NÁRODNÁ BANKA SLOVENSKA
EUROSYSTÉM

Discussion Note

Nowcasting wage growth in Slovakia[1]

For the purposes of 1-quarter ahead wage forecast (wage nowcasting), the method of forecast combination (FC) has been our method of choice so far. This approach brings significantly better results compared with a simple ARMA model. However, we decided to also test a factor model approach (FM). In this analytical commentary, we provide more detailed information about both methods and compare their use for the purposes of a short-term wage forecast. Based on testing of the two methods, the results show that the FM is more appropriate to explain the drivers of current wage developments and to provide wage forecasts for periods T+1 and T+2. It also serves as a tool to extract fundamental information from many monthly indicators. For short-term forecasts of current quarter (T) wage developments, we continue to prefer the originally used FC method. Both methods under comparison will serve as useful complementary tools within our forecasts and analyses.

In this article, we explain to the public and evaluate our approach to forecasting short-term average nominal wage developments in the Slovak economy. The approach is regularly applied in the official NBS forecasts, in the NBS Monthly Bulletins and commentaries.

We present the structure and results of the forecast evaluation of the FC method, which has been a standard wage forecast tool for the current quarter at the NBS. Within this method, we compute a weighted average of results from various OLS fitted equations (so-called bridge equations). The two main explanatory variables within these equations are the available monthly indicators of wages ("Monthly wages in selected branches" published monthly by the Statistical Office of the Slovak Republic, SO SR and monthly figures on social contributions[2] levied on employees provided the Social Insurance Agency, SIA). We compare its results with those of a benchmark ARMA model.

This commentary also compares the FC method with a factor model approach[3]. The factors used within the model are based on monthly indicators from 3 areas of classical wage growth determinants: labour productivity, inflation/inflation expectations and labour market tightness. The factors are used as explanatory variables in a regression equation explaining wage growth.

It seems that as far as the nearest (current) quarter is concerned, the FC approach dominates from the forecast precision perspective. The FM also beats ARMA models, but only marginally. This suggests that the FC model is more appropriate for the 1 step-ahead forecast. The FM is more useful to explain the current wage developments, forecast a few more quarters ahead and extract information important for wage growth from a large number of monthly indicators.

1. Forecast combination method

The forecast combination method is based on simple OLS bridge equations. The explained variable is either the economy-wide wage[4] or wage in the private sector (both published with quarterly

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[1] This is an abridged translation of the Slovak version:
https://www.nbs.sk/_img/Documents/_komentare/AnalytickeKomentare/2017/AK44_Nowcasting_miezd.pdf

[2] We use only a part of the social contributions called accident insurance, which is completely proportional to the volume of gross wages paid to the employees.

[3] Methodology based on Vávra et al. (2015).

[4] We refer to average wage as "wage" or "wages" interchangeably in this commentary.

frequency), depending on which explanatory variable enters the right-hand side. We use monthly wages in selected branches (WM, closely related to the private sector) and monthly social contributions per employee (SOC_PER_E) as explanatory variables[5].

In case of private sector wage as the explained variable, we add to this with an appropriate weight the assumed wage growth in public sector from the latest NBS official forecast and thus obtain an economy-wide wage growth figure. We use wages in two different methodologies as explained variables. These are the ESA methodology and the national wage methodology, with the latter being our preferred headline indicator. In case there is a significant under-/overvaluation in the former methodology over the past year, we correct the results for this difference, so that the results from individual equations are consistent with each other.

Table 1 Bridge equations specification

Equation nr.	Specification	Method	Correction for heteroskedasticity and autocorrelation?	Equation weight
1	%Y-o-Y(W_PRIV) C %Y-o-Y(W_PRIV(-1)) %Y-o-Y(WM)	OLS	-	0.28
2	%Q-o-Q(W_PRIV) C %Q-o-Q(W_PRIV(-1)) %Q-o-Q(WM)	OLS	-	0.28
3	%Y-o-Y(W_TOT) C %Y-o-Y(W_TOT(-1)) %Y-o-Y(SOC_PER_E)	OLS	-	0.18
4	%Y-o-Y(W_ESA) C %Y-o-Y(W_ESA(-1)) %Y-o-Y(SOC_PER_E)	OLS	-	0.13
5	%Q-o-Q(W_ESA) C %Q-o-Q(SOC_PER_E)	OLS	Y	0.13

Note: The dependent variable is followed by explanatory variables; W_PRIV = average wage in the private sector (national economy less sections O,P,Q of the NACE classification); W_TOT = average wage in the national economy; W_ESA = average wage in the national economy according to the ESA methodology; WM = average wage in selected branches of the private sector (monthly indicator, based on author's calculations); SOC_PER_E = average social contributions per employee

Out of the 5 bridge equations, we obtain 5 estimates of annual average wage growth, which we need to weight based on their respective forecast accuracy. The weighting is captured by the following formula:

$$(1) \qquad w_i = \frac{1/MAE_i}{\sum_{j=1}^{5}(1/MAE_j)} \quad ,$$

where w_i is the weight of the i-th equation and MAE_i is the mean absolute deviation of the annual growth estimate from the i-th equation vis-à-vis actual growth. An equation with an x times greater deviation relative to another equation therefore receives x-times smaller weight in the computation of the resulting nowcasting. The coefficients in the individual equations are statistically significant and have the expected signs.

We evaluated this approach over the 2013Q1 to 2015Q4 time horizon. For each of these quarters, we computed 6 separate values of nowcasting in a quasi-real-time setting. From the first (earliest) to the 6th (latest) estimate, we are using a realistic data set according to the actual data availability at that time. The reason for 6 estimates per quarter is that there can be 6 new data points per quarter, given that we have 2 monthly explanatory indicators. Altogether, we have 72 values of nowcasting for the period under evaluation. The missing monthly data until the end of the quarter is forecast using an ARMA model. The data and bridge equations are updated in each nowcasting. In this way, we obtain a recursive out-of-sample forecast. The estimates from all 5 bridge equations make up the weighted sum according to the criterion in Equation 1[6].

The evaluation results are presented in Table 2. The FC method is being compared with an ARMA model evaluated for the same period. Nowcasting by FC yields almost 35 % more precise results using

[5] The individual equations also include lagged explained variable as a further explanatory variable on the right-hand side, to help correct autocorrelation problems, if necessary. After inclusion, they are free from autocorrelation and heteroskedasticity.
[6] The weights are fixed for the whole evaluation sample. To increase the robustness of the conclusions, we also present a version with updating weights below.

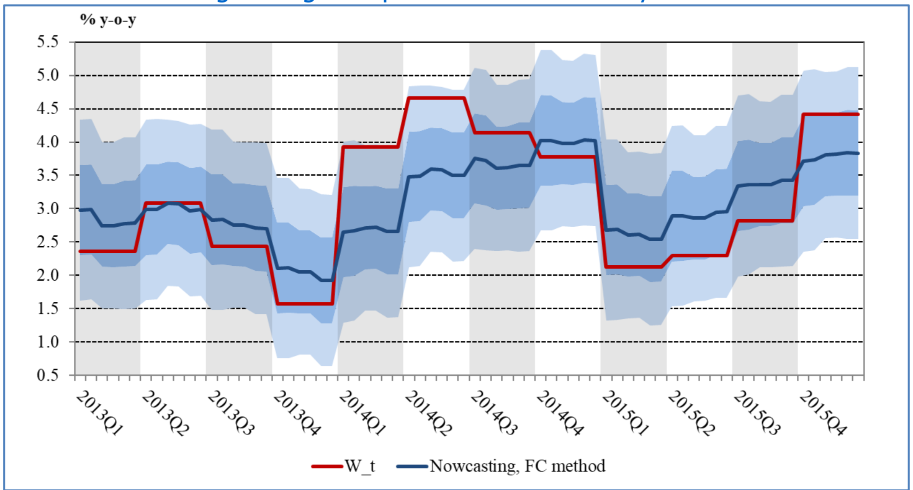
the MAE criterion. Using RMSE, the FC is 40 % more precise. The mean absolute distance of nowcasting from actual wage growth rate is approximately 0.6 p.p. Positive and negative deviations offset each other and as a result, nowcasting is not biased. Therefore, the FC method dominates the ARMA approach using all three evaluation criteria (MAE, RMSE and bias). The recursive estimates as well as actual values are shown in Chart 1. It shows that typically any acceleration (or deceleration) implied by the FC method is followed by a change of the actual wage growth dynamics in the same direction.

Table 2 Evaluation of the FC method vs. an ARMA benchmark

Nowcasting approach	MAE	RMSE	% diference of MAE vs. ARMA	Bias*
Forecast combination (5 equations)	**0.56**	0.65	-34.6	-0.03
ARMA(4,1)	**0.85**	1.07	-	-0.42

Note: RMSE = root-mean-square error. Explained variable: annual average wage growth; deviations calculated against actual annual growth; *average overvaluation (+) or undervaluation (-) of nowcasting against actual values in p.p.; the ARMA model estimated on the 2010 to 2015 horizon, but conclusions are the same, when a longer sample (2000 – 2015) is used. The ARMA specification was selected based on minimum AIC (Akaike information criteria). Bridge equations are estimated on a sample from 2009 to 2015.

Chart 1 Nowcasting for a given quarter and uncertainty bands



Source: SO SR, Social Insurance Agency, author's calculations. W_t is actual annual nominal wage growth (based on seasonally adjusted data). For each quarter, there are estimates in the chart. The uncertainty bands are given by the distance +/- RMSE and +/- 2*RMSE.

To verify the robustness of the previous results, we also tested an alternative evaluation version, where the weights of each equation are being updated for every nowcasting[7]. Table 3 confirms that this alternative evaluation method supports the above results with similar precision statistics.

Table 3 Evaluation of the FC method with alternative weights

Nowcasting approach	MAE	RMSE	% diference of MAE vs. ARMA	Bias*
Forecast combination (5 equations)	**0.51**	0.61	-39.9	-0.02
ARMA(4,1)	**0.85**	1.07	-	-0.42

See note under Table 2.

[7] The updating was carried out in a setting with 24 quasi-real-time databases (2 per quarter from 2013Q1 to 2015Q4) and 24 resulting nowcasting outcomes.

2. A factor model as an alternative nowcasting method

At the turn of the millennium, factor models (FM) were popularised by authors such as Bernanke, Boivin and Eliasz (2004). An example of its application for the Slovak economy in case of GDP forecasts is a study by Vávra et al. (2015). The FM approach assumes that a set of several monthly indicators can be represented by a single[8] fundamental time series (so-called factor), which captures as much of the overall variability of the input monthly indicators as possible. In this way, we can summarise a large amount of information with the help of just one variable. The factor represents a quantification of a fundamental driving force, which might not be obvious from looking at many monthly indicators[9]. An advantage related to these factors stems from the fact that one does not need to include many monthly indicators in regression equations, which would weaken the reliability of results.

Within the FM approach, we view wage as being driven by four fundamental influences:

$$(2) \qquad W_t = f(\underset{+}{PROD}, \underset{+}{INF}, \underset{+}{TIGHT}, \underset{-}{COMP})$$

PROD stands for the labour productivity factor, INF is an inflation factor, TIGHT is a labour market tightness factor and COMP represents a so-called compositional effect (in upturns, when employment grows, average wage tends to be slowed down by hiring of new, relatively low-paid employees and vice versa in downturns[10]). The theoretical influence of these variables on wage is shown under Equation 2.

Each of the first three explanatory variables in Equation 2 is obtained as a factor representing several monthly indicators[11]. The COMP variable is approximated by annual employment growth in the ESA methodology in the given quarter. Table 4 provides an overview of the input (mainly monthly) indicators used in the computation of each factor. The productivity factor is based on standard measures of economic performance and some "soft indicators" from EC business and consumer surveys. The inflation factor is based on indicators of price developments, which might be key for consumers' and employees' views of inflation pressure. The tightness factor captures interactions between labour demand and supply and the resulting surplus or shortage of labour force. The three factors should be procyclical, whereas the COMP variable is expected to be countercyclical. The input variables for individual factors were selected based on the spectrum of available monthly and other timely economic indicators of the domestic economy. In the Annex, we present a graphical view of the factors and their related input indicators.

Table 4 Timely economic indicators and their mapping to individual factors

LABOUR PRODUCTIVITY FACTOR	INFLATION FACTOR	LABOUR MARKET TIGHTNESS FACTOR
Productivity out of monthly turnover	HICP inflation	Perceived shortage of labour force*
Productivity out of monthly export	Consumers' current inflation perceptions	Vacancies to unemployed ratio
Economic sentiment indicator (ESI)	Consumers' inflation expectations	Employers' employment expectations
Consumers - opinion on current economic developments	HICP inflation - food	Consumers' unemployment expectations
Consumers - opinion on expected economic developments	HICP inflation - energy	
Utilisation of production capacity in industry*	HICP inflation - transport services	
Production trend in recent months**		

Sources: Statistical Office of the Slovak Republic, EC, Labour Offices. The first 2 productivity indicators are in nominal terms. *Quarterly, but very timely indicators. Hard-indicators are being used in annual growth transformation, soft-indicators in levels (vacancies/unemployed also in levels. **Indicator from EC business and consumer surveys weighted for industry, trade, services and construction.

[8] Or other low number.
[9] In the above cited studies as well as in this note, the factor is being estimated by the method of principal components.
[10] A more detailed analysis of this phenomenon is undertaken e.g. by Kľúčik, Valachyová a Šaling (2016).
[11] Some of the indicators are in fact quarterly (Table 4) but are published in a timely fashion (i.e. already during the current quarter) and thus provide early information about wage developments. These indicators have a constant value for all 3 months of the given quarter.

The resulting factors enter a regression equation (2), which we use to estimate the relationship between wage growth and the individual factors. The OLS method is used in the estimation. The dependent variable is annual wage growth in the national economy. The equation includes also a lagged wage growth term as an additional explanatory variable. Various lag lengths of the explanatory variables were tested, as well as moving average transformations. The resulting selected equation is presented in Table 5. All the variables are statistically significant at 10 % significance level. The coefficient signs are in line with prior theoretical expectations and R^2 is relatively high. The significant impact of the lagged explanatory variable signifies some inertia and possibly wage rigidity, which means that wages react to current fundamentals only with some time lags. The estimated equation helps us generate forecasts of wage growth for the near term. It also helps us quantify the influence of individual factors on the current wage growth (Chart 2).

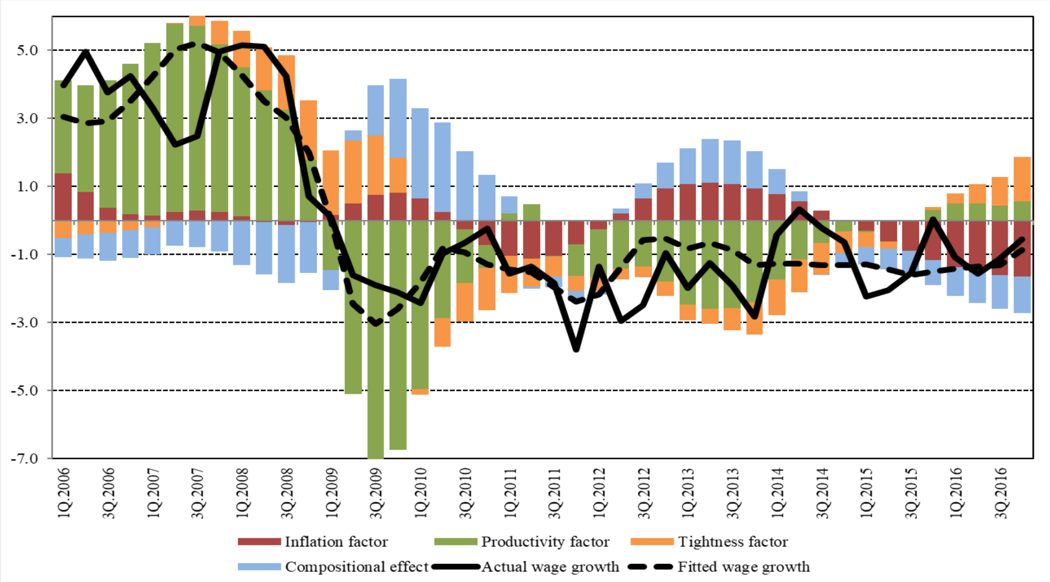
Chart 2 shows that the influence of labour market tightness has been growing recently, which is reflected in a moderate wage acceleration. Employers have been warning for several months that due to the negative demographic developments and continuing economic growth, finding appropriate employees is getting more difficult. The ensuing shortage of labour force is contributing to the wage acceleration. At the same time, economic performance and labour productivity growth had a moderately positive impact. These positive effects remain below their peak influence in the pre-crisis period, nevertheless. We also observe a gradual weakening of the inflation influence on wages due to low inflationary pressures. In times of stronger employment growth, the model implies a negative compositional effect limiting wage growth.

Table 5 Estimation results

Dependent variable: Wage growth (%, YoY)		
Sample: 2003Q1 2015Q4		
Variable	**Coefficient**	**p-value**
C	2.56	0.00
Inflation	0.29	0.01
Productivity	0.66	0.00
Labour market tightness	0.31	0.04
Compositional effect	-0.31	0.07
Lagged dependent variable	0.58	0.00
R-squared	**0.85**	
Adjusted R-squared	**0.84**	
Durbin-Watson statistic	**2.03**	

Source: author's calculations. Note: The productivity factor is transformed using a 2-quarter moving average. The inflation and tightness factors are lagged by 3 and 4 quarters respectively. The inflation factor is transformed using a 4-quarter moving average.

Chart 2 The contributions of factors to wage growth (YoY, %, p.p.)



Source: author's calculations. Note: Fitted wage growth and contributions created based on a dynamic simulation of Equation 2 (Table 5). Contributions and growth rates represented as deviations from the long-run average (2006-2016). The chart depicts average nominal wage.

We also look at the predictive ability of the above factor model by comparing it to the FC and ARMA approaches. The results from Table 2 are extended in Table 6 by including the evaluation results of the factor model. The factor model was evaluated in the same way as the FC method (72 quasi-real-time estimates for the nearest quarter within the period 2013Q1 to 2015Q4). The factor model is not as successful as the FC method, although it beats the ARMA approach[12]. This implies that nowcasting for the nearest quarter should continue to be based on the FC method, even though the factor model is theoretically appealing.

However, the FC approach can only be used to forecast the current unknown quarter (quarter T). For quarters T+1 and T+2, there are no explanatory variables available within this approach. In contrary, the factor model is applicable for wage forecasts precisely for these future periods, as it largely uses lagged values of explanatory variables.

Table 6 Evaluating the predictive ability of the factor model for the nearest quarter

Nowcasting approach	MAE	RMSE	% difference of MAE vs. ARMA	Bias*
Forecast combination (5 equations)	**0.559**	0.648	-34.6	-0.03
ARMA(4,1)	**0.855**	1.073	-	-0.42
Factor model	**0.785**	1.004	-8.2	-0.09

Source: author's calculations.

3. Conclusion

Nowcasting of annual wage growth in Slovakia for the current period (T) is typically carried out using the forecast combination method averaging results from several regression equations. It achieves lower prediction errors in comparison with alternative methods. The theoretically richer factor model can quantify contributions of the main fundamental wage drivers. It helps us extract summary information from many monthly and other timely indicators and is available to forecast for the T+1

[12] The factor model beats the optimal ARMA model also for the T+1 and T+2 horizons (evaluation for the 2015Q1 to 2016Q4 period).

and T+2 periods. Both methods should be viewed as complementary, which supports their future use in wage growth analyses.

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Literature

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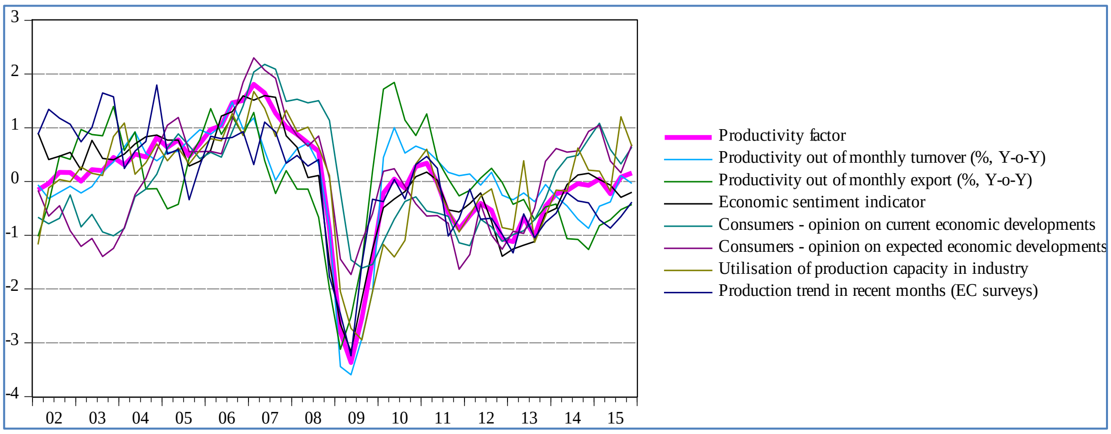
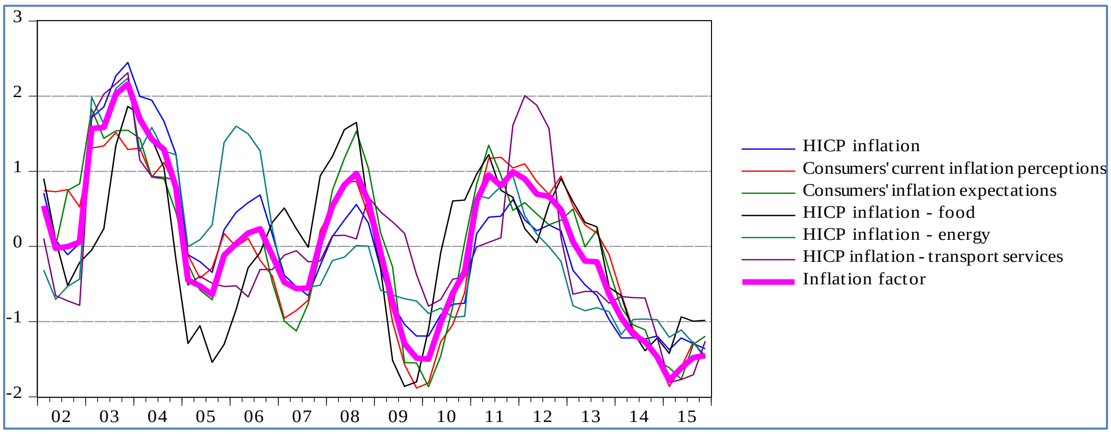
2. Bernanke, B., Boivin, J., Eliasz, P. (2004): „Measuring the effects of monetary policy: A factor-augmented vector-autoregressive (FAVAR) approach." NBER Working Paper Series, 10220.
3. Huček, J., Karšay, A., Vávra, M. (2015): „Short-term forecasting of real GDP using monthly data." NBS Occasional Paper, 1/2015.
4. Karšay, A. (2016): „Nowcasting employment." NBS Analytical commentary nr. 33.
5. Kľúčik, M., Valachyová, J., Šaling, M. (2016): „Pohyby na trhu práce menia dynamiku rastu miezd." CBR Commentary 2016/03.

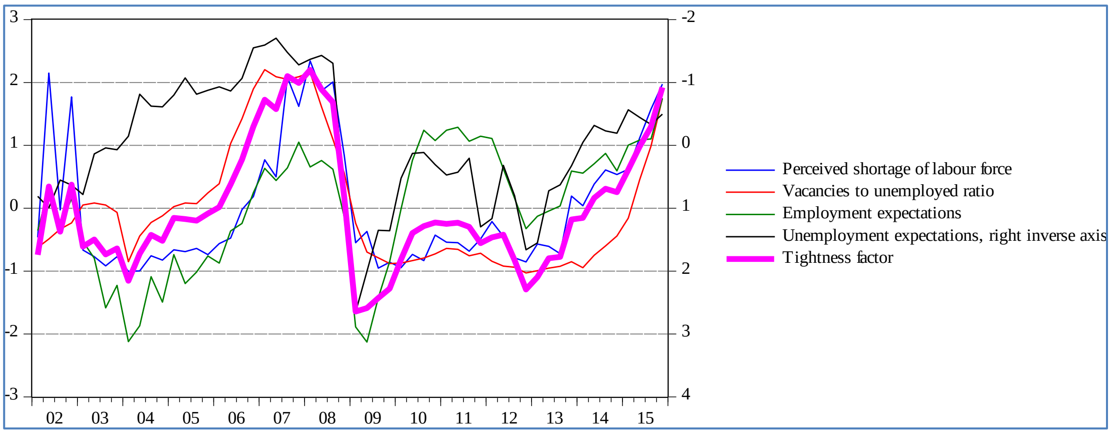
Annex – overview of monthly indicators and the factors



Source: author's calculations. Time series in the chart are standardised. The productivity factor captures 62 % of the variability of the early indicator set in the chart.



Source: author's calculations. Time series in the chart are standardised. The inflation factor captures 77 % of the variability of the early indicator set in the chart.



Source: author's calculations. Time series in the chart are standardised. The tightness factor captures 62 % of the variability of the early indicator set in the chart.