Are the Confidence Indicators Meaningful for Forecasting Real Economy?[1]

Testing Power of Confidence Indicators for Industry Output, Prices and Employment in the Visegrád Group Countries

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Abstract

This paper examines predictive power of the confidence indicators for developments in industrial output, producer prices and employment in the Czech and Slovak Republics, Hungary, and Poland (V4 countries). The Granger Causality tests are used for establishing potential causation between the confidence indicators and real economy data. The best OLS models with autoregressive terms complemented by confidence indicators are selected and their predictive accuracy is tested against the ARMA benchmarks with the Diebold-Mariano test. All OLS models performed better than the naïve ones .We conclude that the actual CI variables seem to reflect future patterns of economic development in next 1 – 2 months, and not just opinions by economic agents based on current or past economic trajectories.

Keywords: *forecasting, confidence indicators, ARMA models*

JEL Classification: E37, C53

Introduction: Confidence Indicators

Short-term forecasts ('nowcasts') provide policy makers and business agents with valuable knowledge on current and near-future trends in national economy. There is high demand on timely and reliable information on output, prices and employment in sectors and industries of a national economy. Timely and reliable information is no easy to get. Most important economic data are published with

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significant delay of two or three months. The January data on industrial production, for example, are published in mid-March in most EU Member Countries. Confidence ('soft') indicators (CI) are alternative source of information on near-future trends. They usually are published by end of current month and present expectations by businesses on developments in next three months. Confidence indicators account for a number of advantages over hard statistical data: (a) early release (one-three months before publications of hard data for most time series); (b) limited amount of follow-up corrections and revisions, and (c) signals on expected economic activity in key sectors of national economy provided by relevant economic agents (mostly business leaders in particular economic sectors). The industry confidence indicator therefore brings more and timely information about the evolution of gross domestic product and/or of industrial production index (Gagea, 2012; 2014).

There is plethora of research evaluating performance of forecasting models with the confidence indicators in OECD Member Countries. Most studies concentrate on short-term forecasts of gross domestic product (GDP), and use industrial confidence indicators (ICI) and Economic Sentiment Indicator (ESI) variables (provided by the Eurostat's Business Survey) as predictors (see for example Mourogane and Roma, 2002; Claveria, Pons and Ramos, 2007; Bulligan, Golinelli and Parigi, 2010). Frale et al. (2009) examined usefulness of Business Survey data for forecasting leading indicators and GDP growth in the Euro Area. They found the survey-based factor plays a significant role for two components of GDP: industrial value added and exports.

Several studies found that the variations in economic sentiment have impacts on important macroeconomic variables, e.g. output, retail sales and unemployment in the Euro Area and USA (van Aarle and Kappler, 2012; Milani, 2011). Dees and Brinca (2013) analysed link between the consumer sentiment and consumption expenditures for the United States and the Euro Area. They found that confidence indicators have increasing predictive power during episodes of large changes in consumption expenditure. Zalewski (2009) used monthly index of industrial production to construct leading composite indicator and provide early warning signals of possible turning points in the reference series.

Use of 'soft' indicators, of course, is not without problems. Forecasting power of confidence indicators of predicting growth in real economy significantly varies among the OECD Member Countries (Santero and Westerlund, 1996). Some researchers doubted confidence indicators had any predictive power at all. Gelper and Croux (2010, p. 61), for example, used the Granger causality analysis and found that the sentiment indicators, 'do not have much additional explanatory power for industrial production compared with autoregressive forecasting methods' in the EU Member Countries. Arnoštová et al. (2010) used sentiment indicators to forecast quarterly GDP growth. Principal components and the dynamic factor model based on the Kalman smoother performed well on the Czech data and the euro area countries. The models, however, performed poorly for some new EU Member Countries (Hungary, Poland and Lithuania). Pošta and Pikhart (2014) evaluated differences in forecasting power of the autoregressive moving-average (ARMA) model supplemented with the composite ESI indicator model predicting GDP and the pure ARMA model. They found that the relationship between ESI and GDP may operate well in relatively peaceful times. When the economy is hit by an unexpected shock, augmented ARMA model performs better in just half a sample of countries.

Ambiguous evidence on predictive power of the confidence indicators raises questions about the real value of ‘soft’ information for policy makers and business agents:

- How far these indicators point to future patterns of economic development, and by how much they just reflect opinions based on current or past economic trajectories?
- Do these indicators have meaningful forecasting power or do they provide for only an imprecise and unreliable barometer of economic development? The first question essentially refers to time-lag between ‘now’ and ‘then’. Most questions in business surveys are based on expectations over the three-month time period. Is the time lag of three months consistent with actual economic developments or is the best forecasting power obtained for shorter time spans? The second question concerns accuracy and reliability of forecasts based on confidence indicators.

Relationship between the confidence and real economy indicators is rather complex. The arrow of causality may run in several ways. The principal hypothesis is that increase (decrease) in a confidence indicator translates into higher (lower) growth in real economy indicators. The alternative hypothesis is that increases (decreases) in real economy indicators boost (dampen) expectations by economic agents on future economic developments. Finally, a mutually reinforcing process is possible: optimistic expectations may boost growth in real economy and increased growth translates to further increase in expectations. The reinforcing mechanism may operate best in periods of expectation shocks. Sudden and/or significant upturns and downturns in economic activity may affect formation of expectations and capture waves of optimism and pessimism that lead agents to form forecasts that deviate from those implied by their learning model (Milani, 2011).

Forecasting developments in real economy that confidence indicators are a proxy for forward-looking expectations of economic agents about the future developments in economy. The assumption may hold for some countries and variables, but not for other ones. Particular indicators of real economy (output, producer prices and employment) may account for their own patterns of relationship to corresponding confidence indicators. Forecasting power of specific confidence indicator also may depend on importance of industry in economy of a country, and quality of statistical coverage of the industry activities.

This research analyses usefulness of the industrial confidence indicators (ICI) for predicting trends in output, producer prices and employment in industries of the four EU Members Countries: the Czech Republic, Hungary, Poland, and Slovakia (the Visegrád Four – V4 countries). The choice of industry as main testing field is given by high significance the industry occupies in national economies of these. The industry exports are driving force of the economic growth in small open economies. The exports of goods accounted for 29.5% GDP in EU-15, but 71.3% GDP in Slovakia, 64.2% in Hungary, 56.0% in the Czech Republic in 2004 – 2015 (Annex, Table A1). Importance of industry in national economy, of course, varies also among the members of the V4 countries. The industry generated 28.9% of total employment in the Czech Republic, 22.5% in Hungary, 23.1% in Poland, and 24.9% in Slovakia in 2004 – 2015.

The next chapter firstly presents dataset used for modelling developments in real economy via confidence indicators and then turns to analytical methods. The stationarity of time series is examined by the Augmented Dickey-Fuller (ADF) test. The Granger Causality tests are used for establishing potential causation between the confidence indicators and real economy data. The best models with lagged values of the CI indicators are selected and their predictive powers are tested against the ARIMA benchmarks with the Diebold-Mariano tests. The concluding chapter summarises major findings and suggests directions for further research.

1. The Model

1.1. The Data Availability and Coverage

The data for the research were collected from the webpages of the national statistical offices, Eurostat and the Business Survey database. The data on real economy included following variables: *y* – production, *p* – prices, *l* – employment (labour). The 'soft data' (expectations by businesses) included: *ey* – expectations on production, *ep* – expectations on prices, and *el* – expectations on employment (questions no. 5, 6 and 7 of the Eurostat's Business Survey). The Eurostat publishes indices seasonally adjusted monthly based on the 2005 average. These data converted into month-on-month indices. Monthly data on employment were not available for the Czech Republic. The data on employment started in 1993M1 and data on prices in 2003M3 for Slovakia. All other time series in the Czech Republic, Slovakia and Hungary started in 2000M1. All abovementioned time series ended in 2016M8.

Questions in the Business Survey are generally formulated as ‘what do you think about trends in your industrial output (prices, employment) in next three months?’ The multiple choice answers usually include ‘increasing’, ‘decreasing’, and ‘unchanged’. The data are normally compiled as ‘balances’ by subtracting the number answering ‘increasing’ from the number answering ‘decreasing’.

1.2. The Preliminaries: Stationarity and Granger Causality

Some time series may account for non-stationarity. The preliminary check for stationarity of time series entering relationships was performed. The stationarity was examined via the Augmented Dickey-Fuller with constant. The ADF test complemented by Phillips-Perron (PP) test values and their significance levels are reported in Table 1. The first differences of non-stationary series were used in the further analysis.

The Granger Causality (GC) tests are applied to find whether an econometric strategy under consideration is meaningful. The GC tests can identify a specific type of one-way causality, which is based on modelling dynamical structures via lagged values of both variables (Granger, 1969; 1988). We test whether variables y (production, prices, employment) are Granger-caused by the respective. The direct Granger test regresses each variable on lagged values of itself and the other explanatory variable:

We tested the null of the joint significance of parameters β in the two regressions, in case of rejecting the null, the Granger causality is confirmed. F-stats and respective probabilities are shown in Appendix (Table A2) for lags up to three. The results of the GC tests were encouraging in terms of possible capacity of some CI indicators to be employed in forecast models.

1.3. The ARIMA Benchmarks

The autoregressive integrated moving average (ARIMA) models are the most general class of models for forecasting a time series. The naïve models frequently are used for short-term forecasting (‘nowcasting’). The time series for dependent variables are linear and come out from the past values of the same variable and its random errors. Economic performance indicators y, p, and l in our model are all stationary and modelled via the ARMA representations for all countries. Coefficients, standard errors, Akaike information criterion, and adjusted R-squared are reported in Annex Table A3.

T a b l e 1

ADF Tests for Stationarity

	SK		CZ		HU		PL	
	t-stat	*p-value*	*t-stat*	*p-value*	*t-stat*	*p-value*	*t-stat*	*p-value*
Production								
ADF	–19.76	0.00	–19.15	0.00	–18.75	0.00	–18.24	0.00
PP	–20.14	0.00	–18.57	0.00	–18.42	0.00	–18.25	0.00
CI (production)								
ADF	–3.50	0.01	–3.50	0.01	–3.74	0.01	–3.05	0.03
PP	–11.76	0.00	–3.36	0.01	–3.73	0.01	–2.48	***0.12***
Prices								
ADF	–9.05	0.00	–9.64	0.00	–8.37	0.00	–8.92	0.00
PP	–9.09	0.00	–10.81	0.00	–9.27	0.00	–8.89	0.00
CI (prices)								
ADF	–3.30	0.01	–3.55	0.01	–2.46	***0.13***	–3.77	0.00
PP	–6.53	0.00	–3.40	0.01	–2.36	***0.16***	–3.36	0.01
Employment								
ADF	–5.62	0.00			–4.63	0.00	–3.76	0.00
PP	–12.43	0.00			–9.01	0.00	–8.93	0.00
CI (employment)								
ADF	–3.73	0.00			–2.52	***0.11***	–2.02	***0.28***
PP	–3.17	0.02			–3.13	0.03	–2.39	***0.15***

Notes: MacKinnon (1996) one-sided p-values. Results indicating non-stationarity in bold.
Automated selection of lags in ADF test. The test is based on Akaike information criterion.

Source: Authors' computations.

1.4. OLS Regressions – Selecting and Testing Models

Model selection evolved in two phases:

(1) The ordinary least square (OLS) regressions were used to examine whether the CI confidence indicators were useful for forecasting developments in real economy. The real economy variables for production (*y*), producer prices (*p*) and employment (*l*) were dependent variables. The lags higher than those employed in the ARMA models were not used in the OLS models. The corresponding CI indicators (*ey*, *ep* and *el*) or their first differences (*dep* for HU and *del* for PL in stationary time series) were explanatory variables along with the autoregressive terms of the lagged dependent variable. We aimed to keep models as simple as possible trying to avoid serial correlation of residuals at the same time.

(2) In two cases (*ey* for CZ and *ep* for Pl), lagged CI or differenced CI had to be used. Despite the non-stationarity detected by ADF and Phillips-Perron tests, we chose to employ the variable *el* instead of *del* for Poland referring to Baffes (1997). The model performed better in all tests compared to the one with differenced indicator.

Table 2

The Global fit Measures of the ARMA and OLS Models

	SK		CZ		HU		PL	
	ARMA	AR. CI	ARMA	AR. CI	ARMA	AR. CI	ARMA	AR. CI
y	0.10 5.27	0.17 5.54	0.06 3.85	0.15 3.74	0.08 4.68	0.13 4.62	0.06 3.99	0.07 3.97
p	0.12 1.87	0.17 1.81	0.07 1.71	0.09 1.69	0.26 1.42	0.12 2.69	0.19 1.65	0.22 1.62
l	0.17 2.00	0.21 1.97			0.26 1.42	0.33 1.33	0.37 0.23	0.40 0.18

Note: Adjusted R squared and Akaike information criterion.
Source: Authors' computations.

The models selected for comparison with the ARMA benchmark models were based on Akaike information criterion (AIC). The adjusted coefficients of determination for the best-performing models, then AIC and statistical significance of the Business Survey indicators are presented in Table 2.

Selected OLS models were subject to further tests of statistical properties of the residuals (normality, serial correlation, heteroskedasticity) and coefficients (stability over time). The histograms showed residuals symmetrically distributed around zero with an apparent higher-than-normal kurtosis (indicated by high values of the Jarque Bera test statistic in all models). The Lilliefors test confirmed normality on the 0.05 level for most models. The Breusch-Godfrey Serial Correlation Lagrange multiplier (BGSLM) test examined presence of serial dependence. The test was not expected to detect any autocorrelation of order 1. The models captured the autoregressive structure by the lag of dependent variable to a sufficient extent. This was also confirmed by significance of either AR or MA terms in ARMA models (see Annex Table A2 for details). The employment model for Poland was the only exception and did not seem properly modelled by OLS regression. The serial correlation was tested up to 12th lag and revealed presence of the autocorrelation in one single model (production for Slovakia). The White heteroscedasticity test results did not suggest any serious problems in most models. Some residuals alternatively passed the Breusch-Pagan-Godfrey test. For exceptions, we report heteroskedasticity-robust estimates.

The Chow test is used in time series analysis to test for the presence of a structural break (see Annex Table A4). We used the Chow test to examine stability of coefficients over time, given a break at 2008M4 which is a mid-point for the most of the time series. Huge shock of the crisis was present in the second half of the sample, and we did not expect stable coefficients estimates to be confirmed. Instability of the coefficients presents no concern in terms of comparing model types since we do not infer on any numerical values of the coefficient estimates. The statistical properties of the models are reported in the Annex (Table A4).

The global fit of selected models is presented in Table 2. In all cases but one (prices, HU) confirming additional explanatory power of CI, however forecasting accuracy should be tested by means of pseudo-real time forecast simulation.

1.5. Comparing Forecasts – Diebold-Mariano Tests

Comparisons of forecasting errors by OLS models (a) the naïve (ARMA), and (b) models with the CI indicators should indicate whether the confidence indicators are useful for forecasting developments in real economy or not. Diebold and Mariano (1995) introduced widely applicable test of the null hypothesis of no difference in the accuracy of two competing forecasts. We generated series of RMSEs of 4-periods-ahead forecasts based on rolling sample starting 2006M1 through 2016M8 (covering substantial shocks in time period of economic crisis were likely to impact accuracy of the forecasts) for both ARMA and OLS models and checked for statistical significance of the differences. Results of comparisons are presented in Table 3. The coefficient significantly different from zero implies difference in the forecasting accuracy of the two models at the given significance level. A positive difference is in favour of the model with the confidence indicator.

In all the cases the ARMA models perform worse than the models with the confidence indicators, and in 5 out of 11 models the difference is significant at least on the 0.05 level.

T a b l e 3

The Diebold-Mariano Test

	SK	CZ	PL	HU
Production	0.03 *0.56*	0.09 ***0.01***	0.03 ***0.00***	0.00 *0.99*
Prices	0.02 *0.34*	0.02 ***0.01***	0.03 ***0.03***	0.02 *0.43*
Employment	0.04 ***0.01***		0.01 *0.80*	0.04 *0.18*

Source: Authors' computations.

2. Conclusions and Directions for Future Research

Many studies found predictive power of 'soft' indicators varying among OECD Member Countries. These findings were confirmed in our research. We found that confidence indicators had some predictive power for forecasting economic developments in the V4 countries, but the predictive power varied across countries and indicators. Absolute values of the adjusted R-squared were relatively low, but significantly higher than those in studies using consumer confidence indicators for forecasting GDP growth and consumer spending in the USA and Euro Area. The CI-based models generated adjusted R-squared 0.07 – 0.17 for industry output, 0.09 – 0.22 for producer prices and 0.21 – 0.40 for industry employment in the V4 countries. The Granger tests may suggest one-way causation between the lagged CI variables and trends in output and employment in most cases, but not in producer prices. It suggests that the CI variables have some explanatory power for forecasting future economic patterns in industry.

Time series under analysis included periods of economic boom and boost of economic downturn. The best results for (i) establishing causal relationships between soft and hard data, and (ii) forecasting economic activity were obtained for industry output and employment in the V4 countries. The GC tests indicate possible time lags 1 and 2 for confidence indicators on price, output and employment could be employed in the nowcasting model. The OLS models, however, performed best with no time lags (except for 2 cases).

We conclude that the actual CI variables seem to reflect future patterns of economic development in next 1 – 2 months, and not just opinions by economic agents based on current or past economic trajectories.

All OLS models performed better than the naïve ones, and in 5 OLS models (out of 11) the differences were statistically significant on the (at least) 0.05 level.

We assume that businesses have more control and are able to forecast industry employment with higher accuracy than output and producer prices. In period of three months, for which enterprises report their expectations in the Business Survey, industry employment is less flexible when reacting to turning points in economic trends than producer prices and output. In most developed OECD Member Countries hiring and firing labour force is subject to stringent regulations on notice periods and compensation payments for job loss. Predictability of the industry output proved lower than that of employment, but higher than predictability of producer prices. Industry output is subject to contractual arrangements. Our research indicates that soft indicators retain some predictive power over period of economic up- and downturns.

Model results indicated that CI indicators may be an important source of information for nowcasting economic activity in industry in the Czech and Slovak Republics, Hungary, and Poland. The CI indicators improve reliability of short--term economic forecasts and are valuable tools for business analysts and policy--makers in the V4 countries.

The interesting question is which factors are responsible for diverse predictive powers of ‘soft’ indicators across V4 countries? The predictive power of national indicators results may be impacted by a number of factors:

- number and significance of unexpected economic shocks;
- industry structure of national economy; same industries are more susceptible to economic shocks than other ones;
- use of in-sample or out-of-sample testing framework (Gelper and Croux, 2010);
- quality of statistical coverage and its relevance for forecasting trends in specific sectors of national economy; Forecasting power of confidence indicators may depend on sample size and coverage. Effective sample coverage depends on (i) sample coverage in terms of employment, turnover, and gross value added and (ii) targeted response rate. Particular countries significantly differed in their effective sample coverage. Hungary, for example, had a relatively large sample of 3 500 businesses, but employment coverage was 10 – 15% of total and targeted response rate 23 – 27% (Annex, Table A1). Effective sample coverage, adjusted for employment coverage and targeted response rates in industry, was 56.3% for Poland, 48.7% for Slovakia, 46.8% for the Czech Republic, and 3.2% for Hungary in period 2004 – 2016. Low effective sample sizes may result in noisy estimates of predicted values.

The abovementioned factors are not mutually exclusive. They may combine in various patterns and contribute to higher or lower predictive power of a short--term forecast.

There are several options for increasing explanatory power of the confidence indicators. The most obvious one is to compare at the sectoral and industrial structure of a national economy to structure of businesses included in the Business Survey. By this analysis, we hope to have shown a potential for enhancing confidence indicators-based forecasting in the V4 countries.

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Annexes

Table A1

Industry: Basic Indicators and Overview of Samples for the Business Survey

	CZ	HU	PL	SK	RO	BG
Industry gross value added, turnover and exports						
Gross value added, EUR	41.1	21.8	75.8	15.8	22.4	5.2
Employment, as % of total	28.9	22.5	23.1	24.9	23.2	21.3
Employment, thousands persons	1 337.0	896.6	3 313.9	490.9	2 148.4	763.8
Exports of goods, % GDP	58.4	65.0	33.4	73.1	26.9	51.7
Business survey (industry)						
Sample size, no of enterprises	1 000	1 500	3 500	756	2 338	1 194
Sample coverage, employment, %	55.0	10.0 – 15.0	58.0	61.3	n.a.	45.6
Sample coverage, turnover, %	65.0	n.a.	n.a.	71.8	n.a.	71.7
Response rate (targeted), %	85.0	23.0 – 27.0	97.0	79.4	90.0	97.1

Notes: The annual averages for 2004 – 2015. The data on the industry gross value added are in the constant 2010 prices.

Sources: Eurostat (2016a); Eurostat (2016b).

Table A2

Granger Causality Tests

Lags		SK	CZ	HU	PL
Production					
1	y does not GC CI	0.94	0.10	0.97	0.06
	CI does not GC y	0.00	0.00	0.00	0.81
2	y does not GC CI	0.31	0.02	0.06	0.17
	CI does not GC y	0.00	0.01	0.00	0.21
3	y does not GC CI	0.69	0.00	0.06	0.00
	CI does not GC y	0.00	0.18	0.00	0.01
Prices					
1	p does not GC CI	0.37	0.60	0.05	0.01
	CI does not GC p	0.05	0.03	0.24	0.29
2	p does not GC CI	0.62	0.83	0.15	0.01
	CI does not GC p	0.12	0.03	0.44	0.13
3	p does not GC CI	0.56	0.85	0.25	0.02
	CI does not GC p	0.11	0.08	0.68	0.22
Employment					
1	l does not GC CI	0.44		0.00	0.00
	CI does not GC l	0.00		0.00	0.00
2	l does not GC CI	0.56		0.02	0.00
	CI does not GC l	0.00		0.00	0.00
3	l does not GC CI	0.98		0.03	0.02
	CI does not GC l	0.05		0.00	0.00

Notes: Probabilities of F-stat under the null reported. Differenced CI instead of non-stationary CI series.

Source: Authors’ computations.

T a b l e A3

ARMA Benchmarks

Benchmark ARMA for production								
	SK		**CZ**		**PL**		**HU**	
	coeff.	*t-stat*	*coeff.*	*t-stat*	*coeff.*	*t-stat*	*coeff.*	*t-stat*
const	0.58	3.49	0.31	2.88	0.43	4.27	0.36	2.63
AR(1)	–0.34	–5.06	–0.21	–3.04	–0.25	–3.65	–0.29	–4.19
AR(2)								
AR(4)								
AR(11)								
MA(1)								
MA(2)	–0.07	–3.57	0.12	176.2				
R2_adj	0.10		0.06		0.06		0.08	
SE	3.35		1.65		1.77		2.50	
AIC	5.27		3.85		3.99		4.68	
Benchmark ARMA for prices								
	SK		**CZ**		**PL**		**HU**	
	coeff.	*t-stat*	*coeff.*	*t-stat*	*coeff.*	*t-stat*	*coeff.*	*t-stat*
const					0.15	2.34		
AR(1)	0.34	4.69			0.49	7.59	0.42	6.31
AR(3)							0.20	3.04
MA(1)			0.28	4.11				
MA(2)					–0.16	–6.97		
MA(4)								
R2_adj	0.12		0.07		0.19		0.26	
SE	0.61		0.57		0.55		0.48	
AIC	1.87		1.71		1.65		1.42	
Benchmark ARMA for employment								
	SK		**CZ**		**PL**		**HU**	
	coeff.	*t-stat*	*coeff.*	*t-stat*	*coeff.*	*t-stat*	*coeff.*	*t-stat*
const								
AR(1)					0.92	22.26	0.49	7.83
AR(3)							0.21	2.92
AR(4)	0.14	2.31						
AR(12)								
MA(1)	0.27	4.73			–0.61	–7.43		
MA(2)	0.28	4.73						
R2_adj	0.17				0.37		0.23	
SE	0.65				0.27		0.50	
AIC	2.00				0.23		1.46	

Source: Authors' computations.

Table A4

OLS Results

Production (y)	**SK**		**CZ**		**PL**		**HU**	
	coeff.	*t-stat*	*coeff.*	*t-stat*	*coeff.*	*t-stat*	*coeff.*	*t-stat*
const								
y(–1)	–0.46	–3.21	–0.31	–4.59	–0.27	–3.90	–0.32	–4.77
y(–2)								
y(–11)								
CI	0.03	4.82	0.06	4.13	0.04	4.55	0.06	4.27
CI(–1)			–0.03	–2.37				
R2 adj	0.17		0.15		0.07		0.13	
AIC	5.54		3.74		3.97		4.62	
Reset	0.05		0.19		0.31		0.06	
Heterosked.**	0.01		0.08		0.65		0.08	
Serial corr 1	0.00		0.71		0.23		0.14	
Serial corr 12	0.01		0.12		0.38		0.66	
Chow mid-smpl	0.24		0.51		0.14		0.92	
Prices (p)	**SK**		**CZ**		**PL**		**HU***	
	coeff.	*t-stat*	*coeff.*	*t-stat*	*coeff.*	*t-stat*	*coeff.*	*t-stat*
const	–0.08	–1.65					0.17	2.52
p(–1)	0.27	3.73	0.20	3.05	0.36	5.37	0.32	4.72
p(–2)								
p(–3)								
CI	0.01	3.40	0.01	3.08	0.04	3.46	0.03	1.97
CI(–1)					–0.03	–2.76		
R2 adj	0.17		0.09		0.22		0.12	
AIC	1.81		1.69		1.62		2.69	
Reset	0.11		0.64		0.36		0.97	
Heterosked.**	0.46		0.00		0.01		0.83	
Serial corr 1	0.47		0.03		0.01		0.12	
Serial corr 12	0.82		0.31		0.20		0.18	
Chow mid-smpl	0.87		0.51		0.71		0.20	
Employment (l)	**SK**		**CZ**		**PL**		**HU**	
	coeff.	*t-stat*	*coeff.*	*t-stat*	*coeff.*	*t-stat*	*coeff.*	*t-stat*
Const	0.14	2.59			0.12	4.52		
l(–1)	0.27	4.66			0.20	2.77	0.27	3.84
l(–2)								
l(–4)								
CI	0.01	2.59			0.01	6.71	0.02	5.54
R2 adj	0.21				0.40		0.33	
AIC	1.97				0.18		1.33	
Reset	0.00				0.05		0.04	
Heterosked.**	0.15				0.24		0.19	
Serial corr 1	0.01				0.23		0.69	
Serial corr 12	0.20				0.01		0.76	
Chow mid-smpl	0.00				0.00		0.00	

Notes: * differenced CI instead of level; ** In case of heteroskedasticity HAC *t*-ratios reported.

Source: Authors' computations.