \\ e_{1t-1} \\ e_{1t-2} \\ e_{1t-3} \\ e_{2t} \\ e_{2t-1} \\ e_{2t-2} \\ e_{2t-3} \\ e_{3t} \\ e_{3t-1} \\ e_{3t-2} \\ e_{3t-3} \end{pmatrix} = \begin{pmatrix} \phi_1 & \phi_2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \psi_{11} & 0 & 0 & \psi_{14} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \psi_{21} & 0 & 0 & \psi_{24} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \psi_{31} & 0 & 0 & \psi_{34} \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{pmatrix} \times \begin{pmatrix} i_{t-1} \\ i_{t-2} \\ e_{1t-1} \\ e_{1t-2} \\ e_{1t-3} \\ e_{1t-4} \\ e_{2t-1} \\ e_{2t-2} \\ e_{2t-3} \\ e_{2t-4} \\ e_{3t-1} \\ e_{3t-2} \\ e_{3t-3} \\ e_{3t-4} \end{pmatrix} \tag{13}$$

The Markov-Switching Dynamic Factor Model

(1) Measurement equation: $j_t = H\beta_t$:

The matrices and vectors are the same as in (12).

(2) Transition equation: $\beta_t = R_{S_t} + F\beta_{t-1} + \nu_t$:

$$R_{S_t} = \begin{pmatrix} \mu_{S_t} - \phi_1\mu_{S_{t-1}} - \phi_2\mu_{S_{t-2}} \\ \\ \mathbf{0}_{13\times 1} \end{pmatrix} \tag{14}$$

The other matrices are the same as in (13).

B.2 Hungary

The Linear Dynamic Factor Model

(1) Measurement equation: $j_t = H\beta_t$:

$$\begin{pmatrix} y_{1t} \\ y_{2t} \\ y_{3t} \end{pmatrix} = \begin{pmatrix} \gamma_{10} & \gamma_{11} & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \gamma_{23} & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \gamma_{32} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \end{pmatrix} \times \begin{pmatrix} i_t \\ i_{t-1} \\ i_{t-2} \\ i_{t-3} \\ e_{1t} \\ e_{1t-1} \\ e_{1t-2} \\ e_{1t-3} \\ e_{2t} \\ e_{2t-1} \\ e_{2t-2} \\ e_{2t-3} \\ e_{3t} \\ e_{3t-1} \\ e_{3t-2} \\ e_{3t-3} \end{pmatrix} \tag{15}$$

(2) Transition equation: $\beta_t = F\beta_{t-1} + \nu_t$:

$$
\begin{pmatrix} i_t \\ i_{t-1} \\ i_{t-2} \\ i_{t-3} \\ e_{1t} \\ e_{1t-1} \\ e_{1t-2} \\ e_{1t-3} \\ e_{2t} \\ e_{2t-1} \\ e_{2t-2} \\ e_{2t-3} \\ e_{3t} \\ e_{3t-1} \\ e_{3t-2} \\ e_{3t-3} \end{pmatrix}
=
\begin{pmatrix}
\phi_1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & \psi_{11} & 0 & 0 & \psi_{14} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \psi_{21} & 0 & 0 & \psi_{24} & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \psi_{31} & \psi_{32} & 0 & \psi_{34} \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0
\end{pmatrix}
\times
\begin{pmatrix} i_{t-1} \\ i_{t-2} \\ i_{t-3} \\ i_{t-4} \\ e_{1t-1} \\ e_{1t-2} \\ e_{1t-3} \\ e_{1t-4} \\ e_{2t-1} \\ e_{2t-2} \\ e_{2t-3} \\ e_{2t-4} \\ e_{3t-1} \\ e_{3t-2} \\ e_{3t-3} \\ e_{3t-4} \end{pmatrix}
\tag{16}
$$

The Markov-Switching Dynamic Factor Model

(1) Measurement equation: $j_t = H\beta_t$:

The matrices and vectors are the same as in (15).

(2) Transition equation: $\beta_t = R_{S_t} + F\beta_{t-1} + \nu_t$:

$$
R_{S_t} = \begin{pmatrix} \mu_{S_t} - \phi_1 \mu_{S_{t-1}} \\ \\ \mathbf{0}_{15\times 1} \end{pmatrix}
\tag{17}
$$

The other matrices are the same as in (16).